# Stock Liquidity and Investment Efficiency

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Doctor of Philosophy in Accounting

A thesis submitted for the degree of Doctor of Philosophy at
Monash University in 2017
Department of Accounting
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# ABSTRACT

This thesis examines whether high stock liquidity promotes firm investment efficiency. That is, whether high stock liquidity increases investment in firms that are more likely to under-invest, and whether high stock liquidity decreases investment in firms that are more likely to over-invest. Stock liquidity is a key feature in capital markets, and its importance has been studied extensively. However, prior research provides conflicting predictions and evidence regarding the directional relationship between stock liquidity and investment efficiency. Using a dataset of U.S. listed firms from 1995 through 2012 and an ordinary least squares regression methodology that tests investment efficiency from the perspectives of under- and over-investments, my thesis seeks to contribute to the ongoing debate on the effectiveness of stock liquidity on investment efficiency.

Two dominant explanations emerge from the liquidity literature regarding stock liquidity's informational and governance roles. First, high stock liquidity increases the informativeness of the stock price, and thereby improves transparency and market feedback, which in turn promotes investment efficiency. Second, high stock liquidity enhances the governance role of institutional investors through threat of voice and threat of exit and, thus, influences managers to invest efficiently. Consistent with these predictions, this thesis shows that stock liquidity is positively associated with investment efficiency. My inferences are robust to a battery of sensitivity and endogeneity tests, including two-stage least square regressions, change specifications, and alternative measures of dependent and test variables. As part of my additional tests, I also evaluate whether the observed relationships vary with firms that suffer from greater information asymmetry problems and that have greater ownership by monitoring institutions. The results from these analyses show that the impact of stock liquidity on investment efficiency is greater among young firms and high business risk firms, in which the presence of information asymmetry is more pervasive. Further, I find that the effect of stock liquidity on investment efficiency is more pronounced among firms with a high proportion of monitoring institutions.

In sum, my findings highlight the importance of the informational and governance roles that high stock liquidity plays in promoting investment efficiency among firms, particularly when firms' information environment is opaque and the proportion of monitoring institutions is high.

## DECLARATION

This thesis contains no material which has been accepted for the award of any other degree or diploma at any university or equivalent institution and that, to the best of my knowledge and belief, this thesis contains no material previously published or written by another person, except where due reference is made in the text of the thesis.

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**ACKNOWLEDGEMENTS**

The completion of my doctoral thesis was only made possible with the assistance, expert advice, and encouragement of many people. I am especially indebted to my thesis supervisors, Professor Vic Naiker and Dr Janto Haman, for their unyielding support and inspiration. Their feedback was invaluable in assisting me to complete this most challenging and yet most satisfying undertaking.

I also wish to express my gratitude to my independent assessor, Dr Dean Hanlon, and the discipline representative on my pre-submission panel, Professor Farshid Navissi.

I am most fortunate to be able to share knowledge, programming tips, life experience, and career aspirations with my cohorts who come from diverse backgrounds. In particular, I wish to thank my fellow PhD members for simply being there when I needed them. They are Chloe, Van, Enas, Edwin, Mehdi, Dhayani, Iliyas, Jennifer, Mars, Egor, and Samuel.

I truly appreciate the lecturing and tutoring opportunities at undergraduate and postgraduate levels provided by the Monash University Accounting department. This challenging face-to-face teaching experience has equipped me to be a more effective and flexible educator.

A big thank you to my many friends who provided me the encouragement to persevere with my PhD studies. In particular, I wish to thank Kheng, Sharon, Dr Choong, Alan, Diana, Dr Wong, Eric, Suan Yee, Lydia, Lai Ling, Jennifer, and Joan.

Richard Subber of Natick, MA, USA, an independent freelance editor, provided standard professional proofreading services.

Finally I wish to express my gratitude to my family – my spouse, Chin Leong, and my two sons for their continuous support and encouragement.

I dedicate my thesis to my parents.

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# Chapter 1: Introduction

## 1.1 Motivation and objective

Recent times have witnessed increased interest in understanding what drives a firm's investment efficiency because firms are known to not behave or invest as predicted by the friction-free capital market model of Modigliani and Miller (1958). This is because, in the real world, information asymmetry and agency problems are major frictions that distort firms' optimal investment behaviour (Stein 2003). Curative mechanisms that have been argued to mitigate the adverse effects of these frictions include the legal environment, auditing standards, incentive contracts, financial intermediation (Stein 2003), and financial reporting quality (Biddle and Hilary 2006; Richardson 2006; Biddle et al. 2009). While prior research has examined the usefulness of these curative mechanisms on firm investment (Wurgler 2000; Tong and Sapra 2009; Frederickson and Hilary 2010), the curative impact of stock liquidity on investment efficiency has not attracted much research attention. This research question is important because recent studies suggest that high stock liquidity can play an important role in mitigating the effects of information asymmetry and agency problems on investment outcomes (Edmans et al. 2013; Bharath et al. 2013). My thesis aims to fill this void in the literature by examining whether the extent of stock liquidity promotes investment efficiency by mitigating the extent of over-investments and under-investments in firms.

Efficient corporate investment dictates that firms allocate capital to value-increasing projects and withdraw capital from value-decreasing projects (Biddle et al. 2009; Bushman et al. 2011). Corporate capital allocation should be of great interest to researchers, managers, investors, and regulatory agencies, as such corporate decisions have long-term implications not only for firm value but also for country-level prosperity. For example, Gross Private Domestic Investment (GDI) contributes significantly towards expenditures included in the national Gross Domestic Product (GDP).[1] Specifically, GDI accounted for about 16 percent of the U.S. GDP in 2006-7, 11 percent in 2009, and 12.8 percent in 2012 (Fraser Federal Reserve Archive 2013). Thus, from a macroeconomic perspective, it is clear that efficiency in capital allocation has major ramifications for the real economy. It has profound effects on the future productive capacity of the economy and employment outlook. From a microeconomic perspective, efficient capital allocation can generate wealth to a firm's shareholders.

Ever since the seminal work by Modigliani and Miller (1958), researchers have devoted considerable efforts toward examining the determinants of corporate investment behaviour (Hubbard 1998; Stein 2003).[2] These studies seek to understand what influences corporate investment behaviour in an imperfect market infiltrated with information asymmetry and agency problems. It is well established that problems of asymmetric information, and the costs of adverse selection and moral hazard, represent the overriding forces that hamper efficient capital allocation (Hubbard 1998). Important determinants of investment behaviour identified in prior studies include financing constraints, agency-related factors, efficient stock prices, and financial reporting quality.

Firm capital investment literature in the context of financing constraints states that cash-poor and high-debt firms are more likely to have lower investments (Fazzari et al. 1988; Hoshi and Kashyap 1991) because investments in these firms are sensitive to the availability of internally generated funds due to costly external financing. Agency-related literature suggests that managers may not act in their shareholders' best interest by undertaking value-destroying investments (Jensen and Meckling 1976; Shleifer and Vishny 1997). For example, the presence of greater financial slack may incentivise managers to engage in empire building by over-investing (Jensen 1986). The efficient stock price

[1] Gross Private Domestic Investment has three components: (1) non-residential investment: expenditures by firms for machines and tools; (2) residential investment: expenditures by households and firms on apartments, buildings, and factories, and (3) change in inventories in a given period.

[2] According to Modigliani and Miller (1958), a firm's investment is only determined by the profitability of its investment opportunities as measured, e.g., by its value of Tobin's (1969) Q. A firm's financing structure and its reserves of cash and securities play no role in affecting firm investment behaviour.

literature suggests that informative prices can also affect managerial investment decisions (Subrahmanyam and Titman 2001). Empirical evidence in support of this view include Qi, Goldstein and Jiang (2007) who show that price informativeness is positively associated with value-enhancing investments. Other studies show that higher accounting information quality can improve investment efficiency by reducing information asymmetry, because an increase in transparency can facilitate better monitoring and contracting, and thereby help resolve adverse selection and moral hazard problems. Prior studies lending support for this view include Biddle and Hilary (2006), Biddle et al. (2009), Chen et al. (2011), and Balakrishnan et al. (2014b).

A separate stream of literature has investigated the impact of stock liquidity on various aspects of firm performance. Stock liquidity is defined as the ability to transact stocks swiftly in large quantities without causing material price changes (O'Hara 1995; Harris 2003; Amihud and Mendelson 2012). Public firms raise external equity from capital markets to finance their investments with expected positive net present value (NPV). Capital markets play an important role in this respect by channelling capital to its highest productive uses, which is essential to the vibrant growth of a national economy (Hubbard 2007). One of the main features of the capital market that facilitates this process is stock liquidity, which has been extensively studied in the context of asset pricing and market microstructure. It is theorised that high stock liquidity can play an important role in mitigating information asymmetry that undermines the efficient functioning of capital markets. Following the Global Financial Crisis of 2007-2009, the Committee on Capital Markets Regulation (CCMR) have put forward proposals to increase transparency (Committee on Capital Markets Regulation 2009).[3] High stock liquidity should reduce both adverse selection and moral hazard by improving transparency. Thus, higher stock liquidity may serve to enhance firm performance by mitigating these frictions.

Prior studies have linked stock liquidity to firm value, financing and dividend

[3] The Committee on Capital Markets Regulation is an independent and non-partisan research organisation with an objective of improving the regulation and transparency of U.S. capital markets.

policies, corporate investment, corporate governance, earnings management, and managerial incentives (e.g., Banerjee et al. 2007; Lipson and Mortal 2009; Bharath et al. 2013; Chen et al. 2015). Amihud and Mendelson (1986) argue that firms with higher stock liquidity command lower cost of equity due to greater transparency. The resultant lower cost of equity increases firm value (Amihud and Mendelson 1986, 1989), entices firms to issue capital (Lipson and Mortal 2009), and raises the level of investments (Amihud and Mendelson 2012). Alternatively, firms with less liquid stocks tend to pay dividends to compensate for the difficulty of selling their stocks (Banerjee et al. 2007). Recent studies show that liquid stocks lure institutional investors into accumulating large stakes and so allows these investors to influence firm decisions (Maug 1998; Admati and Pfleiderer 2009; Edmans 2009). Bharath et al. (2013) document that an exogenous increase (decrease) in stock liquidity improves (reduces) firm value, with a stronger effect in firms where executive compensation is more sensitive to the stock price. More recently, Chen et al. (2015) find that firms with higher stock liquidity are less likely to undertake accrual-based and real earnings management.

Despite the increasing research interest in the role of stock liquidity, little is known about the effect of stock liquidity on firm investment efficiency, which is an important element of corporate performance. My focus on providing insight into this is motivated by recent theories suggesting that stock liquidity can play important informational and monitoring roles in firms, which can lead to positive economic implications such as increased investment efficiency. This leads to my main research question: Do firms with higher stock liquidity invest more efficiently?

This thesis identifies two groups of theories that predict a positive association between stock liquidity and investment efficiency, namely (1) capital market-based, and (2) corporate governance-based explanations. Specifically, both explanations suggest that, if high stock liquidity resolves asymmetric information frictions through capital market-based and governance-based mechanisms, high stock liquidity is likely to have a positive impact on investment efficiency.

The capital market-based explanation focuses on why stock liquidity can improve corporate investment efficiency through higher information content of stock price. Informed investors are generally attracted to more liquid stocks, and their active and informed trading behaviours are instantly incorporated into stock prices. Informative stock prices can affect corporate investment decisions in two ways. First, informative stock prices improve transparency. As a result, it makes managers' actions more visible to shareholders and, thus, allows market participants to more closely scrutinise firm decisions. In this case, under-investments arising from adverse selection are less likely in the absence of a "lemon's problem" because firms are able to raise capital in external markets at a lower cost of capital due to investors' correct valuation of the firm (Myers and Majluf 1984). Hence, with lower cost of external financing, firms with liquid stocks are able to invest more efficiently. Second, informative stock prices improve the quality and velocity of market feedback to firm managers about the effectiveness of their actions (Durnev et al. 2004; Khanna and Sonti 2004). Thus, it induces managers to pay attention to shareholders' needs (Bond et al. 2010), especially if their compensation is tied to their firms' stock prices because movements in stock prices affect managerial wealth. This suggests that managers who are informed through the feedback of informative stock prices are likely to invest efficiently. The above two arguments are based on the premise that high stock liquidity accelerates the incorporation of private information into prices, causing prices to reflect the true value of a firm (O'Hara 1995; Subrahmanyam and Titman 2001; Khanna and Sonti 2004). As a result, stock liquidity increases transparency and feedback by generating informative stock prices, which in turn is expected to improve investment efficiency by resolving adverse selection and moral hazard problems.

The corporate governance-based explanation argues that the positive impact of stock liquidity can arise through enhancing the governance role of institutional investors. Improved stock liquidity also can help attract institutional investors who can positively affect corporate capital allocation decisions, because recent studies suggest that stock liquidity can have a positive effect on corporate investment via institutional investors' direct and indirect intervention. Maug (1998) argues that higher stock liquidity allows block (large stake) formation without causing significant stock price movement. Subsequently, large shareholders (blockholders) are incentivised to actively engage in information collection and direct intervention with the objective of improving firm value, realising that they can profit from trading against uninformed investors. Further, Admati and Pfleiderer (2009), Edmans (2009), and Edmans and Manso (2011) argue that blockholders also can enhance corporate control by possessing the ability to exit at ease, which also is promoted through increased stock liquidity. This form of indirect intervention (threat of exit) creates ex ante incentives for managers to invest optimally so as to satisfy well-informed institutional investors' demand for long-term value creation. Taken together, the enhanced governance role of institutional investors through increased stock liquidity can mitigate agency conflict by reducing information asymmetry, thereby increasing investment efficiency.

A common synthesis of the above arguments is that stock liquidity can improve investment efficiency by resolving information and agency frictions arising from the separation of ownership and control. Based on these arguments, the primary focus of this thesis is to investigate whether stock liquidity is positively associated with investment efficiency. As part of my additional tests, I also evaluate whether this positive relationship (if any) is more pronounced in firms that suffer from greater information asymmetry problems and have greater ownership by monitoring institutions.

## 1.2 Overview of research design

This section briefly describes the research design employed in my study. Following Biddle et al. (2009), a conditional ordinary least square regression methodology is employed in this study to investigate the effect of stock liquidity on investment efficiency. In order to test for both over- and under-investment simultaneously in the models, a composite variable representing the likelihood of a firm over-investing is computed by averaging the decile rank values for cash and leverage. Given that there is no single measure of stock liquidity capable of fully capturing stock liquidity, I use four measures of stock liquidity: (1) cost of trading as a percentage of prices, (2) zero-return days, (3) share turnover, and (4) a composite measure of stock liquidity that I develop by standardising and aggregating the three individual measures of stock liquidity. To test my main hypotheses, I regress the investment levels on stock liquidity conditional on a given firm's likelihood of over-investing, by interacting my measures of stock liquidity with the variable capturing the likelihood of over-investment in firms. I also control for a large vector of covariates identified in prior studies and perform a series of endogeneity and sensitivity tests to support the robustness of my main findings.

In examining the extent to which the relationship between stock liquidity and investment efficiency varies in the presence of greater information asymmetry problems, I examine how my main findings vary with a firm's (1) age and (2) business risk, proxied by operating income volatility. This is investigated by splitting the main sample into two-subsamples based on the median values of firm age and income volatility, and then estimating my main regression analysis separately for the subsamples. Likewise, to investigate whether the relationship between stock liquidity and investment efficiency varies with the proportion of monitoring institutional ownership, I rerun the main regressions separately for two subsamples representing firms with high and low proportions of monitoring institutional ownership.

The data used in the empirical tests are mainly obtained from public databases including *Standard & Poor's Compustat,* the *Centre for Research in Security Prices (CRSP), Thomas Reuters 13F,* and the *Institutional Brokers' Estimate System (IBES).*

## 1.3 Overview of main findings

This section summarises the sample selection and my main findings. I investigate my research question using the U.S. firms that are listed on the NYSE, AMEX, and NASDAQ for the period 1995 to 2012. My main findings show that stock liquidity is positively (negatively) and significantly associated with investments among firms with a higher likelihood of under-investing (over-investing), thereby supporting my two main hypotheses that collectively propose that higher stock liquidity improves investment efficiency. My findings are broadly robust to a series of endogeneity tests and other additional tests. My results are consistent with prior studies (Maug 1998; Subrahmanyam and Titman 2001; Khanna and Sonti 2004; Admati and Pfleiderer 2009; Edmans 2009) that outline the beneficial effects of stock liquidity in influencing firm decisions in other settings. These views suggest that higher stock liquidity encourages firms to undertake investments that increase shareholders' wealth in the long run, thus resulting in greater investment efficiency.

In my additional tests, I demonstrate that the relationship between stock liquidity and investment efficiency is more pronounced when firms are younger and have greater business risk (higher operating incomes volatility), consistent with the beneficial effects of higher stock liquidity being more prominent in situations where a firm's information environment is more opaque. These results are consistent with the view that higher stock liquidity increases the information content of stock prices, which improves market feedback to influence firm managers to make value-creation decisions (Subrahmanyam and Titman 2001; Khanna and Sonti 2004) and increases transparency so as to facilitate more effective oversight of a firm's decisions (Wurgler 2000; Durnev et al. 2003). I further show that higher stock liquidity has greater impact on investment efficiency when a firm has higher proportion of monitoring institutions that predominantly possess a long-term focus and are willing to commit to monitoring. These results support the view that higher stock liquidity facilitates large monitoring institutions' efforts to control and monitor firms' decisions, thereby enhancing investment efficiency.

Overall, my findings highlight the importance of informational and governance roles that stock liquidity plays in promoting investment efficiency among firms, particularly when firms' information environment is opaque and the proportion of monitoring institutions is greater.

### 1.4 Contributions and implications

This thesis makes several contributions to the literature. It provides initial evidence on the link between stock liquidity and real investment decisions by examining both under-investment and over-investment simultaneously, a departure from prior studies that focus on the impact of stock liquidity on the *levels* of specific type of investments such as investment in innovation (e.g., Fang et al. 2014). My study contributes to the extant stock liquidity literature by providing evidence of a positive impact of stock liquidity on investment *efficiency,* thus helping to inform the ongoing debate regarding the contrasting effects of stock liquidity on firm performance (Fang et al. 2009; Bharath et al. 2013; Fang et al. 2014; Chen et al. 2015). My findings are consistent with higher stock liquidity serving to improve the information environment and enhance monitoring, providing support to the proposition that firms can benefit from higher stock liquidity via greater transparency, feedback effects (Subrahmanyam and Titman 2001; Khanna and Sonti 2004; Bond et al. 2010), direct intervention (Maug 1998), and indirect intervention (Edmans 2009; Edmans and Manso 2011). In support of this interpretation, I document that the beneficial effect of stock liquidity on investment efficiency is more pronounced among firms with higher information asymmetry, suggesting that stock liquidity plays an informational role in increasing transparency and providing feedback to managers. I also document that the impact of stock liquidity on investment efficiency is greater among firms with higher monitoring institutional ownership, implying that high stock liquidity enhances the monitoring and governance roles of monitoring institutions. These results provide insight into discussion on the effectiveness of high stock liquidity as a form of corporate governance.

From practical viewpoints, my results should be of great interest to stock exchanges, regulators, investment managers, institutional investors, and boards of directors. Acquiring a better understanding of the role that stock liquidity plays as a curative device should increase investor confidence in capital markets, and increase their understanding of how stock liquidity affects the efficiency of capital allocation. The results from this thesis also can provide insights to institutional investors on how higher stock liquidity promotes their governance role in improving firms' corporate capital allocation. Board directors may wish to consider the stock liquidity levels in their firms to vary their oversight efforts on managerial investment decisions. For example, directors can seek ways of increasing monitoring efforts in firms with less liquid stock due to lower prominence of market feedback or external monitoring. My findings also have important implications for policies and regulations. With an improved understanding of the effect of stock liquidity and illiquidity on firm decisions, stock exchanges and regulators can implement strategies and measures to promote optimal liquidity so as to encourage value-enhancing investments in firms.

### 1.5 Structure of the thesis

The remainder of this thesis is structured as follows. Chapter 2 provides a comprehensive review of the determinants and consequences of investment and stock liquidity. Chapter 3 discusses the various theories that can explain how investment efficiency can be influenced by stock liquidity. A conceptual framework is drawn to pinpoint various mechanisms through which the levels of stock liquidity can affect investment efficiency. Chapter 4 discusses the research method, data, and sample selection. Chapter 5 presents the summary statistics. Chapter 6 reports the empirical results and robustness test results for the main tests. Chapter 7 covers the empirical results for the additional tests. Chapter 8 concludes.

# Chapter 2: Literature Review

## 2.1 Introduction

The main objective of this thesis is to examine how stock liquidity affects investment efficiency. This section reviews the literature related to the two main concepts pertinent to my research question: stock liquidity and investment efficiency. Section 2.2 organises the stock liquidity literature into two subsections: studies investigating the *determinants* of stock liquidity (Section 2.2.2), and studies on its *consequences* (Section 2.2.3). Similarly, Section 2.3 discusses the literature of corporate investment in two subsections: studies looking into the *determinants* of investment efficiency (Section 2.3.2), and studies on its *consequences* (Section 2.3.3). It is important to note that the streams of research on the consequences of stock liquidity and the determinants of investment efficiency are of particular relevance to this thesis.

## 2.2 Stock liquidity

The literature on stock liquidity is immense. It constitutes studies that associate stock liquidity with stock return (i.e., stock liquidity and asset pricing: for reviews, see Amihud et al. 2005; Amihud and Mendelson 2012), studies drawing from market microstructure literature that focus on trading mechanisms and the sources of illiquidity (e.g., O'Hara 1995; Madhavan 2000), research on the relationship between microstructure and asset pricing (e.g., Easley and O'Hara 2003), and recent but limited literature emphasising the role of stock liquidity in mitigating information asymmetry and agency problems (e.g., Maug 1998; Subrahmanyam and Titman 2001; Admati and Pfleiderer 2009; Edmans 2009).

Liquidity is important for market participants. Traders prefer liquidity because they can execute their trading strategies cheaply. Exchanges favour liquidity because it draws traders to their markets. Regulators advocate liquidity because liquid markets are usually less volatile than illiquid ones (Hasbrouck 2007).[4]

### 2.2.1 Definition of stock liquidity

Liquidity by itself is an ambiguous word. It can refer to any one of these concepts: market liquidity (on a stock exchange), stock liquidity (at the firm level) or an accounting perspective of liquidity (solvency). In this study, liquidity is used to refer to stock liquidity, which is commonly defined as the ability to transact stocks swiftly in big quantities without causing material price change.[5] High stock liquidity implies that there are always myriad willing buyers and sellers ready to take opposite positions of any trade at the current price. Hence, stocks are transacted more efficiently and with lower costs.

It is important to note that stock liquidity possesses multi-dimensional characteristics. For example, stock liquidity can be defined as "depth, breadth, and resiliency" (Hasbrouck 2007). *Depth* refers to the number of shares that can be traded at given bid and ask prices. *Breadth* indicates the size of market participants who are unable to exercise significant market power regardless of the size. Finally, *resiliency* means how quickly prices return to previous levels after experiencing price changes that are associated with the trading process (such as initiated by uninformed traders) — in short, the extent of price impact. These three dimensions do not operate alone but are interrelated. The definition used in this study captures all three dimensions of stock liquidity discussed above. Having formally defined stock liquidity, the scope of my review of liquidity literature is restricted to studies on stock liquidity. In the next section, I begin with a review on the determinants of stock liquidity.

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[4] However, stock liquidity should not be confused with liquidity risk. The latter, which also has been the focus of recent studies, refers to a systematic risk that investors face when markets are not perfectly liquid (Ng 2011). Liquidity risk (i.e., liquidity variability and covariability) is defined as the sensitivity of stock returns to unexpected changes in market liquidity (Ng 2011).

[5] Harris (2003) defines liquidity as the ability to trade a large number of shares quickly, at low cost, when traders want to trade. O'Hara (1995) views liquidity as the ability to trade large quantities with the least effect on price. Amihud and Mendelson (2012) define liquidity as the extent to which a firm's securities can be traded quickly and at low cost.

### 2.2.2 Determinants of stock liquidity

Contrary to the frictionless markets paradigm, prior literature (e.g., Stoll 2000) suggests that stock liquidity measured by bid-ask spread is determined by two sources of friction: real friction (e.g., inventory holding costs and order processing costs) and information friction (e.g., asymmetric information costs). I organise the determinants of stock liquidity into three categories: (1) information quality, (2) firm characteristics and capital structure, and (3) external factors. Broadly speaking, the link between these determinants and stock liquidity is established through reducing information asymmetry (see e.g., Glosten and Milgrom 1985; Kyle 1985; Welker 1995; Healy et al. 1999; Leuz and Verrecchia 2000).

#### *2.2.2.1 Information transparency*

Lang, Lins and Maffett (2012) find that greater corporate information transparency (as measured by lower earnings management, better accounting standards, higher quality auditors, more analyst following, and more accurate analyst forecasts) is positively related to stock liquidity across 46 countries over the period 1994-2007. The effect of firm-level transparency on stock liquidity is more pronounced in countries with higher opacity, during periods of greater investor uncertainty and higher level of ownership concentration.[6,7] Overall, they suggest that transparency plays a vital role in promoting stock liquidity under conditions that stunt liquidity. Consistent with Lang et al. (2012), Balakrishnan, Billings, Kelly and Ljungqvist (2014a) find that stock liquidity increases as a result of voluntary disclosure.

The above empirical results are consistent with the theoretical models of Diamond (1985) and Diamond and Verrecchia (1991) such that an increase in transparency through

[6] Country opacity is proxied by self-dealing, disclosure requirements and media penetration. High self-dealing, weak disclosure requirements, and low media penetration imply high opacity.

[7] Lang, Lins and Maffett (2012) reason that the effect of transparency on stock liquidity is enhanced for firms situated in countries with higher opacity, likely reflecting greater demand for firm-specific information in opaque countries. Similarly, the effect of high volatility (investor uncertainty is proxied by country-level share price volatility) on liquidity is attenuated for firms with higher transparency. Finally, transparency is likely to be important to stock liquidity for firms with high levels of ownership concentration.

revealing more firm information can reduce information asymmetry, and consequently cost of capital. This leads to an increase in stock liquidity and ultimately stock price (Amihud and Mendelson 2012).[8]

#### *2.2.2.2 Firm characteristics and capital structure*

Dass, Nanda and Xiao (2012) find that innovative firms (proxied by higher R&D investment and greater patents/citations) are more likely to have liquid stock. The authors argue that such firms are usually subject to financial constraints and are likely to increase stock liquidity in order to reduce the cost of raising external equity. They find evidence of innovative firms taking action (e.g., increase frequency of earnings guidance or split their stock) to increase the levels of stock liquidity of their firms.

Ownership structure also has been found to be a determinant of stock liquidity. Bhide (1993) argues that stock liquidity can be enhanced by more diffused ownership. That is, large shareholding is likely to reduce disclosure by self-serving owners, and thus reduces stock liquidity. This theoretical view is empirically supported in Attig, Fong, Gadhoum and Lang (2006); their results show that a closely-held firm with large shareholding is associated with lower stock liquidity than a widely-held firm. In a similar vein, increasing a firm's investor base can also improve stock liquidity (Amihud and Mendelson 2012). A firm can increase its investor base through splitting stock, advertising, and hiring designated market-makers (see evidence cited in Amihud and Mendelson 2012). For example, Grullon, Kanatas and Weston (2004) provide evidence that greater advertising is linked to a higher investor base and better stock liquidity. They argue that greater visibility attracts both individual and institutional investors. Their study complements the research that documents investors' preference for geographic proximity. For example, Loughran and Stultz (2005) show that firms located in urban areas have higher stock liquidity; arguing that this may be due to the reduced information asymmetry from having a wider base of potential investors

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[8] Poor transparency imposes greater adverse selection problems in these stocks, and hence liquidity providers may post wider spreads and smaller depths to compensate for the losses to informed investors (Glosten and Milgrom 1985; Stoll 2000).

familiar with the firm in comparison to firms situated in rural areas.

Literature linking firm capital structure and stock liquidity suggests that increasing debt in the capital structure leads to information asymmetry in the remaining equity. Evidence in Lesmond, O'Connor and Senbet (2008) show that firms relying on a higher proportion of debt financing have lower stock liquidity. Last but not least, Chung, Elder and Kim (2010) find that better corporate governance improves stock liquidity by resolving potential information asymmetry problems.

##### *2.2.2.3 External factors*

Market-wide liquidity shocks have been documented to affect stock returns negatively, with the effect being more pronounced in small firms, which are usually less liquid (Amihud 2002). During a financial crisis, investors dispose of less liquid stocks and shift to high liquid portfolios. In doing so, this decreases the liquidity of stocks that are already less liquid. Chung (2006) demonstrates that firms operating in countries with weak shareholder protection are likely to have less liquid stocks. They argue that a weak investor protection regime exacerbates asymmetric information problems, and thus decreases stock liquidity. In this case, liquidity providers will incur higher costs, resulting in higher bid-ask spreads. This effect is more pronounced for stocks trading in weak investor protection countries during a financial crisis when the agency costs are expected to be particularly high.

### 2.2.3 Consequences of stock liquidity

This section reviews the literature on the consequences of stock liquidity and discusses the recent literature on how stock liquidity can act as a curative device for mitigating managerial misbehaviour. This review is grouped under three categories of stock liquidity effects: (1) stock price, (2) corporate governance, and (3) corporate decisions and policies, which include financing and dividend policies, management compensation structure, earnings management, and corporate investment levels.

### *2.2.3.1 Stock price*

This section reviews how stock liquidity affects valuation and the informativeness of stock prices, of which the latter is of particular relevance to my thesis.

#### *2.2.3.1.1 Stock price valuation*

Liquidity-based asset pricing literature (Amihud and Mendelson 1986, 1989; Brennan and Subrahmanyama 1996; Amihud 2002) suggests that stock liquidity affects asset prices in that higher stock liquidity can raise a firm's market value by lowering its cost of capital.[9] The rationale is that buying and selling incur illiquidity costs (or equivalently, liquidity costs) that comprise transaction costs (e.g., brokerage commissions, exchange fees, and taxes), demand pressure and inventory risk, the presence of information asymmetry, and search costs (Amihud et al. 2005). The illiquidity costs increase required returns and, thus, depress stock prices because investors want to be compensated for bearing such costs.[10] For example, during the global financial crisis, the dramatic drop in liquidity spawned a host of collapsing stock prices and higher costs of capital (Amihud and Mendelson 2012). Other studies (e.g., Kadlec and McConnell 1994; Elyasiani et al. 2000) find that investors' required returns fall with the subsequent increase in both prices and market values after the over-the-counter stocks (less liquid setting) move to major exchange listings (more liquid setting). For example, Kadlec and McConnell (1994) find a significant increase in share prices when firms announce plans to switch their listings from NASDAQ to the NYSE. They claim that the increase in market values could be attributed to an anticipation of improvement in stock liquidity that follows an NYSE listing.[11]

In an asymmetric information environment, investors "price protect" against losses

[9] In corporate finance theory, a firm's market value is determined by the firm's expected after-tax operating cash flows or earnings, and the risk associated with producing them (Amihud and Mendelson 2012).

[10] In other words, when stock liquidity falls, the costs of illiquidity increase. Therefore, the resulting changes in liquidity induce a fall in stock prices, which are reflected in reduced market values, because the required returns on the securities rise.

[11] Kadlec and McConnell (1994) show that the excess return is weakly associated with the reduction in the bid-ask spread after the listings. They argue that organised exchanges provide superior liquidity services relative to the over-the-counter market; it is expected that the increase in stock price may be due to the higher demand for more liquid stock in major exchange.

from trading with more informed counterparts by demanding *a premium* when selling and *a discount* when buying. This price-impact — an illiquidity cost borne by investors — increases with the degree of information asymmetry between buyers and sellers. This relationship is modeled in Amihud and Mendelson (1986), who show that the expected return on a stock is positively associated with its illiquidity costs. The notion that higher costs require higher compensation (higher return) for bearing them indicates that illiquidity is priced.

***2.2.3.1.2 Stock price informativeness***

Several studies also have linked stock liquidity to informativeness of stock prices, whereby stock price informativeness is defined as the amount of information about future earnings captured in stock prices (Durnev et al. 2003). This stream of literature is pertinent to the current study because, as discussed later, stock price informativeness constitutes a channel through which stock liquidity can affect investment efficiency.

Prior analytical studies propose that higher stock liquidity facilitates the acquisition of more private information by lowering the cost of information gathering and production (O'Hara 2003; Easley and O'Hara 2004). This in turn improves stock price informativeness through impounding more private information into the stock price via informed trading. Empirically, Chordia et al. (2008) and Chung and Hrazdil (2010) use changes from higher minimum tick sizes to a lower minimum tick sizes regime (i.e., signalling a shift to a more liquid period) as an exogenous shock to show that increased liquidity results in greater incorporation of private information into stock prices.[12] For example, Chordia et al. (2008) find that the autocorrelation of stock returns decreases with the tick size following the introduction of a decimalization regime (more liquid regime).[13] They interpret this result as

[12] Tick size is the smallest increment (tick) by which the price of stock can move. The smaller the tick size that is fixed in a trading market, the more liquid the market since it stimulates more trading on information about fundamentals by decreasing the trading costs (Admati and Pfleiderer 1988).

[13] Between August 2000 and April 2001, the U.S. stock markets converted the price quotes system from fractional pricing (based on a minimum tick of one-sixteenth of a dollar, or about six cents, which represented a higher minimum tick sizes regime) to decimal pricing (based on a minimum tick of one cent, which represented a lower minimum tick sizes regime). This shift towards decimalization resulted in smaller

an indication that higher stock liquidity leads to an increase in more informative stock prices, as evidenced by the lower values of return autocorrelations. Given that firms with higher cash flow uncertainty suffer from greater information asymmetry problems, Fang et al. (2009) argue that such firms are likely to benefit the most from information-laden stock prices induced by higher stock liquidity. Fang et al. (2009) provide empirical support for this view by using the decimalization regime as an exogenous shock to liquidity to show that the effect of stock liquidity on firm performance is more pronounced for firms having high business risk. They interpret this as evidence of high stock liquidity helping managers of opaque firms to improve firm performance through learning from the information embedded in stock prices.

Sadka and Scherbina (2007) show that among firms with higher information uncertainty (proxied by analyst disagreement about future earnings), less liquid stocks are more likely to be overpriced as evidenced by their low future returns. They further find that the prices of overpriced high-information-uncertainty stocks are corrected downwards towards fundamental values when aggregate market liquidity is greater, as evidenced by the negative association between the returns of the initially overpriced stocks and changes in market-wide liquidity. Overall, they find evidence consistent with their hypothesis that high stock liquidity reduces information asymmetry, thus resolving mispricing by converging prices to fundamentals (i.e., downward price correction). Boehmer and Kelley (2009) and He and Shen (2014) evaluate how stock price informativeness is affected by institutional investors and foreign investors, respectively. While not of direct interest to these studies, they control for stock liquidity in their analysis and also find that stock price informativeness is increasing in stock liquidity. Collectively, the evidence from the above empirical studies support the view that stock liquidity improves the informativeness of stock prices.

bid-ask spreads as it allows a greater number of price levels that traders can quote and trade on (Bessembinder 2003; Furfine 2003).

#### *2.2.3.2 Corporate governance*

This section reviews how stock liquidity plays a role in mitigating managerial opportunistic behaviours via blockholders or large shareholders' choice of intervention, which represents another line of research that is of particular relevance to my thesis.

##### *2.2.3.2.1 Institutional investors' direct intervention*

Recent literature argues that higher stock liquidity increases large shareholders' incentives to monitor managerial decisions. This branch of literature starts with a premise (Kyle and Vila 1991; Maug 1998; Kahn and Winton 1998) suggesting that higher stock liquidity allows investors to acquire larger stakes easily and inexpensively. According to Maug (1998), the ability to acquire larger stakes induced by high stock liquidity incentivises large shareholders to increase value-enhancing monitoring, which consists of information collection and shareholder activism. The rationale is that by being actively involved in effective and costly restructuring of underperforming firms, large shareholders can improve a firm's value and stock price. As a result, they profit from trading with the uninformed investors in a liquid market. In doing so, part of the restructuring costs can be transferred to the uninformed investors, thus reducing the impact of the free-rider problem borne by large shareholders. Since large shareholders can cover their monitoring costs through informed trading, they are likely to engage in activism.[14] Consequently, large shareholders' activism involvement is likely to increase with stock liquidity. Maug (1998) concludes that firms with liquid stocks tend to support effective corporate governance.

Consistent with this view, prior studies show that institutional investors have higher propensity to purchase more shares in firms with more liquid stocks (Edmans et al. 2013; Fos 2017). In addition, several prior studies have documented the monitoring role of institutional investors in corporate governance (Barber 2007; Chen et al. 2007b; Burns et al. 2010; Aggarwal et al. 2011; McCahery et al. 2016). Despite not testing the effect of

[14] On the other hand, in a less liquid market, large shareholders prefer a cheaper method of restructuring, as they cannot profit from incurring these costs through trading with uninformed investors. They will engage in less monitoring by holding more diversified portfolios with smaller stakes in more firms (Maug 1998).

institutional monitoring in the context of stock liquidity, these prior studies provide evidence of positive linkage between different types of institutions and different dimensions of operations and governance in firms. For example, Demiralp, D'Mello, Schlingemann and Subramaniam (2011) show that in the setting of seasoned equity offerings (SEOs), a post-issue increase in institutional monitoring is associated with higher contemporaneous stock prices, better long-term stock prices, and greater improvement in operating performance, after controlling for informational advantages of institutional investors.[15] They argue that if the market perceives monitoring as beneficial, institutional monitoring is expected to be positively associated with the SEO announcement period returns.

Taken together, the above discussions suggest that higher stock liquidity can attract institutional investors and, thus, lead to improved governance through direct intervention.

##### *2.2.3.2.2 Institutional investors' indirect intervention*

Admati and Pfleiderer (2009) and Edmans (2009) take Maug's (1998) reasoning a step further, and suggest that higher stock liquidity improves monitoring through the "Wall Street Rule" or "Wall Street Walk", that is, investors voting with their feet and selling their shares. Such an exit itself can be an alternative activism used by large shareholders to influence management.[16] Large shareholders have strong incentives to gather costly information about the firm's fundamental value. By trading on private information, they cause the stock price to reflect true value rather than short-term earnings (Edmans 2009). If large shareholders with private information sense that managers do not act in their interest, they can dispose of their holdings before the news become public. Realising that dissatisfied

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[15] Aligned with Jensen's (1986) free cash flow theory, large cash flow received by firms during SEOs creates opportunities for managerial capital misallocation. Hence, this setting is ideal to identify the effect of institutional monitoring in mitigating the free cash flow concerns.

[16] It is also reasonable to expect that the exit strategy is more favourable to large shareholders as compared to employing overt forms of activism (Admati and Pfleiderer 2009) such as takeovers, proxy fights, strategic voting, and shareholders' proposals. Other than the legal barriers limiting direct intervention, one plausible reason for passivity is that large shareholders may not want to bear the full costs of monitoring that also benefits free riders. The trade-off between cost and benefit of monitoring does not justify large shareholders' investment of resources to monitor if cost is greater than benefit. In reality, institutional investors play a limited role in shareholder activism (Armour et al. 2009) because they are typically small and face significant legal and institutional barriers (see Black 1990; and Becht et al. 2009, for details of such barriers). Hence, exit can be an alternative curative device.

and well-informed large shareholders have the ability to sell their shares easily in a liquid market, managers, whose compensation is sensitive to stock price, would have to take heed of large shareholders' needs and adjust their actions accordingly (Admati and Pfleiderer 2009). This is because a falling share price can impact negatively on manager's wealth and reputation. In exit threat theories, the disciplinary effect of a large shareholder's exit is more credible because firm managers' compensation is linked to stock price.

Empirically, a series of recent studies provide support for the arguments discussed above. Edmans, Fang and Zur (2013) show that higher stock liquidity encourages filing of a 13G (indicating passive investment), implying that blockholders (large shareholders) can exert governance through exit threats, with the effect being stronger in firms with higher managerial compensation tied to stock prices. Similarly, using three natural economic events that dramatically affect stock liquidity as conditions for making blockholders' threat of exit more compelling, Bharath, Jayaraman and Nagar (2013) show that an exogenous increase (decrease) in stock liquidity improves (reduces) firm value, especially for firms with a high proportion of blockholders.[17] Their findings provide evidence to support the view that stock liquidity is important for the credibility of blockholder exit threats.

In addition, Edmans (2009) argues that this mechanism induces managers to undertake value-enhancing investment even though some large shareholders may be unable to intervene.[18] This is because by virtue of having superior information, large shareholders' presence increases market efficiency through impounding their private information into stock prices. In this case, they add value through trading, rather than intervention (Edmans 2009).

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[17] The natural experiments include the decimalization implemented in the New York Stock Exchange (increased liquidity), the Russian default crisis, and the Asian financial crisis (decreased liquidity).

[18] When blockholders (as in Edmans (2009)) are defined as 5 percent shareholders, Holderness (2009) finds that 96 percent of U.S. firms have a blockholder. However, when the minimum ownership is defined as 20 percent, La Porta et al. (1999) document that 20 percent (10 percent) of large (medium) U.S. firms have a blockholder. Hence, blockholders are prevalent in the United States, but tend to lack control rights (Edmans 2009, p2483).

#### *2.2.3.2.3 Competing view*

Contrary to the theories and empirical evidence discussed in Sections 2.2.3.2.1 and 2.2.3.2.2, some studies argue that high stock liquidity can also impair corporate governance (Coffee 1991; Bhide 1993). Bhide (1993) assumes that the voice and exit strategies of blockholders are mutually exclusive, and argues that high stock liquidity is undesirable because it encourages blockholders to exit rather than remain to intervene in firms' affairs. However, as discussed in the previous two sections, recent theories and evidence generally support the favourable role of stock liquidity played in governance. Taken as a whole, it appears that high stock liquidity can influence firm outcomes in a positive way by attracting formation of larger stakes by blockholders (large shareholders), and thus facilitating governance through "voice" and “exit”.

### *2.2.3.3 Corporate decisions and policies*

Given the positive effects of stock liquidity on stock price informativeness and corporate governance (as discussed in Sections 2.2.3.1 and 2.2.3.2), numerous studies have considered the direct effects of stock liquidity on corporate decisions and policies such as financing and dividend policies, management compensation structure, earnings management, and the level of corporate investments.

#### *2.2.3.3.1 Financing and dividend policies*

A number of prior studies show that firms with higher stock liquidity are associated with greater equity financing in their capital structure because of their lower cost of equity capital. For example, Lipson and Mortal (2009) and Baker and Stein (2004) find that firms with more liquid stock in a given year tend to raise equity rather than debt in the following year. Bharath, Pasquariello and Wu (2009) demonstrate that firms adopting a higher proportion of debt financing have lower stock liquidity. Also, stock liquidity appears to play a role in reducing investment bankers' fees for issuing equity (Butler et al. 2005).

Amihud and Mendelson (2012) argue that firms with less liquid stocks tend to pay dividends. This branch of literature suggests that investors regard a cash dividend as a substitute for less liquid stock in the sense that cash dividends provide "liquidity" to investors to compensate for high trading costs of converting less liquid stocks to cash.[19] Consistent with this view, Banerjee, Gatchev and Spindt (2007) show that firms with less liquid stock have a higher propensity to pay dividends. They reason that managers are incentivised to pay dividends because dividends induce higher valuation for firms with less liquid stock when dividends are expected to reduce trading friction.

In summary, empirical evidence shows that firms with more liquid stock are likely to raise external equity due to their lower cost of equity capital, whereas firms with less liquid stock tend to pay dividends to offset the higher trading costs associated with disposing less liquid stocks.

#### *2.2.3.3.2 Managerial compensation*

Recent studies suggest that a firm's stock liquidity may affect managerial compensation. For example, Jayaraman and Milbourn (2012) provide evidence that firms with higher stock liquidity rely less on cash-based executive compensation and more on stock prices in determining pay-for-performance sensitivity. They argue that stock liquidity plays an important role in explaining the current trends in executive compensation, as firms lean towards using stocks and stock options to remunerate managers. The reasoning is that higher stock liquidity induces more informative stock prices and, thus, managers are more sensitive to firm performance when their compensation is equity-based. Consistent with this view, prior studies find that the effect of stock liquidity on various firm outcomes is stronger in firms with higher managerial equity compensation (Fang et al. 2009; Bharath et al. 2013; Edmans et al. 2013).

#### *2.2.3.3.3 Earnings management*

Chen, Rhee, Veeraraghavan and Zolotoy (2015) document that higher stock liquidity also can improve the quality of financial information by reducing firms' accrual-based and

[19] This view contradicts Merton and Modigliani (1961), who state that the dividend is irrelevant because investors who want liquidity can dispose their holdings at no cost in a frictionless market. Hence, investors are neutral with respect to receiving a dollar of dividends and selling a dollar's worth of their holdings.

real earnings management. They further demonstrate that stock liquidity affects earnings management more greatly when the managerial pay-for-performance sensitivity is higher, consistent with the view that the beneficial effect of stock liquidity on earnings management emanates from the mechanism of exit threats.

***2.2.3.3.4 Corporate investments***

Given the evidence showing that higher stock liquidity lowers a firm's cost of equity (Amihud and Mendelson 2012), it is plausible to expect stock liquidity to have a positive effect on corporate investment because a lower hurdle rate increases the likelihood of investments. In other words, more investment projects may meet or exceed the hurdle rate (or minimum rates of return) in order to qualify for funding.

However, the empirical findings on the effects of stock liquidity on firm investments are mixed. Using additions to the S&P 500 stock index as an exogenous shock to liquidity (i.e., increased liquidity), Becker-Blease and Paul (2006) document a positive relationship between changes in stock liquidity and changes in capital and R&D investments. In contrast, following Becker-Blease and Paul's (2006) methodology but using the context of deletion from the FTSE 100 stock index as a negative shock to liquidity (i.e., reduced liquidity), Gregoriou and Nguyen (2010) find no association between changes in stock liquidity and changes in capital and R&D expenditures.

Fos (2016) argues that the *threat* of shareholder intervention through a proxy contest can serve as a governance mechanism. He hypothesises that high stock liquidity promotes the threat of shareholder intervention as it reduces investors' cost of acquiring large blocks of shares in the secondary market. Consistent with this view, he shows that firms with higher stock liquidity are likely to experience higher likelihood of a proxy contest. Fos (2016) also finds that the positive relationship between stock liquidity and the likelihood of a proxy contest leads to lower capital and R&D investments. He suggests that this is because proxy contests allow shareholders to influence management investment proposals. His evidence is also consistent with the theoretical model of Maug (1998), who shows that high stock liquidity allows investors to accumulate large stakes easily and with lower cost without causing drastic price impact, thereby facilitating shareholder activism. Finally, using decimalization as an external shock to liquidity, Fang et al. (2014) find a negative relationship between stock liquidity and the outputs arising from R&D investments (measured by patents and citations per patent). They further document that firms with large increases in stock liquidity are associated with large increases in ownership of non-dedicated institutional investors, suggesting that transient investors attracted by high stock liquidity are likely to influence managers to curtail long-term intangible investments.

To summarise, the evidence with regard to the impact of stock liquidity on investments provides mixed results. While prior literature documents a positive or negative relationship between stock liquidity and investment levels, it is difficult to use these prior findings to make inferences on the impact of stock liquidity on investment efficiency. For example, empirical evidence of a positive (negative) relationship between stock liquidity and investment levels could lead to investment levels exceeding (falling below) the optimal investment levels, which would be suggestive of over-investment (under-investment) problems. As such, my study seeks to extend this line of research by examining the impact of stock liquidity on investment efficiency directly. Specifically, I seek to investigate how stock liquidity causes the level of investments in firms to deviate from their optimal levels in firms that are likely to under- or over-invest. Such an analysis is expected to extend the stream of research that investigates the effect of stock liquidity on investments by providing direct insights into how stock liquidity enhances investment efficiency through reducing problems relating to under- and over-investments.

### 2.3 Investment efficiency

Investment is a real economic activity that impacts greatly on a nation's growth as a whole. For decades, the study of corporate investment behaviour has captivated the attention of research communities especially in macroeconomics, public economics, industrial organisation, and corporate finance (Hubbard 1998). Capital investment is an important research topic because capital misallocation not only costs shareholders dearly but also incurs a deadweight loss to a nation due to the inefficient use of capital transferred from suppliers of funds to firms.

To respond to firms' expansion needs, managers can draw on various financing sources internally (e.g., retained earnings) or externally (e.g., debt or equity financing). Prior studies focus on the debates over which theoretical models are able to accurately predict investment behaviour and how the monetary and tax policy can affect investment beneficially (Hubbard 1998). The overarching theories that form the premise of the various analytical models include information asymmetry and agency theories. These theories explain how capital market imperfections affect managerial investment behaviour. Specifically, because managers, as agents acting on behalf of owners, know the project's prospect more intimately than outside shareholders, they can vary their investment policies depending on their self-interested motives.

Broadly speaking, investment can be studied from the perspective of investment levels and the extent of deviation from the optimal investment level (i.e., degree of investment efficiency).

### 2.3.1 Definition of investment efficiency

Investment level is defined as the amount of capital a firm invests in plant and equipment, inventory, R&D, mergers, and acquisition. The degree of investment efficiency is defined as the difference between the current and expected optimal investment level. The smaller the deviation (delta), the more efficient is a firm's investment policy. Thus, investment efficiency manifests in situations where capital is channelled into projects expected to be value increasing or is withdrawn from projects with a grim outlook (Bushman et al. 2011).

### 2.3.2 Determinants of investment levels and investment efficiency

In a perfect market, managers only have to consider the trade-off between the expected future profit and the firm's cost of capital before committing to an investment. However, in an imperfect market infiltrated with information asymmetry problems, the frictions of adverse selection and moral hazard are the overriding forces that influence corporate investment decisions. Hence, the review in this section mainly focuses on research that looks into the impact of information asymmetry and agency problems on firm investment behaviours. The determinants of firm investment are divided into four broad categories: (1) financing constraints, (2) agency-related factors, (3) accounting information quality, and (4) firm stock price. It is important to note that most studies in this area have focused on the determinants of investment levels and not investment efficiency, which is of more interest to this thesis. The small stream of studies on investment efficiency has mostly focused on how investment efficiency is affected by accounting information quality.

#### *2.3.2.1 Financing constraints*

In a perfect world of Modigliani-Miller (1958), investments of financially constrained firms should solely depend on their investment opportunities, as measured by Tobin's (1969) Q. However, prior studies show that in practice capital structure is relevant to investment due to the capital-market imperfections (Stein 2003; Chen et al. 2007a). The two main frictions include information asymmetry (Myers and Majluf 1984) and agency problems (Jensen and Meckling 1976), arguing that adverse selection and moral hazard induce higher cost of external finance. Hence managers prefer using internal funds to finance investment.[20] In particular, Myers and Majluf (1984) argue that the information asymmetry between managers and outside investors imposes challenges to firms in raising enough external equity because investors view such equity issuance as bad news and demand higher returns.

Consistent with the argument above, prior studies document that firms with more cash on hand and less debt invest more after controlling for investment opportunities

[20] From the incentive problems perspective, external equity financing dilutes management's ownership stake, thereby exacerbating incentive problems by creating a greater disparity between ownership and control. From the information problems perspective, if managers are better informed than investors about their firms' prospects, the firms' securities may be underpriced, thereby increasing the cost of external finance.

(Fazzari et al. 1988; Hoshi and Kashyap 1991; Whited 1992; Schaller 1993; Bond and Meghir 1994; Calomiris and Hubbard 1995; Chirinko and Schaller 1995; Hubbard et al. 1995; Lang and Ofek 1996; see a survey in Hubbard 1998).[21] While internal cash flow is a significant determinant of investment, its importance is more pronounced when firms become more financially constraints. Prior studies show that financing constraints arise primarily from information asymmetry problems that impose different financing costs between internal and external financing (Chirinko and Schaller 1995; Hubbard 1998). Hence, financially constrained firms prefer internal cash flow to external financing due to lower cost. Consistent with this assertion, Chirinko and Schaller (1995) find that the effect of internal funds on investment is more pronounced for financially constrained firms. Using dividend payout ratios as a proxy for financial constraints, Fazzari et al. (1988) find that cash flow has greater effect on the investment of low-dividend firms. They argue that low-dividend firms are incentivised to retain higher earnings for future positive NPV investment because they are more likely to be financially constrained. Hence, internal funds have greater effect on investment for cash-constraint firms that are more likely to experience information asymmetry problems in comparison to cash-rich firms.

In sum, the investments of financially constrained firms are more sensitive to cash flows. The evidence is consistent with the view that financially constrained firms rely on internally generated funds for their investments because the information asymmetry problems hinder these firms from raising external funds.

#### *2.3.2.2 Agency-related factors*

Shleifer and Vishny (1997) argue that managers' investment outcomes may mirror their personal interests rather than those of the investors. The separation of ownership and control gives rise to agency conflicts (Jensen and Meckling 1976) that lead to misalignment in incentives between these two parties. Increased agency costs may result in managers

[21] These studies examine the effect of financial slack on investment spending as measured by plant and equipment, inventory (Carpenter et al. 1994; Kashyap and Lamont 1994), and R&D (Hall 1992; Himmelberg and Petersen 1994).

distorting investments because of the following reasons: (1) empire building (Stulz 1990; Shleifer and Vishny 1997) and diversifying acquisitions (Morck et al. 1990), (2) perquisite consumption (Jensen and Meckling 1976), (3) career concerns (Holmström 1999), (4) preference for a "quiet life" (Bertrand and Mullainathan 2003), (5) herding behaviour (Scharfstein and Stein 1990), and (6) overconfidence (Malmendier and Tate 2008).

For example, Bertrand and Mullainathan (2003) document that the overall investment level falls in response to the insulation from market discipline brought by antitakeover law passage. They argue that managers tend to choose a quiet life to preserve the status quo. In accordance with Jensen's (1986) free cash flow theory, managers choose to squander the free cash rather than return it to investors. For example, in the mid-1980s petroleum companies had generated excess cash flow from oil price increases. Instead of paying out to shareholders, managers wasted those funds on expensive exploration and development despite excess capacity, and also on unprofitable diversification (Jensen 1986). Prior studies provide evidence in support of this view (e.g., Blanchard et al. 1994; Harford 1999; Opler et al. 1999; Bates 2005; Richardson 2006). For example, using a sample of 487 takeover bids, Harford (1999) finds that cash-rich firms tend to lose value in acquisitions. Further, Richardson (2006) shows, using a much larger sample of 58,053 firm-years during the period 1988-2002, that firms with excess free cash flow are associated with over-investment. However, he documents that firms with certain governance structures, such as the presence of activist shareholders and the provision of certain anti-takeover, are less likely to over-invest their free cash flow.

#### *2.3.2.3 Accounting information quality*

Recent accounting research has examined the effect of accounting quality on investment efficiency. It is widely believed that transparent accounting reporting (high accounting quality) can mitigate both adverse selection and moral hazard problems, which are the main obstacles in the investment process. Thus, better accounting quality increases transparency, and promotes external monitoring and better contracting, thereby facilitating optimal investment.

Using firms from 34 countries, Biddle and Hilary (2006) find that higher accounting quality leads to lower investment-cash flow sensitivity, taken to be a proxy for investment efficiency.[22,23] They argue that countries with higher accounting quality are associated with a lower information asymmetry environment where adverse selection and moral hazard problems are relatively contained. For example, financially constrained firms can easily raise external equity and managers from cash rich firms are less likely to squander free cash flow. In this transparent environment, it is expected that the sensitivity of investment to cash flows is lower in response to a decrease in the reliance on internal funds (due to reduced adverse selection problems) and managerial wastage of free cash flow (due to reduced agency problems).

Other related studies (Verdi 2006; Biddle et al. 2009; Chen et al. 2011) provide empirical support for this view. For example, Biddle, Hilary and Verdi (2009) investigate the effects of financial reporting quality on both over-investment and under-investment simultaneously. Their findings show that higher quality financial reporting reduces the investment levels in firms that tend to over-invest (i.e., cash rich and unlevered firms) but increases investment levels in firms that tend to under-invest (i.e., cash constrained and highly levered firms). In addition, the investment levels of those firms with higher quality financial reporting are less likely to deviate from optimal levels. They reason that higher financial reporting quality increases transparency, thereby mitigating information asymmetry problems. For example, higher financial reporting quality could help financially constrained firms reduce the cost of raising external equity by making the positive NPV projects more visible to investors. Likewise, higher financial reporting quality could improve investors' ability to monitor managerial behaviour because the detection of value-

[22] Proxies for accounting quality used in Biddle and Hilary (2006) include earnings aggressiveness, loss avoidance, earnings smoothing, and timeliness.

[23] The standard approach to estimating investment-cash flow sensitivity entails regressing firms' capital investment on operating cash flow and Tobin's Q (to control for investment opportunities). The estimated coefficients (slopes) of operating cash flow capture the investment-cash flow sensitivity.

decreasing investments becomes easier. Also, it could facilitate optimal contracting by aligning managers' interest with that of shareholders. Overall, their results suggest that financial reporting quality can increase investment efficiency through reducing adverse selection and moral hazard problems.

The informational role of financial reporting quality in enhancing corporate investment is further supported by Balakrishnan, Core and Verdi (2014b) in the context of real estate shocks. In a financially constrained environment, real estate can be used as collateral to fund new investments. Shocks to the real estate value can influence investment levels (Chaney et al. 2012). For example, a negative shock to real estate values can result in reduced investment. However, better reporting quality can mitigate this impact, as evidenced in Balakrishnan et al. (2014b), who find that financing and investment by firms with higher reporting quality is less sensitive to changes in collateral value. They argue that firms with higher reporting quality experience lower financial constraints because of the reduced information asymmetry between firms and external capital providers, thus lowering the tendency to rely on collateral. Hence, investment levels of these firms are less influenced by shocks to collateral values. Their study suggests that financial reporting quality plausibly improves investment efficiency by alleviating financing problems associated with reduced collateral values.

Financial disclosure plays an important role in efficiently channelling capital from investors to corporate investment (Kumar et al. 2012). Based on this premise, using a sample of firms from 25 countries, Bushman, Piotroski and Smith (2011) document that timeliness of accounting recognition of economic losses (TLR) in a country is more likely to induce firm managers to engage in investing optimally, especially in deteriorating investment conditions. The TLR accounting regime relies on conditional accounting conservatism in that bad news disclosure takes precedence over good news in financial reports. Bad news about a deteriorating investment situation is timely transmitted to investors who may then discipline the firm. Hence, firm managers in a TLR regime have incentives to avoid value-decreasing investments and to terminate unprofitable investments in order to satisfy well-informed investors.

McNichols and Stubben (2008), using a large sample of firms that misreport their accounts, document that firms involved in earnings management are positively associated with over-investment during the misreporting period.[24] They argue that the inflated accounts may mislead certain groups of insiders into believing the incorrect status of a company in relation to the investment decisions.

Collectively, the evidence from prior studies suggests that higher accounting quality can encourage value-enhancing investment.

#### *2.3.2.4 Stock price informativeness*

While no prior studies have provided direct evidence of the impact of stock price informativeness on firms' investment efficiency in the manner considered in the current thesis, there are several prior studies that provide strong evidence to suggest a positive link between stock price informativeness and firms' investment efficiency. For example, the theoretical literature on the informativeness of stock prices starting with Hayek (1945) suggest that prices convey information that improves the efficiency of real investment decisions (e.g., Leland 1992; Dow and Gorton 1997; Subrahmanyam and Titman 1999, 2001; Dow and Rahi 2003). The information reflected in the stock price is the product of information aggregated from a diverse group of traders who provide information concerning different perspectives on firms. These traders typically include institutional investors or individuals, who exert significant effort to gather private information about the profitability and other prospects of the firm with the intention of profiting by trading on their private information. The aggregation of such information will eventually converge to an accurate assessment of firm value. Consequently, firm managers to some extent use the information reflected in the stock price to guide their investment decisions.

[24] The sample comprises firms investigated by the SEC for accounting irregularities, firms sued by their shareholders for improper accounting, and firms that restated financial statements.

This mechanism of informational feedback from stock prices has received empirical evidence that supports the view that managers incorporate private information generated by informed traders into their investment decisions (Durnev et al. 2004; Luo 2005; Chen et al. 2007a; Kau et al. 2008; Bakke and Whited 2010). For example, Chen et al. (2007a) find a positive relationship between measures of the amount of private information in stock price and the sensitivity of corporate investments to stock prices. They interpret this as evidence of investments being more sensitive to stock prices when the price contains more information that is new to managers, which allows managers to learn from this information and apply it to their investment decisions. More recently, Bakke and Whited (2010) examine whether mispricing or informative stock price affect corporate investment levels (measured by the sum of capital expenditures and R&D) by decomposing stock-price movements into two components: relevant for investments (private investor information) and irrelevant for investments (mispricing). They empirically find that investment levels are affected by informative stock price only, which is consistent with the view that managers utilize external private information embedded in the stock price to improve their investment decisions.

In the context of mergers and acquisitions (M&As), Luo (2005) examines whether companies learn from the market to improve their investment decisions during M&As. He shows that merging companies appear to utilize information from the market's reaction to the M&A announcement and incorporate the information in the M&A deal completion decision. This finding is also consistent with the notion that companies are more likely to learn from information reflected in the movements in stock prices. Using a similar setting, Kau et al. (2008) find that M&A deals are more likely to be completed when the market reacts positively to the announcement with higher stock returns, whereas the deals are more likely to be discontinued when market reacts negatively with lower returns. These findings are consistent with those reported in Luo (2005).

Durnev et al. (2001, 2004) argue that greater variation in stock returns reflects more informative stock prices and show that this can facilitate more efficient corporate investments.[25] Specifically, they find that firms tend to make capital budgeting decisions that maximize market value (reflected in Tobin's marginal q ratios that are closer to one, which reflects the theoretical optimum in an industry) in industries whose stocks exhibit higher firm-specific stock return variation (more informative stock prices).[26] They argue that their results support the view that informative stock prices can mitigate Myers-Majluf's (1984) "lemon's" problem associated with raising external equity, and subsequently help lower the cost of external financing.

Prior studies have generally focused on the impact of stock price informativeness on investment levels or the sensitivity of investments to firm value as a response variable, although these may not serve as direct evidence of how stock price informativeness alleviates problems relating to under- and over-investments in firms. Overall, however, these studies provide collective evidence that supports the view that any increase in stock price informativeness triggered by an increase in stock liquidity can improve the efficiency of firm investments.

### 2.3.3 Consequences of investment efficiency

While this thesis is not concerned with examining the consequences of investment efficiency, it is important to note that several studies also have investigated the effects of investment and investment efficiency. Investment levels are expected to be positively correlated with firm valuation and contemporaneous stock returns (Lamont 2000). The positive relationship arises because an increase in value-enhancing investment leads to an increase in stock prices and higher firm valuation (since optimal investment is expected to bring positive future cash flows). However, increases in value-enhancing investments

[25] Roll (1988) shows that firm-specific return variation is largely unassociated with public announcements, and argues that firm-specific return variation is therefore chiefly due to trading by investors with private information.

[26] Marginal q ratios are defined in Durnev et al. (2001) as the amount by which the firm's value rises per unit increase in its stock of capital goods. Under-investment leaves the firm with a marginal q above one, whereas over-investment leaves the firm with a marginal q below one. The optimal value in marginal q is one, which indicates efficient investment.

should lead to lower future expected returns (Lamont 2000).

There is some evidence suggesting that negative consequences can arise from over-investments due to availability of free cash flows. For example, Titman, Wei and Xie (2004) find that firms with abnormal capital investment are associated with poor future stock returns. The effect is more pronounced in firms that have higher investment discretion (i.e., firms with high cash flows and lower debt ratios). Fairfield, Whisenant and Yohn (2003) document that firms with substantial growth in net operating assets are more likely to have lower future return on assets (ROA). They argue that the negative relationship occurs because diminishing marginal returns on extensive investments tend to reduce profitability for growing firms.

## 2.4 Conclusion

Section 2 reviews the determinants and consequences of both stock liquidity and investment. Sections 2.2.3 and 2.3.2 are of greater relevance to this thesis. The review in Section 2.2.3 considers how stock liquidity affects stock prices, corporate governance, and corporate decisions and policies such as financing and dividend policies, management compensation structure, earnings management, and corporate investment levels. Of particular interest to this study is the effect of stock liquidity on corporate investments (Section 2.2.3.3.4). However, prior research in this area mainly focuses on the cost of equity as the underlying force whereby more liquid stocks lower the cost of capital to firms, which should increase investment — an asset pricing perspective. Further, the empirical findings on the effects of stock liquidity on firm investments are also mixed. In Section 2.3.2, the review covers the important factors that have been documented to contribute significantly to firm investments and investment efficiency. To the best of my knowledge, no prior study has investigated the effect of stock liquidity on investment efficiency.

As noted in previous section, while recent accounting studies have employed innovative constructs for investment efficiency that explicitly captures both over- and under-investment (as in Verdi 2006; Biddle et al. 2009; Chen et al. 2011), earlier studies examined investment efficiency using proxies such as Tobin's Q and sensitivity of investment-cash flow (e.g., Biddle and Hilary 2006). The latter may only consider one dimension of investment efficiency such as either over- or under-investment. This study seeks to utilize the more comprehensive construct of investment efficiency as employed in Biddle et al. (2009) and Chen et al. (2011) to examine how stock liquidity affects investment efficiency.

The next section in this thesis discusses the linkage between stock liquidity and investment efficiency, and develops the hypotheses.

# Chapter 3: Hypothesis Development

## 3.1 Introduction

In Chapter 2, I review the extant literature to provide systematic exploration of the determinants and consequences of stock liquidity and firm investments, the key variables employed in my study, with a focus on the role of stock liquidity in the context of real investment outcome. Investment decisions made by managers are of great interest to shareholders, as these decisions have marked impact on the total shareholder returns. Therefore, shareholders require managers to invest efficiently so as to increase the firm's value. Investment efficiency is defined as a firm investing optimally if it undertakes all and only projects with positive net present value in the absence of no market frictions such as adverse selections and agency costs (Biddle et al. 2009). Conversely, inefficient investment entails under-investing by passing up investment opportunities that would have positive NPV and/or over-investing in projects with negative NPV (Durnev et al. 2001; Biddle et al. 2009).

This section investigates the linkage between stock liquidity and investment efficiency, and argues that by mitigating information asymmetry, higher stock liquidity can enhance investment efficiency based on two explanations drawn from prior literature: capital market-based and corporate governance-based explanations. Section 3.2 shows how information asymmetry between firm managers and shareholders leads to investment inefficiency. It also expands the discussion of the consequences of moral hazard and adverse selection problems arising from information asymmetry on investment efficiency. Section 3.3 develops a theoretical framework that outlines how stock liquidity can positively affect investment efficiency by mitigating information asymmetry. The theoretical framework developed in Section 3.3 is based on capital market and corporate governance explanations that support the positive relationship between stock liquidity and investment efficiency. Specifically, Section 3.3.1 discusses the capital market-based explanation, which proposes that stock liquidity can enhance investment efficiency by increasing transparency and improving market feedback effect. On the other hand, in Section 3.3.3, the corporate governance-based explanation suggests that stock liquidity can enhance investment efficiency by increasing institutional monitoring ("threat of voice") and facilitating institutional "threat of exit". Sections 3.4 and 3.5 present the testable hypotheses and additional tests.

### 3.2 Information asymmetry and investment efficiency

In corporate finance theory, firms maximise profit or market value by investing until the marginal benefits of an investment equal its marginal costs, allowing for adjustment cost of the investment (e.g., installation cost). If the rate of return on an investment proposal is larger than or equals to the cost of capital, the investment is worth undertaking. Otherwise, the project is less likely to increase the firm market value. According to Modigliani-Miller's (1958) frictionless market model, all positive NPV projects should be funded regardless of a firm's financial attributes such as liquidity position (solvency), leverage and dividend payments.[27]

However, information imperfection in capital market prohibits all positive NPV projects from being funded or implemented. Achieving optimal investment levels can be hindered by moral hazard and adverse selection problems, which are caused by the presence of information asymmetry between firms and external investors (Myers and Majluf 1984). A moral hazard is a situation in which a party is willing to take risk knowing that the costs of wrong decisions are not fully borne by him/her. Moral hazard problems are commonly present in agency conflicts due to the separation of ownership and control (Jensen and Meckling 1976). An adverse selection is a situation in which bad products or services are more likely to be selected because buyers and sellers possess different degrees of

[27] That is, firm market value is independent of its financial structure but depends only on the income stream generated by its assets. Modigliani-Miller's (1958) rationale is that the gain from debt financing (due to tax deductibility) is neutralised by the higher payout to shareholders and bondholders from this excess income. As a result, capital structure that is made up of any possible combination of equity and debt will yield a similar weighted average cost of capital, and thus the firm value remains unchanged.

information about the quality of a product or service before the transaction takes place.

The friction of information asymmetry arising from the separation of ownership and control (Jensen and Meckling 1976; Fama and Jensen 1983) results in managers possessing more information about the firm value and prospects (and also the profitability of new projects). Furthermore, incomplete contracts (Williamson 1985) grant residual control rights to managers (Grossman and Hart 1986; Shleifer and Vishny 1997) because it is essentially impossible to spell out all desired behaviours in contracts for managers. Thus, managers who have private information have incentives to use their discretion to make decisions that benefit themselves (e.g., Shleifer and Vishny 1997) when they are not closely monitored. In this situation, moral hazard arises when managers start pursuing goals that are not in shareholders' interests. For example, moral hazard occurs when over-investment activities are undertaken by managers for personal perquisite consumption and "empire building" rather than for promoting the interests of shareholders (Jensen 1986). Specifically, agency problems can lead to poor project selection due to managers' tendency to maximise personal wealth and prestige. For example, evidence shows that managers have incentives to engage in empire building in order to enhance their prestige and standing in the business community (Avery et al. 1998).[28]

There are many studies explaining other reasons for managerial self-interested behaviours that have direct implications for investment (for a survey, see Stein 2003). These reasons for managers to distort investments include career concerns (Holmström 1999), preference for a "quiet life" (Bertrand and Mullainathan 2003), and overconfidence. With regard to career concerns, Fama (1980) argues that managers are concerned with how their actions influence their reputation in the labour market, and ultimately their compensation. Building on Fama's (1980) work, Holmström's (1999) analytical model shows that career concerns can be beneficial as well as detrimental, depending on how closely the manager's

[28] Avery et al. (1998) use the number of board seats offered to an executive as a proxy for executive prestige and the business community's perception of the executive's abilities and competence. Their results show that CEOs who completed acquisitions are significantly more likely to gain outside directorships than those who did not complete acquisitions.

concern for human capital returns and the firm's concern for financial returns are aligned. Further, other theoretical research reveals that managers concerned with their labour-market reputation are incentivised to choose short-term performance (e.g., raise reported earnings by under-investing or impress the stock market or labour market by over-investing) rather than increasing shareholder value (Narayanan 1985; Bebchuk and Stole 1993). In summary, managerial career concerns can give rise to efficient or inefficient investment decisions. The "quiet life" preference literature (Bertrand and Mullainathan 2003) argues that managers are reluctant to make difficult decisions such as closing down unprofitable branches (which equates to over-investment) or expanding into promising new territories (which leads to under-investment). Finally, another theory that links the empire-building and costly-external-finance literature (which is discussed in the following paragraph) is the model of managerial overconfidence in the prospects of their firms. Roll (1986) and Heaton (2002) theorise that managerial overconfidence can lead to over-investment and this view is supported by Malmendier and Tate (2008) who document that overconfident CEOs overpay for target companies and undertake suboptimal mergers.

Information asymmetry can also affect the cost of raising funds and adverse selection of projects (Myers and Majluf 1984), which in turn can influence investment efficiency. Myers and Majluf (1984) argue that the persistence of information asymmetry between managers and outside shareholders increases the cost of external financing. Adverse selection problems arise when managers (agents) have more private information regarding their decisions than prospective shareholders (potential principal). The asymmetric-information environment incentivises managers to sell their company shares at a higher price by timing the issuance of securities (i.e., a "lemon's" problem). Hence, prospective shareholders will interpret the event of external equity financing as bad news and demand a higher return and subsequently lower price (Asquith and Mullins Jr 1986; Masulis and Korwar 1986; Mikkelson and Partch 1986).[29] As a consequence, costly external

[29] By not raising outside equity at a lower price when the market is less informed about the value of the firm's future cash flows, managers can prevent wealth transfer from old shareholders to new shareholders.

financing discourages benevolent managers from committing to positive NPV projects, thereby leading to under-investment (Myers and Majluf 1984; Lambert et al. 2007). This is especially expected for financially constrained firms as they usually find it more challenging to raise external capital for their value-increasing projects due to the adverse selection problems (Fazzari et al. 1988).

In summary, the aforementioned discussion suggests that information asymmetry can lead to over- or under-investment by inducing frictions such as moral hazard and adverse selection problems. Next, I discuss how stock liquidity can enhance investment efficiency by mitigating information asymmetry and agency costs (i.e., reducing the frictions of moral hazard and adverse selection).

### 3.3 Theoretical framework

This section develops a theoretical framework drawn from various theories to predict a positive effect of stock liquidity on investment efficiency. A large investment literature identifies managerial agency problems and adverse selection problems as factors affecting firm investment.[30] This section discusses how stock liquidity can mitigate these two-pronged problems.

Stock liquidity has been an important focus in academic studies relating to issues such as asset pricing, the financial crisis, market manipulation, and short selling (Amihud and Mendelson 2012), especially in the wake of financial crisis of 2008-2009 (Sadka 2011). However, despite a growing literature emphasising the role of stock liquidity in mitigating information asymmetry and agency problems, no empirical study has yet examined the impact of stock liquidity on investment efficiency. Stock liquidity is defined as the ability to transact shares swiftly in large quantities without causing material price changes. This dissertation argues that high stock liquidity can improve investment efficiency by reducing

[30] It is plausible that liquidity of a firm's stock can affect corporate investment decisions through reducing the firm's cost of equity. It is more likely that companies will increase investment with the reduced cost of capital because they have a lower hurdle rate to overcome (Amihud and Mendelson 2012).

information asymmetry and agency costs. Specifically, if high stock liquidity reduces information asymmetry (adverse selection costs), it can be associated with investment efficiency through reducing external financing costs and through decreasing the likelihood of firms obtaining excessive funds because of temporary mispricing. Further, by reducing agency problems, high stock liquidity can improve investment efficiency by encouraging shareholders to monitor managers.

Given that the literature on stock liquidity spans various fields, I group the theories into two broad categories, i.e., capital market-based and corporate governance-based explanations.[31] In the liquidity literature, liquidity is commonly regarded as desirable due to its attraction to informed traders who prefer liquid stocks. Their trading behaviours cause prices to incorporate more information. Typical work in this literature argues that liquidity promotes informative stock prices, which serve as the premise for the two explanations identified above.

The first explanation – capital market-based – argues that the market possesses more information when stock prices are informative. As discussed in Section 2.2.3.1.2, higher stock liquidity can improve stock price informativeness through facilitating the incorporation of more private information of informed traders into stock prices. As such, firms with liquid stocks are more transparent to external shareholders. As a result, managers tend to behave under watchful eyes. Simultaneously, an informative stock price also improves market feedback to managers. Price movements reflect market intents of which managers are incentivised to take heed by adjusting their actions accordingly. For instance, prior studies show that managers vary their investment decisions after observing the market's reaction to their acquisition announcements (Luo 2005; Kau et al. 2008). Hence, it is reasonable to conclude that both effects of transparency and feedback resulting from high

[31] It is possible that the effect of stock liquidity on investment efficiency could arise through other mechanisms. For example, it is possible that higher stock liquidity attracts more financial analysts who also exert monitoring to ensure efficient investment in firms.

stock liquidity can influence managers' decisions, particularly when their equity compensation is tied to stock prices.

The second explanation – governance-based – contends that high stock liquidity can enhance the governance role of institutional investors. Higher stock liquidity spurs institutional investors to collect more information and trade on it, a process that generates informative stock prices (O'Hara 2003). An increase in liquidity of a firm's stock also enables institutional investors to become more influential through share accumulation at less volatile prices. Endowed with the ensuing intervening power as well as "voting with their feet" power (explained in the following sections) through higher stock liquidity, institutional investors with high enough stakes in a firm are able to motivate managers to invest efficiently.

As discussed above, the capital market-based and governance-based explanations share the common premise that high stock liquidity increases the information content of stock prices. The first explanation focuses on the impact of stock liquidity on the roles of an informed market, whereas the second explanation stresses its impact on informed institutional governance roles. It is important to note that these two explanations are not mutually exclusive. The following sections discuss these explanations in more detail to support the formulation of my study's hypothesis, which predicts a positive relationship between stock liquidity and investment efficiency. Figure 1 summarises the theoretical premises of my study.

<<<INSERT FIGURE 1 ABOUT HERE>>>

### 3.3.1 Stock liquidity, capital markets, and investment efficiency

Khanna and Sonti (2004) and Easley and O'Hara (2004) use an analytical model to highlight the important informational role that stock liquidity plays in the capital market by allowing more private information to be incorporated into stock prices. In line with this idea, I argue that high stock liquidity increases the informativeness of stock prices, which in turn affects managerial decisions on capital allocation. Recall that stock price informativeness represents the amount of information about future earnings captured in stock prices (Durnev et al. 2003). Informative stock prices can have implications on managers' investment decisions. First, they increase transparency and allow shareholders to more closely monitor managers. Second, they improve the feedback from shareholders (market) to firm managers so that managers take corrective actions based on information inferred from stock prices. These effects of informative stock prices arguably are expected to induce managers to invest efficiently.

It has been long debated that stock markets play a vital economic role in mitigating information asymmetry and agency conflicts through generating informative stock prices and, thus, plausibly improving corporate capital allocation (Wurgler 2000; Durnev et al. 2003; Bushman et al. 2011).[32] Tobin (1987) argues that the condition for stock prices being able to direct capital to efficient uses is that stock prices track firm fundamentals closely, a phenomenon that manifests itself in a liquid stock (Easley et al. 2002; Easley and O'Hara 2004). There are sound theoretical reasons to believe that stock liquidity, a key feature of stock markets, will positively affect investment efficiency by incorporating more private information into prices (O'Hara 1995).

It is commonly argued that high stock liquidity attracts informed investors into trading. Informed traders are those who are more informed about the fundamental value of a security (Harris 2003). They are willing to invest time to produce and gather information, and they also have the capacity and incentives to generate information due to their expertise or larger stakes in the firm. High stock liquidity also attracts other sophisticated players such as analysts and institutional investors. Their informed activities induce more information production, thereby further reducing information asymmetry (i.e., more informative prices) (Busse et al. 2012; Crawford et al. 2012). For example, mutual funds divulge their private information through their investment, and sell-side analysts disclose

[32] Since markets can provide liquidity and price discovery (O'Hara 2003), it is widely accepted that stock market, stock price and stock liquidity are closely related.

their investment opinions through earnings forecasts and stock recommendations. Collectively, stock prices reflect firm fundamental value when the private information of informed market participants such as analysts and institutional investors is incorporated into prices (Subrahmanyam and Titman 2001; Khanna and Sonti 2004).[33]

Market microstructure analytical models (Grossman and Stiglitz 1980; Kyle 1985; Easley and O'Hara 2004) predict that informed traders vary their trading intensity as a function of stock liquidity, thereby determining the extent of information content of stock prices (i.e., amount of private information incorporated into stock price). Thus, it is plausible that high stock liquidity would speed up the formation of the true price because of the intense trading by informed traders. Indeed, empirical evidence documented by Chordia et al. (2008) shows that higher stock liquidity stimulates arbitrage activity, which in turn improves market efficiency by infusing more private information into prices. As discussed earlier in Section 2.2.3.1.2, the positive link between stock liquidity and stock price informativeness is supported in numerous other empirical studies including Sadka and Scherbina (2007), Fang et al. (2009), and Chung and Hrazdil (2010).

An informative stock price produces at least two effects that have positive implications in a manager's investment strategies. It increases transparency as well as improves market feedback effects; they work in tandem to mitigate the distortion of firm investment decisions. Sections 3.3.1.1 and 3.3.1.2 examine the mechanisms through which stock liquidity affects firms' investment decisions via the effects of transparency and market feedback.

[33] To understand how price converges to a firm’s fundamental value, the market microstructure literature provides an analysis of the underlying process through which prices are formed in an asymmetric information environment (O'Hara 1995). Unlike the economic perspective in which prices are determined simply by matching supply and demand in equilibrium, market microstructure argues that prices emerge through the interaction between informed and uninformed trading. Informed and uninformed traders watch market data, update their beliefs about their private information by drawing inferences about the underlying true value of an asset, and set trading prices. Informed traders are better informed about stock fundamental values and are more knowledgeable about other traders’ strategies (Harris 2003). Uninformed traders infer the latest information from observing informed investors’ trading activities. Over time, the process of trading, and learning from trading, results in prices converging to full information levels.

#### 3.3.1.1 *Stock liquidity, transparency, and investment efficiency*

As Section 3.3.1 indicates, informed traders plausibly make stock prices more informative through high liquidity of a firm's stock. More informative stock prices are likely to reduce information asymmetry by making managers' behaviour more visible to investors, and therefore increasing investors' ability to monitor managerial investment decisions. As a result, investors are likely to detect opportunistic managerial investment decisions in a more transparent information environment. If high stock liquidity aids investors in monitoring managerial investment activities, it can promote investment efficiency by reducing moral hazard problems.[34]

Some support for this view is provided by Wurgler (2000). His study shows that countries with stock markets that promote liquidity exhibit a better allocation of capital by incorporating more firm-specific information into individual stock prices.[35] This is because more informative stock prices help investors distinguish good investments from bad ones through a more accurate measure of firm value (Wurgler 2000; Durnev et al. 2003). As a result, it is reasonable to expect that market participants are able to monitor managerial investment behaviours by observing and influencing stock prices, especially so in firms with higher stock liquidity.

If informative stock prices arising from higher liquidity of firm stock enable investors to possess more or better quality information, it can be associated with investment efficiency by reducing adverse selection problems too. Adverse selection problems could occur when firms want to raise equity externally (Myers and Majluf 1984) for new positive NPV investments in an asymmetric information environment. Any equity issuance is

[34] This view is supported by several prior studies linking stock price informativeness to investment levels and the sensitivity of investments to firm value (Durnev et al. 2001, 2004; Chen et al. 2007; Bakke and Whited 2010).

[35] Wurgler (2000) does not directly test the link between stock liquidity and investment. His results suggest that liquidity of a firm's stock facilitates higher investment efficiency based on the observation that developed financial sectors (also a more liquid market) increase investment more in their growing industries, and decrease investment more in their declining industries, than those with undeveloped financial sectors (less liquid) across 65 countries. The authors interpret that increment of investment in growing industries and decrement in declining industries as an indicator of efficient investment because the capital is channelled to the growing industries (where capital is needed) and withdrawn from declining industries.

interpreted by uninformed prospective shareholders as bad news because they perceive that a more informed manager is likely to issue new shares at times of stock over-valuation.[36] To mitigate this lemon's problem (Akerlof 1970), the prospective shareholders may demand higher return (Myers and Majluf 1984) and, thus, impose higher cost of equity capital. Realising this, the manager may avoid raising equity from prospective shareholders if he is acting in the interest of the existing shareholders, thereby resulting in under-investment. In the same scenario, if the manager chooses to go ahead with equity issuance, his firm may pursue fewer projects that are able to meet the higher cost of equity capital, hence also leading to under-investment. By reducing such adverse selection costs, stock liquidity can mitigate under-investment by allowing stock prices to reflect true firm performance.

Stock liquidity can promote investment efficiency through reducing external financing costs and decreasing the likelihood of firms obtaining excessive funds because of temporary mispricing. That is, if investors can see through the managerial investment strategies, they will price the related managerial decisions correctly. Hence, this may prevent firms from under- or over-investing in projects because firms are able to raise funds at the optimal level in a transparent information environment. In summary, if high stock liquidity reduces moral hazard and adverse selection costs, it can improve investment efficiency by increasing transparency, and, thus, reducing the costs of external financing.

#### *3.3.1.2 Stock liquidity, market feedback, and investment efficiency*

High stock liquidity can also improve investment efficiency through facilitating market feedback to firm managers via informative stock prices. Khanna and Sonti (2004) argue that investors have incentives to influence prices to induce firms to undertake certain investments. Hence, the movement of stock prices can act as a feedback device by conveying investor sentiments to managers, allowing managers to make more informed decisions. Higher stock liquidity attracts more informed investors who trade more

[36] Firms appear to take advantage of higher prices of their stock by making more acquisitions. This phenomenon was particularly noticeable in the recent dot-com boom. There is also substantial evidence that firms raise more external funds when stock prices are high (see anecdotes quoted in Khanna and Sonti, 2004).

intensively based on their information on managerial behaviour, thus making stock prices more informative to firm managers and other stakeholders. This is expected to increase the importance of the market feedback effect (Subrahmanyam and Titman 2001) on manager's decisions.

The price of a firm's stock both affects and reflects managerial decisions. Information-laden stock prices provide valuable feedback about the quality of managerial decisions to managers (Durnev et al. 2004; Khanna and Sonti 2004; Fang et al. 2009). For example, it is plausible that a lower price indicates investors' dissatisfaction with poor managerial investment decisions, whereas a higher price correctly reflects investors' expectations of managerial efficiency in the use of corporate capital. As prices change in response to firm investment decisions, managers seek to continuously glean information from market prices and then take actions that affect the value of the security (Subrahmanyam and Titman 2001; Bond et al. 2010). To attract investors' interest in firm stocks, Subrahmanyam and Titman (2001) argue that the feedback from stock prices can influence managerial incentives to increase firm value such as by investing efficiently. This explains why managers pay a great deal of attention to the movements of stock prices to gauge how they should respond. For example, the market expects that CEOs must maintain higher stock prices so as to retain their positions and avoid shareholder activists' scrutiny (Bond et al. 2010). As such, it is widely believed that managerial investment decisions are influenced by their firms' stock prices (Bond et al. 2010). This argument is supported by numerous studies discussed in Section 2.3.2.4 (Durnev et al. 2001, 2004; Luo et al. 2005; Chen et al. 2007; Kau et al. 2008; Bakke and Whited 2010). For example, Kau, Linck and Rubin (2008) find evidence of managers listening to the market by showing that managers are more likely to abandon investments when the market reacts negatively to the related announcements with lower stock returns, and complete investment deals when the market reacts positively with higher returns.[37]

Based on the above arguments, it is plausible to expect that managers have incentives to take corrective actions based on the information inferred from a firm's stock prices (Bond et al. 2010). Given that corporate investment efficiency is sought by investors, the feedback from informative stock prices that incorporate investors' expectations can influence managers (Subrahmanyam and Titman 2001) to invest efficiently. Thus, it is likely that high stock liquidity enhances investment efficiency through a feedback effect, as high stock liquidity attracts informed investors who increase the information content of stock price.

### 3.3.2 Stock liquidity, corporate governance, and investment efficiency

The governance-based explanations introduced by Maug (1998) and Edmans (2009) suggest that high stock liquidity can enhance the disciplining role of large institutional investors. Institutional investors mainly comprise investment advisers, investment companies, bank trust departments, insurance companies, foundations, and pension funds (Gillan and Starks 2000). With the steady growth in the levels of institutional ownership in U.S. companies from 10 percent in 1953 to over 70 percent in 2006 (Gillan and Starks 2007), institutional investors can play a prominent role in corporate governance due to their fiduciary duty to their own shareholders. Through liquidity, they can employ voice or exit strategies to discipline managers who deviate from the creation of shareholders' wealth.

In this section, I argue that high stock liquidity is positively associated with firms' investment efficiency via corporate governance. In particular, higher stock liquidity encourages institutional investors to monitor firms in order to improve managerial decisions, such as corporate capital allocation. Because higher stock liquidity helps

[37] Informative stock prices also convey meaningful signals to the financial market about the need to intervene when managerial investment decisions are of poor quality. Curative mechanisms, such as shareholders' lawsuits, executive options, institutional investor pressure, and the market for corporate control, depend on stock prices (Durnev et al. 2004). These mechanisms induce better monitoring so that managers are more likely to invest efficiently (Durnev et al. 2004). Hence, high stock liquidity can increase transparency and the feedback effect by making prices more informative for market participants to take disciplinary actions.

institutional investors acquire larger stakes at less volatile prices, they are more motivated to intervene in firms' affairs. On the other hand, higher stock liquidity also makes it easier and cheaper for institutional investors to exit by selling. The threat of institutional exit can create incentives for managers to invest efficiently.

The following sections consider how high stock liquidity affects the governance of firms. Specifically, Section 3.3.2.1 describes how high stock liquidity encourages formation of large stakes and examines its subsequent role in direct monitoring (i.e., voice threats) of firms' affairs. Section 3.3.2.2 explores how high stock liquidity promotes indirect monitoring by providing an easy exit (i.e., exit threats) for disgruntled institutional investors to liquidate their holdings quickly and at lower costs, which is known as the "Wall Street Rule."

#### *3.3.2.1 Stock liquidity, institutional threat of voice, and investment efficiency*

Several analytical works (Grossman and Hart 1980; Schleifer and Vishny 1986; Admati et al. 1994; Kahn and Winton 1998) have shown that large institutional investors (blockholders) can increase firm value through monitoring. Given the size of their holdings, large institutional investors have the incentives and capabilities to engage in monitoring, and, thus, are likely to encourage management to invest efficiently. When dissatisfied with poorly governed or under-performing firms, institutional investors have various forms of intervention for correcting managerial failure such as takeovers, proxy fights, strategic voting, shareholders' proposal, dialogue with management, or public criticism through media (Gillan and Starks 2007; Admati and Pfleiderer 2009).

A considerable body of research has explored how the monitoring role of institutional ownership affects various aspects of firm outcomes, including executive compensation (Hartzell and Starks 2003), earnings management (Chung and Zhang 2011), earnings quality (Velury and Jenkins 2006), conservatism in financial reporting (Ramalingegowda and Yu 2012), equity prices (Gompers and Metrick 2001), and equity returns (Yan and Zhang 2009). For example, Velury and Jenkins (2006) find that institutional investors positively affect earnings quality measured using abnormal accruals, earnings response coefficient, and several other earnings quality proxies. Ramalingegowda and Yu (2012) demonstrate evidence of a significant positive association between monitoring institutional ownership and conservative financial reporting.[38]

In the liquidity literature, Maug (1998) argue that stock liquidity has a positive effect on corporate control (i.e., liquidity facilitates monitoring). He shows that high stock liquidity increases investors' ability to accumulate large stakes without substantially affecting stock prices and, thus, encourages the formation of larger blockholders who are then incentivised to engage in monitoring (value-enhancing activities comprising intervention and shareholder activism). Consistent with Maug's (1998) view, prior studies find that activist hedge funds are more likely to acquire equity blocks in companies with more liquid stock and, thus, more likely to intervene managers' decisions directly (Edmans et al. 2013; Fos 2016). Hence, it is expected that firms with liquid stocks are more likely to invest efficiently due to the increased institutional monitoring efforts.

#### *3.3.2.2 Stock liquidity, institutional threat of exit, and investment efficiency*

While there is much evidence on the monitoring role that institutional investors can play, there is some evidence to suggest that institutional investors play a limited role in the forms of direct intervention (Admati and Pfleiderer 2009).[39] One possible explanation for this limited active involvement is that institutional investors face a "free rider" problem by having to bear the full cost of monitoring, which can exceed the benefits received (Admati and Pfleiderer 2009). Although a large body of corporate governance research demonstrates that large institutional ownership provides effective monitoring to mitigate the agency problem (Shleifer and Vishny 1997; Dharwadkar et al. 2008), a series of recent corporate accounting frauds suggest the failure of institutional investors to act as an effective

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[38]They define monitoring institutions as those who have long investment horizons, concentrated share holdings, and independence from management (e.g., Schleifer and Vishny 1986; Brickley et al. 1988; Gaspar et al. 2005; Chen et al. 2007b).

[39]Armour, Black, Cheffins and Nolan (2009) find that U.S. shareholders seldom undertake litigation and proxy fights, and rarely succeed if they do.

watchdog. Further, their importance in monitoring managerial behaviour is still largely inconclusive (Hartzell and Starks 2003).

However, recent studies argue that high stock liquidity can enhance the governance role of institutional investors in monitoring without direct intervention. High stock liquidity attracts the entry of institutional investors who as a whole prefer liquid stocks (Maug 1998). If an institutional investor detects managerial failure in improving investment efficiency, high stock liquidity makes it easier for the institutional investor to choose the "Wall Street Rule" or "Wall Street Walk," voting with his feet and selling his shares, rather than engaging in activism (Admati and Pfleiderer 2009; Edmans 2009). Admati and Pfleiderer (2009, 2446) argue that "what seems to have not been widely recognised is that the threat of exit itself can be a form of shareholder activism." This is in contrast to the historical views that high stock liquidity could impair corporate governance by allowing institutional investors to dump their equity holdings easily instead of staying put to rectify suboptimal managerial decisions (Coffee 1991; Bhide 1993).

Recent studies suggest that high stock liquidity can offer recourse to institutional investors.[40] That is, high stock liquidity helps mitigate agency problems by making it easier for institutional investors to exit (Edmans 2009). The threat of exit is in itself a disciplining device (Admati and Pfleiderer 2009; Edmans 2009). The rationale is that institutional investors collect costly information about the firm’s prospects. If they disagree with the suboptimal performance or decisions of the company, they can choose to “cut and run” by selling their holdings in order to reduce future expected losses before the bad news become public (Bharath et al. 2013). Therefore, one might expect that when other investors also learn about the institutional exit, they will follow suit and this can immediately push the prices down. Similarly, if the institutional investors choose to stay with the firm, they signal good news and the stock prices will remain high.

[40] The competing view suggests that high stock liquidity leads to distorted investment by encouraging short-termism (Porter 1992; Bhide 1993). This is because it allows dissatisfied investors to dispose of their holdings easily instead of improving the current suboptimal status in a firm.

As a result, the exit of institutional investors imposes ex post costs on the manager by punishing her through her stock price exposure. Lower stock prices can affect the manager's equity-based compensation, and increase the possibility of job loss and board intervention (Bharath et al. 2013). Therefore, the institutional investors' exit option facilitated by high stock liquidity induces ex ante incentives for managers to improve firm performance, so as to encourage institutional investors to continue to hold the securities of the firm (Bharath et al. 2013). Thus, the threat of selling may mitigate the agency problems by inducing managers to invest efficiently. Based on the above premise, managers of firms with high stock liquidity have incentives to invest efficiently in order to satisfy institutional investors' requirements.

### 3.4 Hypotheses 1a and 1b: Stock liquidity and investment efficiency

As discussed above, high stock liquidity can be associated with investment efficiency through at least two mechanisms based on capital market and corporate governance explanations. In summary, if high stock liquidity resolves information asymmetry between managers and external shareholders by making stock prices more informative, it can improve investment efficiency by curbing adverse selection and moral hazard problems. Similarly, if stock liquidity can alleviate agency conflicts through increasing the governance role of institutional investors, it can promote investment efficiency by reducing moral hazard problems through better direct monitoring (threat of voice) and indirect monitoring (threat of exit). That is, institutional investors who favour active monitoring, and those who prefer passive involvement but instead rely on the ex ante "threat of exit" mechanism, can promote investment efficiency via high-stock-liquidity. As such, I predict that high stock liquidity can reduce both under-investment and over-investment (i.e., investment inefficiency). This leads to this study's two main hypotheses stated in an alternative form:

***H1a:*** *Higher stock liquidity is expected to reduce under-investment.*

***H1b:*** *Higher stock liquidity is expected to reduce over-investment.*

## 3.5 Additional tests

As described in more detail later in Chapter 7, I conduct additional tests to explore whether the positive impact of stock liquidity on investment efficiency is stronger among firms that would get a larger benefit from higher stock liquidity. Drawing upon the stock liquidity literature with respect to its informational role mentioned above, I investigate whether the effect of stock liquidity on investment efficiency is more pronounced among firms with higher information asymmetry, focusing on young firms and high business risk firms that are likely to suffer from higher information asymmetry problems. I argue that higher stock liquidity is more beneficial to these firms as it can increase transparency and feedback effect to these firms, thereby improving firm investment efficiency. I also examine whether the effect of stock liquidity on investment efficiency is more pronounced among firms with a higher proportion of monitoring institutional investors, based on the stock liquidity literature in relation to its governance role discussed earlier. I argue that higher stock liquidity can help monitoring institutions to monitor effectively by enhancing their governance role, thereby enhancing firm investment efficiency.

# Chapter 4: Research Methodology

This section describes the methods for testing my research questions. I employ an ordinary least square (OLS) regression analysis to investigate the relationship between stock liquidity and investment efficiency using a sample of U.S. public firms between 1995 and 2012. Section 4.1 describes the multivariate regression analysis. Section 4.2 discusses variable measurement and predicted outcomes. Section 4.3 outlines the sample selection criteria and data sources.

### 4.1 Conditional relationship between stock liquidity and investment

I adapt the methodology employed in Biddle et al. (2009) to investigate the relationship between stock liquidity and the level of capital investment conditional on whether the firm is more likely to over- or under-invest. Recall that hypothesis H1a (H1b) is concerned with examining whether firm stock liquidity in the current year is negatively (positively) associated with next year's firm investment when firms are more likely to over-invest (under-invest). In order to test these conditional relationships, I partition the sample firms into those that are likely to over- and under-invest based on the firm’s cash balance and leverage. If stock liquidity does play a role in enhancing investment efficiency, I expect it to decrease investment in firms exhibiting an over-investment inclination, and increase investment in firms manifesting an under-investment tendency. The formal regression employed to test the study's two hypotheses is as follows:

$$INV_{i,t+1} = \alpha + \beta_1 LIQ_{i,t} + \beta_2 LIQ_{i,t} \times OverFirm_{i,t} + \beta_3 OverFirm_{i,t} + \sum\nolimits_{\gamma j} Controls_{j,i,t} + \varepsilon_{i,t+1} \qquad (1)$$

The dependent variable, investment *(INV)*, measures the difference between total investment made by the firm and its asset sales. Stock liquidity is measured using four proxies commonly employed in previous studies: the Fong, Holden, and Trzcinka’s (2014) liquidity measure, zero-return days (Lesmond et al. 1999), turnover (Lo and Jiang 2000), and a composite measure obtained from standardising and aggregating these three stock liquidity measures. *OverFirm* is a ranked variable used to distinguish between settings where over- or under-investment is more likely, whereby *OverFirm* is increasing in the likelihood of over-investment. Control variables consist of firm-specific and corporate governance variables, and industry fixed effects. Particularly, I control for accrual quality, percentage of institutional ownership, analyst following, firm size, firm age, sales volatility, and investment volatility, to name a few. The detailed descriptions of all variables are discussed in the following sections and summarised in the Appendix A.

An ordinary least square regression model is employed to estimate Equation (1). Following Fang et al. (2009) and Chen et al. (2015), I use a lagged measure of stock liquidity proxies to mitigate potential endogeneity concerns. Specifically, firm investments generally occur throughout a year, including the start of the year. Measuring stock liquidity at the end of the previous year ensures that all investment activities in a given year (including those that occur at the start of the year) occur after the point in time used to measure stock liquidity. It facilitates a clean assessment of whether stock liquidity in a given year affects the efficiency of the investments in the following year.

To reduce potential model misspecification bias, I cluster the standard errors by firm and year to account for serial- and cross-sectional correlation (Petersen 2009). I also include industry fixed-effects using the Fama and French (1997) 48-industry classification to control for industry-specific shocks to investment.

## 4.2 Variable Measurement

### 4.2.1 Dependent variable: Investment levels

I employ an accounting framework to measure investment levels in this thesis. Specifically, the investment level (*INV*) in a given firm-year is deduced as the sum of capital expenditures, R&D expenditures, and acquisitions, minus sales of property, plant, and equipment, scaled by lagged total assets (Richardson 2006). Following Biddle et al. (2009), all components of capital investment – tangible or intangible – are included in deriving the total investment, which is contrary to some prior studies that have focused on individual components of total investment (e.g., Biddle and Hilary 2006; Francis and Martin 2010; Bushman et al. 2011). By amalgamating all the subgroups of investment, *INV* may accurately reflect overall corporate investment behaviour.

### 4.2.2 Primary independent variable: Stock liquidity measures

Given that stock liquidity possesses multi-dimensional characteristics such as depth, breadth, and resiliency (Hasbrouck 2007) that cannot be perfectly captured using a single measure (Amihud 2002), prior research has employed various proxies to measure stock liquidity. These studies have typically employed "percent-cost" and "cost-per-volume" metrics to measure stock liquidity with the intention of capturing the costs of transaction, information asymmetry and price impact.[41] Stock liquidity metrics can be calculated using high-frequency (intraday) data, which produce direct and sharper measures, but are more resource-intensive in computation. On the other hand, other stock liquidity proxies can be calculated using low-frequency (daily) data, which provide more indirect and coarse measures, but are less resource-intensive in computation and readily available for a longer period.[42] By testing a series of stock liquidity proxies derived from low-frequency (daily) stock data against stock liquidity benchmarks calculated from high-frequency (intraday) microstructure data, Goyenko et al. (2009) conclude that stock liquidity measures based on daily data provide reasonably good measures of transaction costs. Since stock liquidity measures estimated from low-frequency data appear to adequately capture stock liquidity, I rely on daily stock data (i.e., price, returns, and volume), obtained from the Center for Research in Security Prices (*CRSP*), for computing stock liquidity in four different ways, as discussed next.

[41] Conceptually, a "percent-cost" metric reflects the cost of trading as a percentage of the price while a "cost-per-volume" captures the marginal transaction cost per unit of volume as measured in local currency (Fong et al. 2014).

[42] The availability of low-frequency data allows the construction of long time series of liquidity that are necessary to test the effects of liquidity over time (Amihud 2002).

#### *4.2.2.1 FHT's Cost of trading*

The first measure of stock liquidity employed in this study is based on a proxy created by Fong, Holden, and Trzcinka (2014) using low frequency data (*FHT*). *FHT* is a percent-cost proxy that reflects the cost of trading as a percentage of the price. The evidence provided by Fong et al. (2014) shows that the *FHT* measure is highly correlated with percent effective spread, percent quoted spread, percent realized spread, and percent price impact, which are direct measures of stock liquidity using the high-frequency U.S. trade and quote data. Thus, *FHT* appears to outperform other proxies commonly used in prior studies in liquidity literature. The formula for computing *FHT* is as follows:

$$FHT \;=\; 2\sigma N^{-1}\left(\frac{1+ZERO\%}{2}\right) \quad ,$$

where $N^{-1}(\,)$ is the inverse function of the cumulative normal distribution; $\sigma$ is the standard deviation of the daily returns calculated over firm *i's* fiscal year *t,* and *ZERO%* is the proportion of zero returns, calculated as the number of zero-return days divided by the number of total trading days for firm *i's* fiscal year *t*.[43] In summary, the *FHT* measure is an increasing function of both the proportion of zero returns and the volatility of the return distribution. Higher values of *FHT* imply lower stock liquidity exhibited in a stock. To facilitate consistent interpretation of the results across all measures of stock liquidity, I compute *LIQFHT* by multiplying *FHT* by -100 before including it in my tests, so that higher values of *LIQFHT* indicate higher stock liquidity.[44]

#### *4.2.2.2 Zero-return days*

The next measure of stock liquidity is extracted from Lesmond, Ogden and Trzcinka (1999) who measure stock liquidity as the number of zero-return trading days over the firm's fiscal year divided by the total trading days of the fiscal year (*ZERO%*). The rationale for this measure is that if the intensity of an information signal is too weak to exceed the

[43] I thank Prof Charles A. Trzcinka for providing the SAS code to calculate *FHT* measure.
[44] I multiply *FHT* by -100 instead of -1 to enlarge the value of *LIQFHT* coefficient for ease of presentation.

transaction costs, then it is expected that market participants will refrain from trading, thus resulting in an observed zero return (Lesmond et al. 1999). The incidence of zero returns captures the effects of transaction costs. Ashbaugh-Skaife, Gassen, and LaFond (2006) also find that a zero-return days metric captures the extent to which firm-specific information is incorporated into share prices, suggesting that firms with a higher proportion of zero-return days are likely to endure higher transaction costs and have less informative stock prices. Hence, stocks with greater *ZERO%* signifies lower stock liquidity. Again, to make the interpretation consistent across all proxies for stock liquidity, I multiply *ZERO%* by -1 to compute *LIQZERO* before employing it in my analysis. As such, higher values of *LIQZERO* indicate higher stock liquidity.

#### *4.2.2.3 Turnover*

The third proxy for stock liquidity is stock turnover, which is defined as the natural logarithm of the ratio of total shares traded annually divided by total number of shares outstanding per fiscal year (*LIQTURN*). Turnover captures trading frequency and, thus, an increase in turnover (*LIQTURN*) reflects an increase in stock liquidity. According to Lo and Jiang (2000), stock turnover is a natural measure of trading activity or volume compared to other measures of volume, which they support using theoretical arguments and empirical evidence.[45] Further, prior studies show that this turnover measure is negatively related to illiquidity costs (Amihud and Mendelson 1986), and its reciprocal (i.e., holding period) is positively associated with bid-ask spread (Atkins and Dyl 1997), suggesting that this measure is a reasonable proxy for stock liquidity. In addition, Jayaraman and Milbourn (2012) argue that this turnover measure, being in a standardised form, implicitly controls for firm size and allows effective comparison across firms and over time.

$$LIQTURN = \ln \left(\frac{1}{Days_{i,t}} \sum_{d=1}^{Days_{i,t}} \frac{Vol_{i,t,d}}{Shrout_{i,t,d}}\right),$$

[45] Other measures of volume used in prior studies include aggregate share volume, aggregate dollar volume, total numbers of trades, and trading days per year, to name a few (see Lo and Jiang 2000).

where $Vol_{i,t,d}$ and $Shrout_{i,t,d}$ are the trading volume in shares and number of shares outstanding for firm *i* in day *d* of fiscal year *t*. Higher values of *LIQTURN* represent higher stock liquidity.

#### *4.2.2.4 Composite stock liquidity*

Given that there is no single stock liquidity proxy that can capture all dimensions of stock liquidity properties, I construct the fourth stock liquidity proxy (*LIQindex*) as a composite measure by computing the standardised average of *LIQFHT, LIQZERO*, and *LIQTURN*. The higher (lower) values of this measure indicate higher (lower) stock liquidity.

### 4.2.3 Likelihood of under-investment and over-investment of a firm

To test the conditional relationship between stock liquidity and investment (Equation (1)), I construct a metric (*OverFirm*) that captures the likelihood of under- and over-investment across firms such that lower (higher) values of *OverFirm* indicate the tendency of a firm to under-invest (over-invest). Following Biddle et al. (2009), I construct *OverFirm* based on two ex-ante firm-specific characteristics (i.e., cash balance and leverage). Prior studies suggest that firms with less (more) cash are more likely to under-invest (over-invest). Put simply, cash poor firms may experience financial constraints and are more likely to under-invest. On the other hand, cash rich firms may be subject to agency problems such as squandering excessive cash in empire building endeavours, which may lead to inefficient over-investment (Jensen 1986; Blanchard et al. 1994; Opler et al. 1999). Similarly, firms with high (low) leverage are more likely to under-invest (over-invest). For example, highly levered firms may face debt overhang problems, which may deter them from pursuing value-enhancing investments, resulting in under-investment problems (Myers 1977).

To compute *OverFirm*, I first rank firms into deciles based on their cash balance and leverage respectively (I multiply leverage by -1 before ranking so that, similar to cash, it is increasing in the likelihood of over-investment) and rescale them to range between zero and one. *OverFirm* is computed by taking the average of the two ranked values based on cash balance and leverage. As such, high values of *OverFirm* indicate a higher likelihood of the firm engaging in over-investment. One advantage of using this composite measure is that it reduces measurement errors, in comparison to relying on individual variables.

### 4.2.4 Control variables

#### *4.2.4.1 Financial reporting quality*

Biddle et al. (2009) indicate that firms with higher financial reporting quality are more likely to be associated with investment efficiency. They argue that firms with higher financial reporting quality exhibit lower information asymmetry environment. In this case, managers are subject to external monitoring that induces them to invest efficiently. I employ accruals quality (*AQ*) to control the effect of financial reporting quality on my results. To estimate accrual quality, I follow Francis et al. (2005), and estimate a regression of total current accruals (*TCA*) on lagged, current, and future cash flows plus the change in revenue and *PPE*. All variables are scaled by firm *j's* average total assets in year *t*.[46]

$$TCA_{j,t} = \emptyset_{0,j} + \emptyset_{1,j}CFO_{j,t-1} + \emptyset_{2,j}CFO_{j,t} + \emptyset_{3,j}CFO_{j,t+1} + \emptyset_{4,j}\Delta Rev_{j,t} + \emptyset_{5,j}PPE_{j,t} + v_{j,t} \quad (2)$$

where

| | |
|---|---|
| *TCA* | = $(\Delta CA - \Delta Cash) - (\Delta CL - \Delta STDEBT)$ = Total Current Accruals, |
| *TA* | = $TCA - Dep$ = Total Accrual, |
| $\Delta CA$ | = change in current assets, |
| $\Delta Cash$ | = change in cash/cash equivalents, |
| $\Delta CL$ | = change in current liabilities, |
| $\Delta STDEBT$ | = change in short-term debt, |
| *Dep* | = depreciation and amortization expense, |
| *CFO* | = *NIBE-TA* = Cash Flow from Operations, |
| *NIBE* | = net income before extraordinary items, |
| $\Delta Rev$ | = change in revenue, and |
| *PPE* | = gross property, plant, and equipment. |

I estimate Equation (2) cross-sectionally for each industry-year combination with at least 20 observations whereby industries are defined using the Fama and French's (1997)

[46] Extreme values of each continuous variable are winsorized at the 1 and 99 percentiles.

48-industry classification. Accruals quality (*AQ*) at year *t* is the standard deviation of the firm level residuals from Equation (2) during the years *t-4* to *t*.

$$AQ_{j,t} = \sigma(v_j)_t \qquad (3)$$

Larger standard deviations of residuals (higher values of *AQ*) indicate poorer accruals quality. I multiply *AQ* by -1 as the financial reporting quality measure so that higher values of *AQ* signify higher financial reporting quality. I also add an interaction term between *OverFirm* and *AQ* to control for the effect of *AQ* on over- and under-investment.

#### *4.2.4.2 Governance*

Prior research shows that the corporate governance mechanism has an impact on investment efficiency (Biddle et al. 2009). My first governance proxy is based on the anti-takeover protection index (*InvG-Score*) as calculated in Gompers et al. (2003). Firms with higher *InvG-Scores* have more anti-takeover provisions that shield managers from takeover threats, which can act as a monitoring device. This suggests that higher *InvG-Scores* reflect poorer corporate governance. I multiply the score by -1, so that the new measure (*G_Score*) as my first governance proxy is increasing in corporate governance. Following Biddle et al. (2009), I include an indicator variable, *G_Dummy*, coded as 1 if *G_Score* is missing and zero otherwise.

The number of analysts following the firm (*Analyst*) is used as the second proxy for corporate governance. The more analysts following the firm, the higher the external pressure on a firm to promote good corporate governance. In addition, firms with liquid stocks are likely to attract analysts to follow their firms, highlighting the importance of controlling for this variable in my analysis. Following Biddle and Hilary (2006), I assume that firms not covered by *IBES* database have zero analyst coverage.

I also control for the presence of institutional investors using the percentage of firm shares held by institutional investors (*IO*), which is the third proxy for corporate governance extracted from the *Thomson Reuters 13F* database. Prior literature indicates that institutional investors play an important role in influencing managers' behaviours and improving firm performance (Bushee 1998; Gillan and Starks 2000; Hartzell and Starks 2003; Velury and Jenkins 2006; Chung and Zhang 2011; Ramalingegowda and Yu 2012). As such, it is important to control for the effects of this variable that may impact firms' investment decisions.

#### *4.2.4.3 Other control variables*

Innate firm characteristics that may affect investment levels include size (*LogAsset*), cash flow volatility (*σ(CFO)*), sales volatility (*σ(Sales)*), log operating cycle (*OCycle*), and losses (*Loss*) (Verdi 2006; Biddle et al. 2009). Prior studies show that large and unprofitable firms tend to reduce investments. Biddle et al. (2009) document that higher operating volatility in sales and the operating cycle are associated with lower investment, respectively, whereas cash flow volatility induces higher investments. Higher operating volatility increases the uncertainty of generating cash flows that can be used to finance investment. Also, following Biddle et al. (2009), I control for investment volatility (*σ(INV)*) because this measure is positively related to investments.

Fazzari et al. (1988) show that financial constraints in capital markets influence investments. They document that investment-cash flow sensitivity increases in financing constraints measured as dividend payout and firm age. Thus, firm age (*Firm_Age*) and dividend payout (*DIV*) are used to proxy for financing constraints. Mature firms are unconstrained because they have enough cash reserve or less information asymmetry problems (see Lang and Lundholm 1993) due to their established reputation.[47] Thus, mature firms appear to face fewer obstacles in sourcing funds for their investments. At the same time, it is possible that mature firms experience slower growth and have fewer investment opportunities, resulting in lower investments. Consistent with this view, Biddle et al. (2009) document a negative relationship between firm age and investment levels. Fazzari et al.

[47] Lang and Lundholm (1993) show that analyst ratings of corporate disclosure are higher for firms that perform well and for larger firms, among other determinants.

(1988) argue that firms with a lower dividend payout face financing constraints because these firms are likely to retain funds for future financially-constrained situations. Thus, it is expected that low-dividend firms are likely to under-invest.

Firms with more investment opportunities are likely to invest more. Biddle and Hilary (2006) rely on market-to-book ratio (*MB*) and the ratio of operating cash flow to sales (*CFOsale*) to proxy for investment opportunities. Financial pressure to generate cash flows to fund working capital or to service debt may create significant investment distortions. Bankruptcy risk (*Z_Score*) and industry leverage (*Ind_Kstruct*) are used as proxies for financial pressure. Both measures are found to be negatively related to investment levels in Biddle et al. (2009). Almeida and Campello (2007) show that asset tangibility affects the cash flow sensitivity of investment in financially constrained firms, but not in unconstrained firms. The rationale is that an increase in tangibility of firms' assets improves pledgeability that supports more borrowing for investment, especially for financially constrained firms. Their findings suggest that firms with higher tangibility are more likely to be financially unconstrained and, thereby allowing more NPV projects to be funded. Consistent with this view, Biddle et al. (2009) show that firms with higher tangible assets are associated with higher investment. Thus, I include tangibility of firm assets (*Tangibility*) as a proxy for pledgeability and financial constraints.

Finally, to ensure the results are not driven by industry, I include industry fixed-effects based on the Fama-French (1997) 48-industry classifications.

### 4.2.5 Predicted outcomes

Recall that this study tests the two hypotheses (H1a and H1b) by regressing investment levels (*INV*) on stock liquidity (*LIQ*) and the interaction effect between *LIQ* and *OverFirm*, as shown in the regression model below:

$$INV_{i,t+1} = \alpha + \beta_1 LIQ_{i,t} + \beta_2 LIQ_{i,t} \times OverFirm_{i,t} + \beta_3 OverFirm_{i,t} + \sum\nolimits_{\gamma j} Controls_{j,i,t} + \varepsilon_{i,t+1} \qquad (1)$$

Hypothesis H1a predicts that stock liquidity (*LIQ*) is positively associated with investment levels (*INV*) in a setting in which the firm is more likely to under-invest (*OverFirm* = 0). When *OverFirm* equals zero, it represents firms that are financially constrained, and thus are likely to under-invest. In this scenario, I expect that firms with more liquid stock are less likely to under-invest. Stated differently, in a scenario in which firms are likely to under-invest, high stock liquidity is expected to reduce inefficient investment behaviour by increasing investment levels. The coefficient used to test H1a in Equation (1) is $\beta_1$, which is expected to capture the effect of liquidity on investment efficiency in firms that are more likely to under-invest. A significant positive coefficient on $\beta_1$ would provide support for H1a by indicating that firms with higher stock liquidity are associated with increased investments when the firms are more likely to under-invest.

Hypothesis H1b predicts that stock liquidity (*LIQ*) is negatively associated with investment levels (*INV*) when the firm is more likely to over-invest (*OverFirm* = 1). When *OverFirm* equals 1, it implies that firms are more likely to be less financially-constrained, and thus are more likely to over-invest. In cases where firms are likely to over-invest, high stock liquidity can reduce this inefficiency by reducing investment levels. The estimated coefficient on interaction term ($\beta_2$) captures the incremental effect of stock liquidity on investment levels for firms that are more likely to over-invest relative to firms that are inclined to under-invest. It is expected that stock liquidity is more likely to reduce the level of investment in firms that tend to over-invest. Hence, the expected sign of $\beta_2$ is negative. The sum of the coefficients ($\beta_1 + \beta_2$) measures the total effect of stock liquidity on investment for firms that are likely to over-invest. Since H1b predicts that stock liquidity is negatively associated with over-investment, a significant negative sign on the sum of coefficients ($\beta_1 + \beta_2$) will provide support for this hypothesis.

In summary:

| | | | |
|---|---|---|---|
| H1a | $\beta_1 > 0$ | If stock liquidity is higher | Higher investment for firms with higher likelihood of *under-investment* |
| H1b | $\beta_1 + \beta_2 < 0$ | If stock liquidity is higher | Lower investment for firms with higher likelihood of *over-investment* |

### 4.3 Sample Selection

This section discusses the selection of the sample used to test my research question and outlines the data collection process used to derive the final sample for this study. The sample consists of public firms listed on the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX) and the National Association of Securities Dealers Automated Quotations (NASDAQ) with data available from 1995 to 2012 (inclusive). Since financial firms (SIC codes between 6000–6999) have unique accounting and regulatory requirements compared with non-financial firms, they are excluded from the sample.

Panel A of Table 1 outlines the sample selection process for this study. I draw my data from five sources. Stock liquidity and firm age data are collected from *CRSP* (the Center for Research in Security Prices), data for constructing my measure of investment levels and most control variables are derived from *Compustat*, analyst data is from *IBES* (The Institutional Brokers Estimate System), institutional investor data is from *Thomson Reuters 13F*, and data to measure investor protection rights is from Andrew Metrick's website.[48] I begin with 247,541 firm-years spanning 1984-2012 with data available from the *Compustat* Industrial Annual File for constructing the dependent (investment levels) and control variables (e.g., firm characteristics, accruals quality, and *OverFirm*). Next, 99,858 observations with common stocks not being traded on the NYSE, AMEX, or NASDAQ are excluded because some of my stock liquidity variables cannot be estimated for these firms. Following Biddle et al. (2009), 42,331 observations from financial firms (SIC codes 6000-

[48] http://faculty.som.yale.edu/andrewmetrick/data.html

6999) are also excluded because of the unique nature of their investment and financing.[49] As my tests start in 1995, I then eliminate 33,279 firm-year observations before 1995 after estimating variables that require data spanning before year 1995 (e.g., accrual quality). After merging the data with those extracted from *CRSP*, *IBES*, *Thomson Reuters 13F* and investor protection rights data, I arrive at my final sample of 42,455 firm-year observations over the period 1995-2012 with non-missing data for all variables.

<<<INSERT TABLE 1 ABOUT HERE>>>

Panel B of Table 1 reports the industry distribution of my final sample firms based on the Fama and French (1997) industry classification scheme. The Business Services industry represents the largest industry, constituting about 13 percent of the whole sample followed by the electronic equipment, pharmaceutical products, and retail industries, which each representing about 6 percent of the sample. In total, the dataset covers 40 Fama-French (1997) industries, with about 72 percent of the observations in my sample coming from 14 of the 40 industries. Panel C of Table 1 presents the yearly distribution of the observations in the final sample. I find that all years in my sample period are generally evenly distributed in my sample, contributing between 2,252 and 2,672 observations, with the exception of the year 2012, which provides only 1,250 observations. This is not surprising as *Compustat* did not provide full coverage of 2012 data at the time of data collection.

[49] Financial firms have a very different composition of investment compared with non-financial firms. These firms usually do not invest heavily in capital and R&D in view of the nature of their business. Further, high leverage is common in financial firms but denotes financial distress for non-financial firms.

# Chapter 5: Descriptive Statistics

## 5.1 Summary of main hypotheses

This thesis investigates the association between stock liquidity and investment efficiency. Specifically, I seek to address the following research questions: (i) is higher stock liquidity associated with higher investment levels in firms that are likely to under-invest?, and (ii) is higher stock liquidity associated with lower investment levels in firms that tend to over-invest? This section presents the summary statistics for the observations included in my sample. Section 5.2 discusses the descriptive statistics on the key variables employed in the analyses, while Section 5.3 discusses the correlation coefficients between these variables. Lastly, Section 5.4 concludes this chapter.

## 5.2 Summary Statistics

Table 2 presents the descriptive statistics for investment levels, stock liquidity, governance variables and determinants of investments. To minimize the effect of outliers, I winsorize all continuous variables at the top and bottom 1 percentile with the exception of the indicators variables (e.g., *DIV, Loss, and G_Dummy*) and the variable *OverFirm, Analyst* and *Firm_Age* because either the ranges (minimum and maximum) of these variables are consistent with prior studies (e.g., Biddle et al. 2009) or they are binary variables. On average, firms in my sample invest 14.8 percent of their lagged total assets (median=9.7 percent), which is similar to the figures reported in prior studies (e.g., Biddle et al. 2009).

<<<INSERT TABLE 2 ABOUT HERE>>>

The first stock liquidity measure (*LIQFHT*) has a mean (median) value of -0.72 (-0.28), implying that the average (median) cost of trading is 0.72 percent (0.28 percent) of stock price. Descriptive statistics for the second liquidity proxy, *LIQZERO*, indicate that, on average, 7 percent of trading days for the sample firms has zero returns (non-trading days) in a fiscal year (median=4 percent). The highest and the smallest incidences of zero daily returns are 37 percent and 0 percent respectively. *LIQTURN*, the third liquidity proxy employed in this study, has a mean (median) value of 0.81 (0.74). As *LIQTURN* is constructed from taking a natural logarithm of firm's turnover, I take the antilog of firm's *LIQTURN* to revert back to turnover measure for natural interpretation. Correspondingly, the mean (median) (untabulated) for turnover (the original scale of *LIQTURN*) is 0.16 (0.11), indicating that, on monthly average, 160,000 shares are being traded for every one million shares outstanding. Given that there is no single stock liquidity proxy that can capture all dimensions of stock liquidity properties, I construct the fourth liquidity proxy (*LIQindex*) as a composite-based measure by computing the standardised average of *LIQFHT, LIQZERO*, and *LIQTURN*. The mean (median) of *LIQindex* is 0.00 (0.19). The mean (median) *OverFirm* is 0.51 (0.50), indicating that firms are evenly distributed between over- and under-investing likelihood. This is expected due to the fact that *OverFirm* is constructed by averaging decile rankings of two variables (i.e., cash balance and leverage) that measure the level of financial constraints.

Table 2 also provides the summary statistics for the control variables in my model. The average (median) firm in my sample has total assets worth around \$3.00 billion (\$0.37 billion). Since total assets exhibit right-skewness, I transform total assets using a natural logarithm function to mitigate the potential impact of outliers in my subsequent analyses. On average, a sample firm is 19 years old (median=14 years old), with the firm age (*Firm_Age*) values ranging between 1 and 88. The mean (median) market-to-book (*MB*) value ratio is 1.97 (1.48), suggesting that, on average, firms have higher market valuation relative to the book value of their assets. The mean (median) of volatility of sales (*σ(Sales)*) and cash flow (*σ(CFO)*) are 0.29 (0.20) and 0.07 (0.05), respectively. Further, the volatility of investment (*σ(INV)*) has an average (median) value of 14.06 (6.42). The median firm has operating cash flow (*CFOsale*) amounting to 8 percent of its total sales, whereas the mean ratio of cash flow to sales (*CFOsale*) is negative 3 percent.[50] The descriptive statistics of tangibility (*Tangibility*) indicate that the mean (median) property, plant and equipment (PP&E) held by firms is 28 percent (20 percent) of their total assets, whereas mean (median) slack (*Slack*) indicates that firms hold cash worth 3.13 (0.44) times the value of their PP&E. The average (median) log operating cycle (*OCycle*) is 4.61 (4.69). In my sample, 39 percent of average firms pay dividends (*DIV*).

Following Biddle et al. (2009), I also include control variables that capture the effects of firms' liabilities and levels of financial distress. Descriptive statistics on the bankruptcy index (*Z_Score*) shows that the sample firms have an average (median) *Z_Score* value of 1.27 (1.35). Further, the mean (median) firm leverage (*Kstruc*) and 3-digit industry leverage (*Ind_Kstruct*) values are 0.17 (0.09) and 0.17 (0.13), respectively, reflecting firm's average market leverage is around 17 percent. On average, twenty-seven percent of my sample firms experience losses (*Loss*).

Table 2 shows that the mean (median) values of all four governance variables are compatible with prior studies (e.g., Biddle et al. 2009). Particularly, the mean level of institutional ownership (*IO*) is around 52 percent in my sample while on average, each firm is followed by six analysts (*Analyst*). The mean (median) of anti-takeover protection measure (*G_Score*) is -1.1 (0.0). However, eighty-eight percent of my observations have a missing value in *G_Score* (*G_dummy*). The high percentage of missing observations for *G_Score* in my sample reflects the fact that the sample year coverage extends to 2012, which is far beyond the last year of coverage for *G_Score* data (i.e., 2006).[51] The mean (median) value of the variable capturing accruals quality (*AQ*) is -0.06 (-0.04). Overall, the summary statistics of the control variables are similar to those reported in other studies (e.g., Biddle et al. 2009; Cheng et al. 2013), which suggest that my sample is comparable to those employed in prior studies.

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[50] The distribution of the ratio of cash flow to sales (*CFOsale*) is negatively skewed despite the winsorisation procedure has been applied to this variable. Biddle et al. (2009) report similar skewed distribution for this variable with the mean of -0.08 and the median of 0.06.

[51] G scores are available for the 1990, 1993, 1995, 1998, 2000, 2002, 2004 and 2006 fiscal years.

### 5.3 Correlation matrix

Table 3 presents the Pearson correlation matrix among the dependent, test and control variables. The three main stock liquidity proxies (*LIQFHT, LIQZERO,* and *LIQTURN*) are positively and significantly ($p$<.01) correlated with each other, with the correlation coefficients ranging between 0.317 and 0.834. Notably, these coefficients are not high (less than 0.5) except that *LIQFHT* is highly correlated with *LIQZERO*. The low correlation coefficients suggest that these stock liquidity proxies may capture different dimensions of stock liquidity, among which I compute a composite measure (*LIQindex*), that can provide stronger support for my findings if the null hypotheses are rejected using all proxies.

<<<INSERT TABLE 3 ABOUT HERE>>>

Two of the stock liquidity measures (i.e., *LIQFHT* and *LIQTURN*) are significantly ($p$<.01) correlated with investment levels (*INV*), with correlation coefficients of -0.022 and 0.118 respectively. While these statistics suggest that stock liquidity is correlated with investment levels, they do not shed light on the effect of stock liquidity on investment efficiency, which is the focus of this study. *OverFirm* is positively and significantly ($p$<.01) associated with *INV*, confirming that firms with higher cash and lower debt tend to have higher investment levels.

In general, all control variables with the exception of operating cycle (*OCycle*) are significantly ($p$<.01) correlated with investment levels (*INV*). Market-to-book value (*MB*) is positively ($p$<.01) correlated with *INV*, suggesting that high growth firms are associated with higher investment levels. Firm size (*LogAsset*), dividends (*DIV*), and firm age (*Firm_Age*) are negatively and significantly ($p$<.01) related to *INV*, indicating that smaller, younger, and non-dividend-paying firms are associated with higher investments. Surprisingly, I find that losses (*Loss*) are positively ($p$<.01) correlated with *INV*, indicating that loss making firms tend to invest more. As expected, firms with higher bankruptcy score (*Z_Score*), higher leverage (*Kstruc*), and higher 3-digit industry leverage (*Ind_Kstruct*) are associated with lower investment levels (*INV*). Volatility in sales (*σ(Sales)*) is negatively

($p<.05$) related to *INV*, whereas volatility in cash flow (*σ(CFO)*) and in investment (*σ(INV)*) are both positively ($p<.01$) related to *INV*. When firms have a higher operating cash flow relative to their total sales (*CFOsale*) as well as holding a greater PP&E relative to their total assets (*Tangibility*), their investment levels decreases correspondingly ($p<.01$). Firms carrying more cash relative to their PP&E (*Slack*) exhibit higher investment levels ($p<.01$).

The correlation statistics indicate that the governance variables are also highly correlated ($p<.01$) with *INV*. Institutional investors (*IO*) and investment (*INV*) are negatively correlated ($p<.01$), suggesting that higher institutional ownership are associated with lower investment levels. In contrast, higher analysts following (*Analyst*) and higher anti-takeover protection measure (*G_Score*) are associated with higher investment levels (*INV*) ($p<.01$). Further, the indicator (*G_Dummy*) measuring observations with missing *G_Score* is also positively correlated with *INV* ($p<.01$). Consistent with Biddle et al. (2009), accrual quality (*AQ*) is negatively correlated ($p<.01$) with *INV*. Overall, the correlations between each independent variable and *INV* should be interpreted with caution given that they are obtained without controlling for the effects of the remaining independent variables.

The correlation among independent variables shows that the correlation coefficients are generally less than 0.5 with only a few correlation coefficients lying between 0.5 and 0.7. Among those with higher correlation coefficients, firm size (*LogAsset*) is positively correlated ($p<.01$) with *LIQFHT*, institutional ownership (*IO*), and analysts (*Analyst*), reflecting that large firms attract more institutional investors and financial analysts, and that their shares are also actively traded. Further, the untabulated variance inflation factors (VIFs) range between 1 and 7 with the exception of *G_Score* and *G_Dummy* (VIFs < 12).[52] Overall, the correlation results are similar to prior studies (Biddle et al. 2009) and the coefficients are generally lower than 0.5.

[52] I include *G_Score* and *G_Dummy* in my analyses for sake of comparability with prior studies (e.g., Biddle et al. 2009). However, my findings and conclusions remain robust when I exclude one or both of these variables from my analyses.

## 5.4 Chapter summary

In this chapter, I report and interpret the summary statistics and correlations for the variables employed in this thesis. Generally, the statistics are consistent with prior studies. The next chapter presents the empirical results for this thesis' main hypotheses.

# Chapter 6: Empirical Analyses: Stock Liquidity and Investment Efficiency

## 6.1 Introduction

My study's hypotheses (H1a and H1b) collectively predict that firms with higher levels of stock liquidity are positively associated with higher investment efficiency. I test my research question using a regression analysis, where the dependent variable in my analyses is the level of investment in firms (*INV*) while the independent variables of interest are stock liquidity (*LIQ*) and a variable that captures firms the likelihood of firms over-investing (*OverFirm*).[53] To recap, my regression model is as follows:

$$INV_{i,t+1} = \alpha + \beta_1 LIQ_{i,t} + \beta_2 LIQ_{i,t} \times OverFirm_{i,t} + \beta_3 OverFirm_{i,t} + \sum\nolimits_{\gamma j} Controls_{j,i,t} + \varepsilon_{i,t+1} \quad (1)$$

When *OverFirm* equals zero, it represents firms that are financially constrained, and thus are likely to under-invest. In this scenario, I expect that firms with more liquid stock are less likely to under-invest. This is reflected in hypothesis H1a, which predicts a positive coefficient on *LIQ* (i.e., H1a: $\beta_1 > 0$). That is, stock liquidity increases investment levels for firms with higher likelihood of under-investment. Alternatively, firms with a value of 1 for *OverFirm* are expected to be less financially-constrained. These firms are more likely to over-invest. In this case, I expect that the more liquid a firm's stock, the lower the likelihood that the firm will over-invest. Hence, hypothesis H1b predicts that the sum of the coefficients on the main stock liquidity (*LIQ*) and interaction effects (*LIQ* x *OverFirm*) to be negative (i.e., H1b: $\beta_1 + \beta_2 < 0$). That is, higher stock liquidity leads to lower investment for firms with a higher likelihood of over-investment. In addition, I test if the coefficient of the interaction term, which measures the incremental relationship between stock liquidity and investment in the case of over-investment, is less than zero (i.e., $\beta_2 < 0$).

[53] Following Biddle et al. (2009), I construct *OverFirm* based on two ex-ante firm-specific characteristics (i.e., cash balance and leverage), which are likely to dictate the nature of investment inefficiency in a firm.

Section 6.2 presents and interprets the results from estimating the above regression. Recognising that the relationship between stock liquidity and investment efficiency can be endogenously determined, Section 6.3 addresses this concern by discussing findings from robustness tests that employ two stage least-square estimations, change specifications, regression by year exclusions, regression by industry exclusions, alternative stock liquidity proxies and alternative investment proxies. Prior studies suggest that stock price informativeness could drive my main results, I thus run a separate multivariate regression to control for this variable. Section 6.4 concludes this chapter.

### 6.2 Empirical results

Table 4 reports the results of the regression of investment on stock liquidity and control variables conditional on firm's propensity to over- or under-invest. The table depicts four specifications results using different stock liquidity measures. Column (1) presents the results using *LIQFHT* as the measure of stock liquidity. According to Fong et al. (2014), *LIQFHT* resembles the best stock liquidity proxy due to its high correlation with stock liquidity proxies derived from high-frequency (intraday) data such as percent effective spread, percent quoted spread, precent realised spread, and percent price impact.

<<<INSERT TABLE 4 ABOUT HERE>>>

The coefficient on *LIQFHT* is positive and significant at the 1 percent level, suggesting that when the likelihood of under-investing is greater, firms with more liquid stock invest significantly more than firms with lower stock liquidity. This result supports the view that higher stock liquidity can encourage optimal levels of investment in firms that tend to under-invest by increasing their investment levels. To estimate the economic significance of this result, I multiply the coefficient on *LIQFHT* (1.20) by the standard deviation of *LIQFHT* from the summary statistics reported in Table 2 (1.06), to obtain the change in investment levels from a one standard deviation change in *LIQFHT*. Hence, a one standard deviation increase in *LIQFHT* in firms that are likely to under-invest produces an increase in investment levels equating to around 1.27 percent of total assets. Given that the mean investment levels equals to 14.8 percent across the full sample, this incremental effect represents around 9 percent of the average investment levels in my sample.[54] Hence, these results lend strong support to hypothesis H1a.

The coefficient on the interaction term between *LIQFHT* and *OverFirm* is significant and negative ($p$<.01). The sum of the coefficients on *LIQFHT* and *LIQFHT* x *OverFirm*, which measures the extent to which stock liquidity affects investment levels in firms that are likely to over-invest, is also negative and significant ($p$<.01). In terms of the economic significance, increasing *LIQFHT* by one standard deviation decreases investment levels in firms that are likely to over-invest by about 2.15 percent of total assets.[55] This represents a decrease in investment of about 15 percent relative to the mean investment levels in my sample.[56] Thus, the findings provide strong support for hypothesis H1b.

Columns (2), (3) and (4) present the corresponding results after regressing the investment levels (*INV*) on the other three liquidity measures (*LIQZERO, LIQTURN* and *LIQindex*) and the control variables. The results from these analyses indicate that the coefficients on *LIQTURN* and *LIQindex* are positive and significant ($p$<.05) but the coefficient on *LIQZERO* is not significant. In terms of economic significance, the findings suggest that a one standard deviation increase in stock liquidity is associated with an increase in investment levels of 0.72 percent (based on the *LIQTURN*) and 0.84 percent (based on the *LIQindex*) for firms that are more likely to under-invest.[57] The separate effects of *LIQTURN* and *LIQindex* are equivalent to 5 percent and 6 percent of the mean

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[54] To calculate this incremental effect, I divide the increment value in investment levels resulting from a one standard deviation increase in *LIQFHT* (1.27 percent) by the mean investment levels (14.8 percent) to arrive at 9 percent.

[55] The coefficients on *LIQFHT* and *LIQFHT* x *OverFirm* in Table 4 are 1.201 and -3.230 respectively. Therefore, the coefficient of the sum of *LIQFHT* and *LIQFHT* x *OverFirm* is -2.030 [= 1.201+(-3.230)]. To compute the economic significance, I multiply the sum of coefficient (-2.030) by the standard deviation of *LIQFHT* (1.06) to yield -2.15 percent.

[56] Given that the mean investment equals 14.8 percent, I divide the decrement value in investment levels resulting from a one standard deviation increase in *LIQFHT* (-2.15 percent) by the mean investment levels (14.8 percent) to generate -15 percent.

[57] To calculate the economic significance based on the *LIQTURN* proxy, I multiply the coefficient on *LIQTURN* (1.476) with the standard deviation of *LIQTURN* (0.49) to arrive at 0.72 percent. Similarly, the economic significance based on the *LIQindex* proxy is derived from multiplying the *LIQindex* coefficient (1.012) with the standard deviation of *LIQindex* (0.83) to yield 0.84 percent.

investment levels (14.8 percent) across the full sample.[58] On the whole, the results continue to support hypothesis H1a.

The coefficients on the interaction term between stock liquidity (*LIQ*) and *OverFirm* are significant and negative in all three specifications ($p$<.05 or better). The sum of the coefficients on *LIQ* and *LIQ* x *OverFirm* are also negative and significant ($p$<.10 or better) for these three specifications. In terms of the economic significance, increasing *LIQ* by one standard deviation decreases investment levels in firms that are more likely to over-invest by about 1.67 percent (based on *LIQZERO*), 0.38 percent (based on *LIQTURN*), and 1.58 percent (based on *LIQindex*).[59] These effects equal to 11 percent, 3 percent and 11 percent of the mean investment levels in my sample (14.8 percent).[60] Taken together, the evidence is again generally consistent with hypotheses H1b.

The control variables are generally significant ($p$<.05 or better) and have similar signs to those reported in prior studies (e.g., Biddle et al. 2009). Specifically, I find that total investment levels (*INV*) have a positive relationship with the likelihood of over-investing (*OverFirm*), market-to-book ratio (*MB*), cash flow volatility (*σ(CFO)*), investment volatility (*σ(INV)*), and tangibility of assets (*Tangibility*). These results indicate that firms with greater likelihood of over-investing (*OverFirm*), greater market valuation (*MB*), more volatility in cash flow (*σ(CFO)*) and investment (*σ(INV)*), and higher proportion of PP&E to total asset (*Tangibility*) are associated with higher investment levels. Contrary to Biddle et al. (2009), volatility in sales (*σ(Sales)*) is not significant.

[58] To compute the incremental effect relatives to the mean investment based on the *LIQTURN* proxy, I divide the increment value in investment levels resulting from a one standard deviation increase in *LIQTURN* (0.72 percent) by the mean investment levels (14.8 percent) to produce 5 percent. The calculation method is repeated for the *LIQindex* proxy by dividing increment value in investment levels resulting from a one standard deviation increase in *LIQindex* (0.84 percent) by the mean investment levels (14.8 percent) to arrive at 6 percent.

[59] To compute the economic significance for joint coefficients for *LIQZERO* and *LIQZERO* x *OverFirm*, I multiply the corresponding joint coefficient (-20.91) with the standard deviation of *LIQTURN* (0.08) to yield -1.67 percent. Similarly, the economic significance for joint coefficient for *LIQTURN* and *LIQTURN* x *OverFirm* is derived from multiplying the joint coefficient (-0.785) with the standard deviation of *LIQTURN* (0.49) to arrive at -0.38 percent. Likewise, the economic significance for joint coefficient for *LIQindex* and *LIQindex* x *OverFirm* is computed by multiplying the joint coefficient (-1.898) with the standard deviation of *LIQindex* (0.83) to result in -1.58 percent.

[60] Given that the mean investment is 14.8 percent, the corresponding incremental effect relatives to the mean investment is [Δinv / avg(inv)], where Δinv is the increment value in investment levels resulting from a one standard deviation increase in stock liquidity, and avg(inv) is the mean investment levels. Therefore, the incremental effect is (-1.67/14.8)*100 = -11 percent (based on *LIQZERO*), (-0.38/14.8)*100 = -3 percent (based on *LIQTURN*), and (-1.58/14.8)*100 = -11 percent (based on *LIQindex*).

On the other hand, *INV* has a negative association with firm size (*LogAsset*), bankruptcy risk (*Z_Score*), industry leverage (*Ind_Kstruct*), cash flows (*CFOsale*), dividend payout (*DIV*), firm age (*Firm_Age*), operating cycle (*OCycle*), and loss (*Loss*). These results suggest that larger (*LogAsset*), older (*Firm_Age*), financially-distressed (*Z_Score, Ind_Kstruct, Loss*), and dividend-paying (*DIV*) firms are more likely to have lower investment levels. Also, firms with longer operating cycle (*OCycle*) and higher operating cash flow relative to sales (*CFOsale*) are more likely to have lower investment levels.

Interestingly, the accrual quality (*AQ*) results reveal insignificant coefficients on *AQ* x *OverFirm* (using *LIQFHT, LIQZERO, LIQindex proxies*), and on *AQ* (using *LIQFHT*). The results on the association between accruals quality and investment efficiency are inconsistent with those reported in Biddle et al. (2009). Further, investigations reveal that these insignificant findings are caused by the inclusion of *LIQ* and *LIQ* x *OverFirm*, which are not considered in Biddle et al. (2009). This could be because the inclusion of multiple interaction terms involving the variable *OverFirm* induces correlation issues between these interaction terms, resulting in multicollinearity problems. Indeed, the results of *AQ* and *AQ* x *OverFirm* become significant with similar directions reported in Biddle et al. (2009) when *LIQ* and *LIQ* x *OverFirm* are excluded from the regression models. Additionally, some prior studies argue that accounting quality may play a lesser role in mitigating information asymmetry problems when capital suppliers possess other sources of information such as private information, since this information serves as an alternative information-problem-mitigating device (Biddle and Hilary 2006). Indeed, using a debt market setting, Beatty et al. (2010) document a smaller effect of accounting quality on firms' investment-cash flow sensitivity for firms with bank debt than for those with public debt. Since banks can have direct access to private information regarding firm's performance, Beatty et al. (2010) argue that accounting quality has a low influence on investment-cash flow sensitivity when outside capital suppliers such as banks possess private information, thus supporting their hypothesis that private information and accounting quality can serve as substitutes. In line with this view, my findings suggest that the effect of stock liquidity subsumes the effect of accounting quality on investment efficiency when outside investors can obtain additional information from the movement of firm's stock liquidity.[61]

I also find significant relationships between investment levels and some of my corporate governance measures. Specifically, the results depict positive and significant ($p$<.01) coefficients on the variables capturing institutional investors (*IO*) and analyst coverage (*Analyst*), indicating that higher external monitoring are positively related to investment levels. While the coefficient for the measure of anti-takeover protection (*G_Score*) is unexpectedly negative and significant ($p$<.01), this result is similar to that reported in Biddle et al. (2009). I do not include additional independent variables capturing the interaction of these corporate governance variables with *OverFirm* because of two main reasons. First, these additional interaction terms produce high variance inflation factors (VIFs) ranging from 10 to 20 (untabulated). Second, these interactions have generally produced insignificant effects in prior research (Biddle et al. 2009).

The adjusted $R$-squared values from the four regression specifications reported in Table 4 indicate that the explanatory variables collectively explain between 26.29 percent and 26.45 percent of the total variation in investment levels. To evaluate the incremental contribution of *LIQ* and *LIQ* x *OverFirm* to the explanatory power of my regression model, I follow Gujarati (2003) by first reestimating the regression analyses in Table 4 by excluding *LIQ* and *LIQ* x *OverFirm* to obtain $R$-squared values ($R^2_{old}$). The corresponding R-squared value ($R^2_{old}$) is 26.37 percent which is lower than the $R$-squared values (ranging between 26.39 and 26.55) reported for the full models ($R^2_{new}$). Next, I compute the $F$-statistics suggested by Gujarati (2003, 260–264) using the $R$-squared statistics reported for the regressions with and without *LIQ* and *LIQ* x *OverFirm* to test the null hypothesis that the inclusion of *LIQ* and *LIQ* x *OverFirm* as explanatory variables does not increase the

[61] Untabulated results from tests that employ the absolute value of residuals (i.e., discretionary accruals) as a proxy for accounting quality produce qualitatively similar results and conclusions.

explanatory power ($R^2$) of my regression analyses.[62] The Gujarati (2003) *F*-statistics range between 5.767 and 52.019 across the four regression specifications and are significant at the 1 percent level, suggesting that *LIQ* and *LIQ* x *OverFirm* significantly increase the explanatory power of the regression models.

Graph A through D in Figure 2 depicts, for each of the four stock liquidity proxies, how the stock liquidity (*LIQ*) slope changes with increasing values of *OverFirm*. The adjusted mean investment levels on the y axis are graphed with *LIQ* on the *x* axis and with separate lines for four levels of *OverFirm* ranging from 0 to 0.9 in 0.3 unit increments. Notably, the *LIQ* slopes for those firms with lower *OverFirm* values (i.e., *OverFirm* = 0 or 0.3) are positive, whereas the *LIQ* slopes for those firms with higher *OverFirm* values (i.e., *OverFirm* = 0.6 or 0.9) are negative. These results suggest that the marginal effects of stock liquidity on investment levels change from positive to negative when the likelihood of over-investing is increasing, suggesting that stock liquidity can mitigate inefficiency in investment for firms who tend to under- or over-invest. The findings based on *LIQZERO* are less obvious in the scenario where firms are likely to under-invest (see Graph B). This is consistent with the insignificant result obtained using *LIQZERO* in the test of H1a in the regression analysis reported in Table 4. In summary, Figure 2 provides visual support for the positive impact of stock liquidity on investment efficiency, complementing the empirical results reported in Table 4.

<<<INSERT FIGURE 2 ABOUT HERE>>>

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[62] The Gujarati's (2003) $\Delta R^2$ *F*-statistics test the null hypothesis that the inclusion of *LIQ* and *LIQ* x *OverFirm* as explanatory variables does not affect the explanatory power of the regression analyses. The *F*-statistic is given by:

$$\frac{(R^2_{new}-R^2_{old})/n}{(1-R^2_{new})/df},$$

where $R^2_{new}$ ($R^2_{old}$) is the $R^2$ value of the regression model with the inclusion (exclusion) of *LIQ* and *LIQ* x *OverFirm*, *n* equals the number of new regressors being considered (in my model, *n*=two [i.e., *LIQ* and *LIQ* x *OverFirm*]), and *df* is the number of observations minus the number of parameters in the regression model that includes *LIQ* and *LIQ* x *OverFirm* (Gujarati 2003, 260–264).

### 6.3 Robustness and sensitivity tests

#### 6.3.1 Controlling for stock price informativeness

As discussed earlier, one of the channels through which stock liquidity affects investment efficiency is through enhancing the informativeness of stock prices. Given the empirical evidence directly linking informative stock prices to corporate investments (Chen et al. 2007a; Bakke and Whited 2010), one question that arises is whether stock liquidity is of incremental value in explaining investment efficiency, in relation to stock price informativeness. The fact that stock liquidity can affect investment efficiency through other possible channels (e.g., enhancing governance) suggests that stock liquidity should still play an important role in explaining the cross-sectional variation in investment efficiency after accounting for the direct impact of stock price informativeness on investment efficiency. To empirically test whether the relationship between stock liquidity and investment efficiency persists after controlling for stock price informativeness, I repeat my main analyses in the baseline regression model (Equation (1)) after including an additional control variable for stock price informativeness.

Unfortunately, informative stock prices are not easy to measure directly, resulting in prior studies employing a wide range of proxies for informative stock prices such as price non-synchronicity (e.g., Morck et al. 2000; Durnev et al. 2003; Durnev et al. 2004) and Easley and O'Hara's (1996) probability of informed trading or *PIN* (e.g., Chen et al. 2007a; Ferreira et al. 2011; Lee and Liu 2011; He et al. 2013). The proxy of stock price informativeness I employ in my additional tests is the *PIN* measure suggested by Easley et al. (1997) because it closely resonates with my arguments on how stock liquidity affects stock price informativeness, namely through capturing the extent of private information that is incorporated in stock prices as a result of increased trading activities of informed traders. Liquid stocks are more attractive to informed traders who typically possess and have strong incentives to trade on information that is not publicly known. Prior studies indicate that higher *PIN* values reflect an increase in the asymmetric information environment which incentivises informed traders to profit from their private information (Dow and Gorton 1995). This trading behaviour by informed traders is likely to result in uninformed traders experiencing greater adverse selection problems (Wang 1993). On the basis of such arguments, prior studies (Mohanram and Rajgopal 2009; Kelly and Ljungqvist 2012; Kim et al. 2012) have argued that firms with higher *PIN* values represent firms with greater information asymmetry, which is expected to lead to less informative stock prices (Lee and Liu 2011). On the other hand, firms with lower *PIN* values signal reduced information asymmetry problems and more informative stock prices, which reduce the probability of informed trading against uninformed traders (Lee and Liu 2011). Following Lee and Liu (2011), I multiply *PIN* by -1 so that *PIN* is increasing in the informativeness of stock prices. The *PIN* data covering the period 1993 to 2010 is obtained from Professor Stephen Brown's website.[63]

One econometric problem that is introduced by the inclusion of *PIN* in my analyses is high multicollinearity. While the correlation between stock liquidity proxies and informative stock price is around 0.6 (untabulated), the inclusion of *PIN* significantly increases the variation inflation factors for *PIN* to between 9.15 to 10.73 across my regression analyses.[64] These statistics suggest that stock liquidity is positively associated with informative stock prices (*PIN*), and is consistent with prior studies linking higher liquid stocks to greater stock price informativeness (Holmström and Tirole 1993; Easley and O'Hara 2004; Chordia et al. 2008). However, the large variation inflations factors for *PIN* suggest that controlling for *PIN* can inflate the standard errors of the coefficient estimates and render it unstable and difficult to interpret. As a result, these multicollinearity threats can reduce the statistical power and increase the probability of incorrect model specifications. Nonetheless, I execute my analysis after controlling for *PIN* as it is possible that the results for my two hypotheses still remain robust.

[63] http://scholar.rhsmith.umd.edu/sbrown/pin-data?destination=node/998

[64] Two of the four specifications result in *VIFs* for *PIN* which are greater than 10.

Table 5 reports the results for hypotheses H1a and H1b from the estimation of my main analysis after including the proxy for informative stock price, *PIN*, as an additional control variable. The results from this analysis reveal that total investment levels (*INV*) have a positive and significant relationship with *PIN* ($p$<.01), indicating that firms with higher informative stock prices are more likely to have higher investment levels. This finding is consistent with Chen et al. (2007a) who link greater stock price informativeness to higher investments. More importantly, I find that the results for my two hypotheses remain consistent with the results from my main analyses reported in Table 4. Specifically, in relation to the results for hypothesis H1a, I find that the coefficient on three of the four stock liquidity measures (except *LIQZERO*) are positive and statistically significant at the 10 percent level or better, indicating that when the likelihood of under-investing is greater, firms with higher stock liquidity invest significantly more than firms with lower stock liquidity. To test hypothesis H1b, I estimate the sum of the coefficients on *LIQ* and *LIQ* x *OverFirm*. The joint coefficients based on all four stock liquidity measures are negative and statistically significant at the 5 percent level or better. The results support hypothesis H1b and suggest that liquid stocks appear to mitigate the problem of over-investments by reducing investment levels in firms with higher likelihood of over-investing. Overall, I still find the effect of stock liquidity remains an important determinant of investment efficiency even in the presence of price informativeness, suggesting that the effect of stock liquidity is not completely subsumed by informative stock price.[65] The significant findings for stock liquidity support the view that stock liquidity can affect investment efficiency through other potential channels (e.g., governance) too.

<<<INSERT TABLE 5 ABOUT HERE>>>

[65] When I use price non-synchronicity as an alternative measure to informative stock price (Ferreira et al. 2011), my main results for H1a and H1b remain unchanged but the coefficient on price non-synchronicity is not significant (untabulated).

### 6.3.2 Two-stage least square estimation

Endogeneity problems can arise due to the omitted variables, measurement error in the regressors, and simultaneity (regressors and response variable are determined by each other). In the context of this study, unobserved factors could confound the effects of stock liquidity on investment levels. Further, it is possible that firms with higher investment levels may attract more investors to trade their shares, thus inducing greater liquidity. Although the specification of the regression model with interaction terms used in this study mitigates some of the issues such as reverse causality (Rajan and Zingales 1998; Chen et al. 2011), I employ two-stage least squares regressions to further control the potential endogeneity to see if the results are robust.

Following Fang et al. (2009), this study uses the lagged value of the liquidity measure (*LagLIQ*) and the mean liquidity of the two firms in firm *i*'s industry that have the closest size (i.e., market value of equity) to firm $i$ (*TwoLIQ*) as instruments for stock liquidity (*LIQ*). *LagLIQ* and *TwoLIQ* are expected to be valid exogenous variables for instrumenting *LIQ* because both variables are correlated with *LIQ*, but are unlikely to be correlated with the error term in the main regression model.[66] The use of lagged stock liquidity potentially rules out the concerns of omitted variable at time *t* that is correlated with both stock liquidity and investment levels at time *t*. As for the use of the average stock liquidity of two compatible firms, Fang et al. (2009) suggest that the part of firm *i*'s stock liquidity that is correlated with its competitors' stock liquidity is less likely to be correlated with unobservables that affect firm *i*'s investment levels. A reduced form equation (Equation (4)) in the first-stage regression regresses the endogenous variable (*LIQ*) on both exogenous variables (*LagLIQ, TwoLIQ*) and the control variables employed in Equation (1).

$$LIQ_{i,t} = \alpha + \beta_1 LagLIQ_{i,t-1} + \beta_2 TwoLIQ_{i,t} + \sum_{\gamma j} Controls_{j,i,t} + \varepsilon_{i,t} \quad (4)$$

[66] The correlation coefficients between *LagLIQ* and *LIQ* range from 0.836 to 0.893, whereas the correlation coefficients between *TwoLIQ* and *LIQ* are between 0.484 and 0.848 across all four stock liquidity measures used in my main analyses.

Equation (4) estimation generates the instrument as the fitted values (*PrLIQ*) which is derived from a linear combination of these two exogenous variables (*LagLIQ, TwoLIQ*). *PrLIQ* then substitutes *LIQ* in Equation (1) in the second-stage regression as shown in Equation (5).

$$INV_{i,t+1} = \alpha + \beta_1 PrLIQ_{i,t} + \beta_2 PrLIQ_{i,t} \times OverFirm_{i,t} + \sum_{\gamma j} Controls_{j,i,t} + \varepsilon_{i,t+1} \quad (5)$$

The first stage regression results from the two-stage least squares (2 SLS) model are presented in Table 6. Both coefficients on *LagLIQ* and *TwoLIQ* are positive and highly significant ($p$<.01) across all four regressions based on different *LIQ* proxies, suggesting that the instruments are highly correlated with my stock liquidity measures. The results from the second stage regression are reported in Table 7. The second stage regressions generally produce results consistent with the main results reported in Table 4. The coefficients on the fitted values of stock liquidity from the first stage regression (*PrLIQ*) are positive and significant ($p$<.10 or better) and its joint significance tests (*PrLIQ* + *PrLIQ* x *OverFirm*) are negative and significant ($p$<.01) across all four regression specifications except for the regressions based on *PrLIQZERO* and *PrLIQindex*. Using the median industry stock liquidity as an instrument in replacement of *TwoLIQ*, generally produces results similar to those reported in Tables 6 and 7 (untabulated). Overall, the relationship between stock liquidity and investment efficiency is robust, mostly for the over-investment results, to controlling for endogeneity using a two-stage least squares.

<<<INSERT TABLES 6 AND 7 ABOUT HERE>>>

### 6.3.3 Intertemporal relationship between stock liquidity and investment efficiency

In this section, I employ change regression specifications over a period of three years as an additional test to address the endogeneity concerns between stock liquidity and investment efficiency. This extension allows me to test if an increase in stock liquidity over time is associated with an increase (decrease) in investments in firms with higher likelihood of under-investing (over-investing). The use of a longer time period allows enough time for the change in stock liquidity to be reflected in firm investment levels.

<<<INSERT TABLE 8 ABOUT HERE>>>

As described above, this analysis utilises three-year changes (time *t-3* to time *t*) in the dependent (*INV*), test (*LIQ*) and control variables except for G-Score indicator (*G_Dummy*), dividend (*DIV*), loss (*Loss*), firm age (*Firm_Age*) and *OverFirm*, which experience little or monotonic changes across the sample period. Table 8 presents the results for intertemporal relationships between changes in investment efficiency and changes in the four stock liquidity proxies ($\Delta LIQ$). The coefficients on $\Delta LIQ$ are positive and significant ($p<.10$ or better) for all four stock liquidity proxies. While the coefficient on the interaction term ($\Delta LIQ \times OverFirm$) is negative and significant ($p<.05$ or better) in three of the four regressions, the joint significance estimation produces significant results only for $\Delta LIQTURN$ proxy ($\Delta LIQTURN + \Delta LIQTURN \times OverFirm$) ($p<.10$). These results provide strong evidence to support the view that firm-specific increase in investment levels are associated with firm-specific increase in stock liquidity in firms with the likelihood of under-investing. However, result from only one of the four regressions (the specification using the proxy $\Delta LIQTURN$) provides weaker support for the view that an increase in stock liquidity leads to a decrease in investment levels in firms with the likelihood of over-investing. Nevertheless, these results provide some support for the primary results from Table 4.

### 6.3.4 Multinomial logistic regression

Next, following Biddle et al. (2009), I test hypotheses H1a and H1b using an unconditional test by employing a multinomial logistic regression framework to examine the relationship between stock liquidity and the likelihood of firm investments deviating from the expected (optimal) level. I initiate this analysis by first regressing investment levels on sales growth and then use the residuals from this regression to assign the observations into quartile ranks. Next, I create a multinomial variable that takes the value of 1 if a residual from the regression of investment levels on sales growth is in the bottom quartile (classified as under-investing firms), 0 if it is in the middle two quartiles (categorised as optimal-investing firms), and 2 if it is in the top quartile (classified as over-investing firms). Finally, I use a multinomial logistic regression to estimate the probability of a firm falling in the extreme quartiles relative to the optimal quartile. I expect negative coefficients on stock liquidity under both settings if higher stock liquidity can promote investment efficiency. That is, an increase in stock liquidity is more likely to decrease the probability of under- or over-investing.

As part of estimating the multinomial regression analysis, I also perform diagnostic tests to identify if the assumption of independence of irrelevant alternatives (IIA) is violated in the multinomial logistic regression. This assumption requires the odds of one outcome category versus another to be independent of other alternatives. The results of suest-based (seemingly-unrelated estimation) Hausman tests of IIA indicate that the multinomial logistic specifications using all four stock liquidity proxies do not meet IIA assumption ($p$<.01), respectively. This suggests that the multinomial logistic model is not appropriate for my analyses as the IIA assumption is violated. I supplement this inference by also evaluating the extent to which the multinomial logistic model correctly predicts the outcomes of firms' tendency to under-, normal-, and over-invest, respectively. The multinomial logistic models based on four liquidity proxies only classify, on average, 56 percent of firm-year observations correctly, confirming that the models lack accuracy in prediction. While these findings suggest that the multinomial logistic model is not suitable for my setting, I nonetheless estimate this regression analysis for sake of comparability with prior studies (e.g., Biddle et al. 2009).

The results from this analysis (untabulated) support hypothesis H1a based on all four liquidity proxies by documenting negative and significant (at the 1 percent level) coefficients on stock liquidity. However, the results in relation to hypothesis H1b are somewhat inconsistent. The coefficient on *LIQFHT* is positive and significant at the 5 percent level, while the coefficients on the other three stock liquidity proxies are not significant, albeit with the correct signs (i.e., negative). As discussed above, these results should be interpreted cautiously because of the unsuitability of the multinomial logistic regression framework in my setting.

### 6.3.5 Year exclusions

The sample period employed in this thesis covers 18 years spanning 1995 through 2012. To evaluate whether any particular sample year drives the positive impact of stock liquidity on investment efficiency during my full sample period, I run 18 separate regressions after excluding one fiscal year at a time. This exercise generates eighteen sets of coefficients on the liquidity proxies (*LIQ*) and joint coefficients (the sum of the coefficients on *LIQ* and the interaction terms *LIQ* x *OverFirm*) for hypotheses H1a and H1b, respectively. Recall that hypothesis H1a predicts that higher stock liquidity is likely to increase investment levels among firms with the propensity for under-investment, whereas hypothesis H1b predicts that higher stock liquidity is likely to decrease investment levels among firms with the propensity for over-investment. The results from these analyses are presented in Table 9.

<<<INSERT TABLE 9 ABOUT HERE>>>

Recall that the main results reported in Table 4 using the *LIQFHT* and *LIQindex* as the proxies for stock liquidity depict a significant positive coefficient on *LIQ* (test for H1a) at the 5 percent level or better, and a significant negative joint coefficient (test for H1b) at the 1 percent level. Consistent with the main results, the results presented in columns (1) and (4) of Table 9 indicate that the coefficients on the *LIQFHT* and *LIQindex* liquidity proxies are also positive and significant at the 5 percent level or better across all 18 regressions. These results suggest that when the *ex-ante* likelihood of under-investment is greater, high-stock-liquidity firms invest significantly more than low-stock-liquidity firms. The evidence in columns (1) and (4) of Table 9 supports H1a. The sum of the coefficients on *LIQFHT* and *LIQindex* and their interaction terms with *OverFirm*, which measure the extent to which stock liquidity affects investment levels in firms that are likely to over-invest (test relating to H1b), are negative and significant at the 1 percent level across all 18 regressions too. In each instance, the results strongly support hypothesis H1b that firms with higher stock liquidity invest significantly less than firms with lower stock liquidity, when the *ex-ante* likelihood of over-investment is high. In sum, the results based on *LIQFHT* and *LIQindex* as stock liquidity proxies suggest that the association between stock liquidity and investment efficiency reported in my main tests are not driven by any particular year.

When *LIQZERO* liquidity proxy is used in the regression, the main results reported in Table 4 show that the coefficient on *LIQZERO* is positive but not significant, while the joint coefficient is negative and significant at the 1 percent level. The corresponding results reported in the second column of Table 9 indicate that, across all 18 years, while the stock liquidity measure *LIQZERO* is positively associated with investment levels when firms have a greater propensity to under-invest, the effect of *LIQZERO* is statistically significant in two of the 18 regressions only. It appears that by excluding years 1995 and 2008 from the sample, the coefficients on *LIQZERO* in the under-investing scenario become weakly significant at the 10 percent level, suggesting that these two years appear to drive the insignificant results for *LIQZERO* in my main tests. In relation to the over-investment setting (test relating to H1b), the results show that the sum of the coefficients on *LIQZERO* and the interaction term (*LIQZERO* x *OverFirm*) is negative and significant at the 1 percent level across all 18 regressions, ruling out the possibility that a particular year drives my main results.

The main results based on the *LIQTURN* proxy of stock liquidity indicate that the coefficient on *LIQTURN* is positive and significant at the 5 percent level and the related coefficient on the joint test is negative and *weakly* significant at the 10 percent level. The third column of Table 9 presents the regression findings based on *LIQTURN* after the exclusion of each year in my sample period. I find that the coefficients on *LIQTURN* are positive and significant at the 10 percent level or better in all regressions, implying that the positive effect of *LIQTURN* on investments for under-investing firms documented in my main analyses are not driven by any particular year in my sample period. However, for firms that tend to over-invest, the coefficients on the joint test (H1b) become insignificant after excluding each year between 1998 and 2001, 2004 and 2006, and 2008 and 2011 from the full sample. The results of these joint tests suggest that these years are collectively driving the negative relationship between *LIQTURN* and investment level in firms that tend to over-invest in my main analyses. However, these findings require cautious interpretation due to the fact that the main result for the joint test (H1b) reported in Table 4 is *weak* (significant at the 10 percent level) to begin with.

### 6.3.6 Industry exclusions

My full sample consists of 40 industries based on the Fama-French 48-industry classification scheme. In order to explore whether any particular industry drives my main findings of a positive relationship between stock liquidity and investment efficiency, I repeat my main multivariate analyses after excluding one industry at a time. Table 10 presents the results for the forty sets of coefficients and joint coefficients for hypothesis 1a and 1b, respectively. Consistent with the main results reported in Table 4 using the *LIQFHT* and *LIQindex* stock liquidity proxies, all regressions reported in column (1) and column (4) of Table 10 based on these proxies indicate that stock liquidity is positively and statistically associated with investment efficiency at the 5 percent level or better. These results suggest that my findings for H1a and H1b are not affected by the exclusion of any industry in my sample. On the other hand, the results from column (2) based on *LIQZERO* indicate that the relationship between stock liquidity and investment levels is positive but statistically insignificant ($p>.10$) in under-investing firms (H1a), while the relationship between stock liquidity and investment levels is negative and statistically significant ($p<.01$) in over-investing firms (H1b). These results are consistent with those reported for *LIQZERO* in my main tests, which also produce significant findings for H1b only. Overall, these results suggest that industry appears to be a non-driver of my main results based on the *LIQFHT, LIQZERO* and *LIQindex* proxies of stock liquidity.

Column (3) of Table 10 presents the comparative results based on the *LIQTURN* proxy of stock liquidity. The results indicate that the exclusion of any of the 40 industries does not change the main test result for H1a. That is, as for firms that are likely to under-invest, the relationship between stock liquidity and investment levels is positive and statistically significant at the 10 percent level or better. On the other hand, I find that in the setting where firms are likely to over-invest (H1b), the joint coefficient (the sum of the coefficients on *LIQTURN* and the interaction terms *LIQTURN* x *OverFirm*) is insignificant in 16 cases suggesting that 16 industries seem to drive the positive impact of stock liquidity on investment levels (i.e., reducing over-investment). These industries include (1) Aircraft; (2) Automobiles and Trucks; (3) Shipping Containers; (4) Chemicals; (5) Petroleum and Natural Gas; (6) Steel Works Etc; (7) Apparel; (8) Electrical Equipment; (9) Utilities; (10) Restaurants, Hotels, Motels; (11) Business Supplies; (12) Personal Services; (13) Medical Equipment; (14) Measuring and Control Equipment; (15) Pharmaceutical Products; and (16) Retail. Again, these results require careful interpretation since the main result is *weak* to begin with as the joint coefficient based on the *LIQTURN* proxy reported in Table 4 is negative and *weakly* significant at the 10 percent level only.

<<<INSERT TABLE 10 ABOUT HERE>>>

### 6.3.7 Alternative stock liquidity proxies

My main measures of stock liquidity are based on widely cited studies in the stream of research on stock liquidity (Lesmond et al. 1999; Lo and Jiang 2000; Fong et al. 2014). Given that there is no universally accepted measure of stock liquidity due to its multifaceted nature, new stock liquidity proxies with different dimensions of liquidity are being continuously developed. As such, I evaluate the robustness of my findings to four alternative measures of stock liquidity. Specifically, I employ the price impact measure (*LIQAM*) introduced by Amihud (2001), the closing percent quoted spread (*LIQBAS*) developed by Chung and Zhang (2014), the price-based spread proxy (*LIQHL*) employed by Corwin and Schultz (2012), and the serial correlation-based measure (*LIQROLL*) of Roll (1984) as additional proxies of stock liquidity.

Based on Fong's et al. (2014) tests that compare a series of low-frequency liquidity proxies against liquidity benchmarks computed from high-frequency data, these four measures are selected because of their high correlations with these liquidity benchmarks. The *LIQAM* and *LIQROLL* measures have been widely employed in recent studies (e.g., Jayaraman and Milbourne 2012; Edmans et al. 2013; Bharath et al. 2013; Roosenboom et al 2014), while the *LIQBAS* and *LIQHL* measures have been promoted as two of the best liquidity proxies by Fong et al. (2014).[67] The four proxies mentioned above are calculated using daily data. To assess the collective effects of these additional liquidity proxies together with the proxies employed in my main analysis, I develop a composite stock liquidity index (*LIQindex6*) by standardising the three additional measures of stock liquidity (*LIQBAS, LIQHL, LIQROLL*) and the three stock liquidity measures from the main analysis (*LIQFHT, LIQZERO, LIQTURN*) and then calculating the unweighted mean of these six standardised measures.[68] The standardisation allows variables with different scales to be combined to form the composite measure. Higher values of the composite measure (*LIQindex6*) signify higher stock liquidity.

#### *6.3.7.1 Amihud's (2002) illiquidity measure*

The first additional proxy of stock liquidity is a measure developed by Amihud (2002), capturing the lack of stock liquidity. This measure for stock illiquidity is defined as the yearly average of daily absolute return divided by dollar trading volume (*ILLIQ)*:

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[67] I do not include closing percent quoted spread (*LIQBAS*), and price-based spread (*LIQHL*) in my main study because these two metrics have only recently been tested to be two of the top three percent-cost proxies (Fong et al. 2014), some time after I commenced on my PhD study.

[68] I do not incorporate the Amihud's (2002) illiquidity measure (*LIQAM*) into the composite measure of stock liquidity (*LIQindex6*) because I follow Amihud (2002) and compute *LIQAM* for NYSE firms only. In contrast, the stock liquidity proxies included in the *LIQindex6* computation in this study cover firms listed on the NYSE, AMEX, and NASDAQ stock exchanges. However, the results (untabulated) remain qualitatively similar to the main tests when I include *LIQAM* and develop a composite stock liquidity measure for NYSE firms only or for firms listed on the three exchanges.

$$ILLIQ_{i,t} = \frac{1}{Days_{i,t}} \sum_{d=1}^{Days_{i,t}} \frac{1{,}000{,}000 * |R_{i,t,d}|}{DolVol_{i,t,d}} \qquad ,$$

where $Days_{i,t}$ is the number of valid observation days for stock $i$ in fiscal year $t$, and $R_{i,t,d}$ and $DolVol_{i,t,d}$ are the daily return and daily dollar trading volume, respectively, of stock $i$ on day $d$ of fiscal year $t$. The measure can be interpreted as the average price response to one dollar trading volume, thus reasonably capturing price impact (Amihud 2002; Goyenko et al. 2009). A higher (lower) value of *ILLIQ* indicates lower (higher) stock liquidity. The intuition is that more illiquid stocks require lower trading volume to cause price changes than do more liquid stocks. Since the distribution of *ILLIQ* is highly positively skewed (Edmans et al. 2013), I employ the natural logarithm of this measure (1 + *ILLIQ*) in my empirical tests. Further, for ease of interpretation, I multiply the natural logarithm of (1 + *ILLIQ*) by -1 to derive the measure of stock liquidity (*LIQAM*), so that higher (lower) values of *LIQAM* correspond to higher (lower) levels of stocks liquidity.

Following Amihud (2002), I restrict my analysis based on *LIQAM* to firms with stocks traded on the NYSE to minimise the effects of differences in market microstructures between the NASDAQ and the NYSE on stock returns. In addition, stocks that are included in the sample must satisfy the following criteria (Amihud 2002; Fang et al. 2009):

(1) The stock must be listed at the end of its fiscal year *t*;

(2) The stock has at least 200 days of return and volume data available in the CRSP daily files during fiscal year *t* (This allows more reliable estimation of the parameters); and

(3) The stock has a minimum price of $5 at the end of fiscal year *t* because returns on low-price stocks (e.g., penny stocks) are greatly affected by the minimum price variation (i.e., tick size), which renders the estimations less reliable.

#### *6.3.7.2 Closing percent quoted spread*

The closing percent quoted spread, introduced by Chung and Zhang (2014), is my second alternative proxy for stock liquidity. This newly developed measure differs from the bid-ask spread employed in previous studies in that former uses the *CRSP*'s *Ask* (the closing ask price) and *Bid* (the closing bid price) variables in its construction, whereas the latter is computed based on the *CRSP*'s *Ask or High Price* and *Bid or Low Price*. In order to be consistent with the interpretation of the results based on the other stock liquidity measures employed in this study, I generate values for *LIQBAS* by multiplying Chung and Zhang (2014) measure by -1 so that higher values for *LIQBAS* reflect higher stock liquidity. Specifically, *LIQBAS* is defined as below:

$$LIQBAS = -1 * 100 * \frac{1}{Days_{i,t}} \sum_{d=1}^{Days_{i,t}} \frac{Ask_{i,t,d} - Bid_{i,t,d}}{(Ask_{i,t,d} + Bid_{i,t,d})/2},$$

where $Days_{i,t}$ is the number of observations for stock *i* in fiscal year *t*, and $Ask_{i,t,d}$ and $Bid_{i,t,d}$ are the closing ask and bid prices of the stock *i* on day *d* of year *t*, respectively. In other words, *LIQBAS* measures the average difference between ask (i.e., purchase price at market maker's selling price) and bid prices (i.e., sale price at market maker's buying price). In order to eliminate the effect of data errors and outliers, I exclude: (1) daily negative bid-ask spreads (crossed quotes) for which the ask price is smaller than the bid price (Balakrishnan et al. 2014a); and (2) daily bid-ask spread that is greater than 50 percent of the quote midpoint for which the bid-ask spread is unreasonably larger than the mean of ask and bid price (Chung and Zhang 2014).

#### *6.3.7.3 Price-based spread*

The third additional proxy of stock liquidity is the bid-ask spread measure developed by Corwin and Schultz (2012). This measure is computed from daily high and low prices based on the notion daily high (low) prices are almost always buy (sell) trades. The measure consists of two components. The first component is the volatility of the stock, which is positively correlated with the length of the trading interval. The second component is the bid-ask spread which does not vary with the length of the trading interval. I obtain Corwin and Schultz's (2012) high-low spread from Professor Shane A. Corwin's website and multiply it by -1 to construct a variable *LIQHL* so that greater values of *LIQHL* reflect higher stock liquidity.[69]

### *6.3.7.4 Roll's (1984) serial correlation-based spread*

My last alternative proxy for stock liquidity is a measure developed by Roll (1984) that can be estimated from a time series of market prices. This measure is calculated based on the serial covariance of stock price changes on the assumption that the true value of a stock follows a random walk and that $P_t$, the observed closing price on day *t*, is equal to the stock's true value plus or minus half of the effective spread.[70] As shown in the formula below, I multiply the original Roll's measure of stock liquidity by -1 so that greater values reflect higher stock liquidity:

$$LIQROLL = -1 * 100 * \frac{2\sqrt{-Cov(\Delta P_t, \Delta P_{t-1})}}{\bar{P}}, when\ Cov(\Delta P_t, \Delta P_{t-1}) < 0\ ,$$

where $P_t$ is the closing price of a stock on day *t*, $\bar{P}$ is the average yearly price, and $Cov(\Delta P_t, \Delta P_{t-1})$ is the covariance between successive price changes. Roll (1984) argues that trading costs induce negative serial dependence in successive observed stock price changes in an informationally efficient market. The resulting bounce between bid and ask prices contributes to a negatively serially correlation in price changes. As such, the component of effective bid-ask spread $\sqrt{-Cov(\Delta P_t, \Delta P_{t-1})}$ will be greater than zero when $Cov(\Delta P_t, \Delta P_{t+1}) < 0$. Following Goyenko et al. (2009), I assume that $LIQROLL = 0,$ $when\ Cov(\Delta P_t, \Delta P_{t-1}) \geq 0$ as $\sqrt{-Cov(\Delta P_t, \Delta P_{t-1})}$ is not properly defined.

### *6.3.7.5 Empirical results based on alternative liquidity proxies*

Table 11 reports the results for hypotheses H1a and H1b based on the five additional liquidity measures – *LIQAM, LIQBAS, LIQHL* and *LIQROLL* and *LIQindex6*. The findings are generally consistent with the results from my main analyses reported in Table 4. The

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[69] *http://www3.nd.edu/~scorwin/*

[70] The ideal conditions assume that the underlying stock value (ignoring trading effects) follows a random walk, that buy and sell orders are equally probable and serially independent, and that underlying value is independent of the order flow (Harris 1990, 579).

results for hypothesis H1a show that the coefficients on all alternative stock liquidity measures are positive and statistically significant at the 1 percent level, indicating that when the likelihood of under-investing is greater, firms with higher stock liquidity invest significantly more than firms with lower stock liquidity. To test hypothesis H1b, I estimate the sum of the coefficients on *LIQ* and *LIQ* x *OverFirm*. The joint coefficients based on all alternative stock liquidity measures except *LIQHL* ($p$>.1, $t$ = -1.22) are negative and statistically significant at the 10 percent level or better. The results suggest that when the likelihood of over-investing is greater, firms with more liquid stock invest significantly less than firms with lower stock liquidity.[71] Overall, the findings are consistent with the notion that higher stock liquidity improves investment efficiency. Hence, my main results appear to be robust to the use of alternative measures of stock liquidity.

<<<INSERT TABLE 11 ABOUT HERE>>>

### 6.3.8 Alternative investment proxies – *Capex* and *Non-Capex*

The total investment metric used in the main test follows the definition used by Richardson (2006). It is constructed by combining capital expenditure (*Capex*) and non-capital expenditure investment (*Non-Capex*) less receipts from the sale of property, plant and equipment. It is possible that the effects of monitoring and increased transparency brought about by stock liquidity on investment efficiency could be different between investments in tangible assets and investments in intangible assets. Stein (1988) argues that market participants cannot accurately appraise a manager's investment in intangible assets due to the return uncertainty of these assets. Given that intangible assets are associated with higher agency costs arising from higher information asymmetry, the need for monitoring increases in the presence of more intangible assets (Gompers 1995). On the other hand, firm-level tangible capital investments (*Capex*) should be more transparent to the market

[71] As discussed earlier, I follow Amihud (2002) and restrict my analysis based on *LIQAM* to NYSE firms. However, the results (untabulated) remain qualitatively similar to the main tests when I include *LIQAM* into the composite stock liquidity measure for NYSE firms only and for firms listed on three exchanges, respectively.

monitoring due to its nature of tangibility, compared to non-capital investments (*Non-Capex*) such as R&D and acquisitions. As such, stock liquidity may play a more important role in monitoring intangible investments (*Non-Capex*) made by firms.

Similar to Biddle et al. (2009) and Cheng et al. (2013), I investigate whether stock liquidity has similar or differential impacts on mitigating managerial sub-optimal investments across these two types of investment expenditure. I implement this analysis by repeating my main tests in Table 4 using dependent variables representing these two separate components of investment (*Capex* and *Non-Capex*). Following Baker et al. (2003) and Lang et al. (2012), *Capex* is computed as the capital expenditure in year *t*+1 scaled by lagged total assets, whereas *Non-Capex* is calculated as the sum of R&D expenditures and acquisitions in year *t*+1 scaled by lagged total assets.

Tables 12 and 13 report the results from the analyses using *Capex* and *Non-Capex* as two alternative dependent variables, respectively. The results from columns (1) through (4) of Table 12 based on *Capex* depict a positive and significant ($p$<.05 or better) coefficient on three of the four *LIQ* measures (*LIQFHT, LIQTURN* and *LIQindex*) in under-investing firms. With respect to firms with the tendency to over-invest, the sum of the coefficients on *LIQ* and *LIQ* x *OverFirm* is negative and significant for all four measures ($p$<.10 or better). These results are consistent with the main findings, thus supporting H1a and H1b. The results suggest that firms with higher stock liquidity tend to make more (less) capital investments when their likelihood of under-investment (over-investment) is higher.

The results from columns (1) through (4) of Table 13 based on *Non-Capex* depict a positive and significant ($p < .10$ or better) coefficient on two of the four *LIQ* measures (*LIQFHT,* and *LIQindex*) in the under-investing firms. In relation to firms with the tendency to over-invest, the sum of the coefficients on *LIQ* and *LIQ* x *OverFirm* is significantly negative for three of the four measures (*LIQFHT, LIQZERO* and *LIQindex*) at the 1 percent level. These findings generally support the main findings and suggest that firms with more liquid stock tend to invest more (less) on non-capital expenditures too when their likelihood of under-investment (over-investment) is higher. These results are again consistent with H1a and H1b.

The tests above provide evidence that the relationship between stock liquidity and investment efficiency is applicable to both capital expenditure (*Capex*) and non-capital expenditure (*Non-Capex*). Overall, my findings suggest that the higher stock liquidity has a beneficial effect not only on capital investments but also on non-capital investments that are inflicted with informational opacity. Put differently, the results based on non-capital investments suggest that stock liquidity can promote investment efficiency even when non-capital expenditures may not be highly transparent.

<<<INSERT TABLES 12 AND 13 ABOUT HERE>>>

### 6.4 Chapter summary

This chapter reports and discusses the main empirical results for the tests of H1a and H1b, followed by a discussion on the results of the robustness and sensitivity tests. Utilising four stock liquidity proxies in the main test variables, my findings support the main hypotheses that firms with higher stock liquidity are associated with greater investment efficiency compared to firms with lower stock liquidity. The main conclusions continue to hold based on the results from robustness tests – controlling for stock price informativeness, two-stage least square regressions, change specifications (intertemporal relationship model), regressions by year exclusions and by industry exclusions, and alternative measures of stock liquidity and investment. The next chapter discusses additional tests that explore whether the beneficial effect of stock liquidity on investment efficiency are more pronounced in firms (1) with higher information asymmetry, and (2) with greater proportion of monitoring institutional investors.

# Chapter 7: Empirical Analyses: Additional Tests

As discussed earlier, I identify two types of possible explanations of the association of stock liquidity and investment efficiency, namely the capital market-based and corporate governance-based explanations. The capital market-based explanation proposes that stock liquidity increases investment efficiency through its informational role. By increasing the informativeness of stock prices, stock liquidity reduces information asymmetry between firm and external investors, thus allowing the firm to raise external equity to finance value-enhancing projects. This informational role of stock liquidity should bring greater benefits to firms afflicted with informational opacity such as young firms and high business risk firms. On the other hand, the corporate governance-based explanation proposes that stock liquidity increases investment efficiency through its monitoring role. By increasing monitoring effects through the threat of voice or threat of exit, stock liquidity reduces information asymmetry between the firm and shareholders, thereby facilitating institutional monitoring that helps improve investment efficiency. Prior literature suggests that these two explanations are not necessarily mutually exclusive.

This chapter presents the results from these additional tests. Specifically, Section 7.1.1 formally investigates the capital market-based explanation of my findings by evaluating whether the effect of stock liquidity on investment efficiency is more pronounced in young firms, as these firms are prone to information asymmetry problems. Section 7.1.2 further examines the market-based explanation by evaluating whether the effect of stock liquidity on investment efficiency is more pronounced in high business risk firms, as these firms are also likely to face more serious information asymmetry problems. Finally, Section 7.2.1 tests the corporate governance-based explanation by evaluating whether the effect of stock liquidity on investment efficiency is more pronounced in firms with high monitoring institutions that are likely to present both voice and exit threats.

## 7.1 Stock liquidity, capital markets, and investment efficiency

As discussed earlier, capital market-based theories argue that stock liquidity plays an important informational role in incorporating more private information into prices (Easley and O'Hara 2004; Khanna and Sonti 2004) at a greater speed, as higher stock liquidity entices informed traders to trade actively. As a result, stock prices become more informative which can have positive implications for managerial investment decisions. First, it reduces moral hazard problems by increasing transparency, which allows shareholders to more closely evaluate managers (Wurgler 2000; Durnev et al. 2003). Second, it mitigates adverse selection problems by improving feedback from shareholders (market) to firm managers, thereby inducing managers to react accordingly (Subrahmanyam and Titman 2001). As such, I argue that the resultant effects of increased transparency and improved market feedback work in tandem to positively affect firm investment decisions.

To assess the capital market-based explanation of my main findings, I test whether the beneficial effect of stock liquidity on firm investment efficiency is more pronounced in two settings where information asymmetry is acute: (1) young firms, and (2) high business risk firms. As discussed earlier, the capital market-based theories predict that firms with greater information asymmetry problems would get a larger benefit from an increase in transparency brought about by higher stock liquidity. This suggests that the association between stock liquidity and investment efficiency is expected to be stronger among young firms and high business risk firms.

### 7.1.1 Stock liquidity, firm age, and investment efficiency

This section investigates how the effect of stock liquidity on investment efficiency is influenced by firm age. Prior studies show that young firms are more susceptible to financing constraints (Rauh 2006; Fee et al. 2009; Hadlock and Pierce 2010) due to asymmetric information problems (Brown et al. 2009; Fee et al. 2009; Hadlock and Pierce 2010) because they lack performance history in the capital market. Their limited track record makes it more difficult for outside investors to assess their quality and potential.

Prior studies show that young firms use more external funds to finance capital expenditures because these firms have not had time to accumulate their retained earnings (Rajan and Zingales 1998; Pang and Wu 2009; Brown et al. 2012). However, young firms usually experience difficulty in raising such external equity financing due to the higher uncertainty about future prospects and value of these firms (Stiglitz and Weiss 1981) and, hence, are exposed to higher external capital financing costs due to the lemon's premium. For such firms, financing constraints can cause their investments to deviate from the optimal level. Therefore, high stock liquidity is likely to be more beneficial to young firms through increasing transparency and feedback to managers, which should relax financing constraints in young firms (Subrahmanyam and Titman 2001). On the other hand, the effect of stock liquidity on investment efficiency is expected to be weaker for mature firms, since the information environment is more transparent for these firms due to their established track records in the capital market. These firms can finance their investments using internally generated funds or through raising public equity, because outside investors are able to value these firms' potential more correctly. Thus, I posit that by mitigating information asymmetry, stock liquidity can alleviate financing constraints to a greater extent in young firms, thereby being of incremental value in improving investment efficiency in these firms.

#### *7.1.1.1 Empirical results*

To examine the impact of firm age on the relationship between stock liquidity and investment efficiency, I execute my main analyses that examine the effect of stock liquidity on investment efficiency for young firms and mature firms separately. I divide my main sample firms into two subgroups representing young and mature firms based on the median value of firm age. I define firm age (*Firm_Age*) as the number of years since the firm first appears in Compustat with coverage for stock price. Firms are categorised as young if their age is less than or equal to the median firm age (13 years) across all observations in my sample, and mature otherwise. Table 14 presents that the differences between mean values of stock liquidity proxies and other variables across young and mature firms. The *t*-test results reveal statistical differences (at the 10 percent level or better) between the mean values of all stock liquidity proxies and other firm characteristics across the two groups.

Specifically, I find that young firms invest more (*INV*), and are smaller in size (*LogAsset*). Young firms also exhibit higher volatility in sales (*σ(Sale)*), operating cash flows (*σ(CFO)*) and investments (*σ(INV)*), have greater cash flow from operations relative to sales (*CFOsale*), and have a lower operating cycle (*OCycle*). Young firms tend to carry more cash (*Slack*) but hold less tangible assets (*Tangibility*). These firms also have higher market-to-book values (*MB*) but lower leverage (*Ind_Kstruct*) as well as lower likelihood of bankruptcy (*Z-Score*). Thirty-six percent of young firms experience losses (*Loss*), compared to 19 percent in mature firms. Young firms have lower financial reporting quality (*AQ*), institutional ownership (*IO*) and analyst following (*Analyst*), but offer higher investor protection (*G_Score*). Ninety-one percent of young firms do not have a *G_Score* value (*G_Dummy*), compared to 85 percent of mature firms. The results for the stock liquidity measures are inconsistent, whereby young firms exhibit lower *LIQFHT, LIQZERO,* and *LIQindex* values but have higher *LIQTURN* values. These firms also have a higher likelihood of over-investing (*OverFirm*). In conclusion, it appears that young and mature firms are significantly different across all firm characteristics considered in my study, highlighting the importance of gaining an understanding of how stock liquidity affects investment efficiency across young and mature firms separately.[72]

<<<INSERT TABLE 14 ABOUT HERE>>>

Tables 15 and 16 report the results from the regression analyses that assess the impact of stock liquidity on investment efficiency for young firms (Table 15) and mature firms (Table 16). I estimate the regression models for young and mature firms separately rather than using three-way interactions to allow the parameter estimates on my control variables to also vary across the two subsamples of firms and to simplify the interpretation

[72] I repeat the two-sample test using non-parametric Mann-Whitney-Wilcoxon test for medians and find that the results are consistent with *t*-test results.

of the empirical results.

In relation to hypothesis H1a, the results from Table 15 indicate that within young firms with a higher propensity to under-invest, stock liquidity is positively and significantly (at the 10 percent level or better) associated with investment levels (*INV*) using the *LIQFHT*, *LIQZERO, LIQTURN*, and *LIQindex* proxies. The comparable results in Table 16 based on mature firms indicate that only one of the four proxies of stock liquidity (i.e., *LIQFHT*) is positively and significantly associated with investments (*INV*) within mature firms with higher propensity to under-invest. By comparing the magnitude of the coefficients on four *LIQ* proxies across young and mature firms, the coefficients on the liquidity proxies are larger in magnitude for young firms (1.64, 8.47, 2.33, and 1.66 in Table 15), relative to those for mature firms (0.78, 1.17, 0.07, and 0.36 in Table 16), indicating that the effects of stock liquidity on increasing investment levels in under-investing firms appear to be economically larger for young firms. In terms of economic significance, my results suggest that a one percent increment in stock liquidity using *LIQFHT* proxy (*LIQZERO, LIQTURN, LIQindex*) is associated with an increase of 11.20 percent (4.20 percent, 6.83 percent, 8.51 percent) in the investment levels of under-investing young firms. A corresponding smaller increment of 5.72 percent (0.78 percent, 0.25 percent, 2.22 percent) is observed in the investment levels of under-investing mature firms. Overall, my results suggest that for firms with greater propensity to under-invest, the effect of stock liquidity on promoting investments is economically greater for young firms than for mature firms.

Turning to the setting of over-investing firms, the analyses based on young firms, reported in Table 15, reveal that that stock liquidity is negatively and significantly (at the 5 percent level or better) associated with investment levels (*INV*) using *LIQFHT, LIQZERO*, *LIQTURN* and *LIQindex* proxies, as indicated by the joint significance tests (H1b). On the other hand, the comparable results for over-investing mature firms, reported in Table 16, also indicate that negative and significant (at the 5 percent level or better) joint coefficients on only three of the four *LIQ* proxies (*LIQFHT, LIQZERO, LIQindex*). However, the magnitude of the joint coefficients on *LIQFHT, LIQZERO, LIQTURN, and LIQindex* appear to be larger for young firms (-2.07, -28.58, -1.65, -2.48 in Table 15), relative to those for mature firms (-1.53, -11.03, 0.68, -0.78 in Table 16), suggesting that the decreasing effect of stock liquidity on the investment levels of over-investing firms is accentuated within young firms. In terms of economic significance, a one percent increment in stock liquidity using *LIQFHT* proxy (*LIQZERO, LIQTURN, LIQindex*) is associated with a reduction of 14.11 percent (14.17 percent, 4.84 percent, 12.69 percent) in the investment levels of over-investing young firms. The corresponding effect from a one percent increment in stock liquidity based on the *LIQFHT* (*LIQZERO, LIQindex*) proxy in mature firms is a decrement of 11.26 percent (7.34 percent, 4.90 percent) in investment levels (an insignificant increment of 2.49 percent is observed using *LIQTURN* proxy). Thus, the effect of liquidity appears to be more economically significant in over-investing young firms, relative to over-investing mature firms.

Results from Chow tests confirm that there are significant differences between the regression coefficients on the liquidity proxies and their interactions with *OverFirm* across the two subsamples of young and mature firms at the 5 percent level or better (F-statistics reported in Table 16). Overall, my findings in Tables 15 and 16 show that the effects of stock liquidity on investment efficiency appear to be more pronounced in young firms who are more exposed to information asymmetry and financing constraints. My evidence is consistent with the view that high stock liquidity plays a more important informational role in mitigating information asymmetry in young firms, and thus relaxing financial constraints in these firms.

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Figure 3 provides visual support for the multivariate results reported in Tables 15 and 16 for young and mature firms, by depicting how the stock liquidity (*LIQ*) slopes change with increasing values of *OverFirm* across subsample of young firms (Panel A) and mature firms (Panel B), respectively. The adjusted mean investment levels (*INV*) for low and high stock liquidity (*LIQ*) are graphed with *LIQ* on the x axis and with separate lines for the likelihood of under- and over-investment (*OverFirm*). Figure 3 shows that the *LIQ* slopes are more positive (negative) for under-investing (over-investing) firms in subsample consisting of young firms (Panel A of Figure 3) than in the subsample consisting of mature firms (Panel B of Figure 3). The results support the view that the effect of stock liquidity on investment efficiency is significantly stronger for young firms.

<<<INSERT FIGURE 3 ABOUT HERE>>>

#### *7.1.1.2 Conclusion*

Overall, the results reported in this section are consistent with the capital market-based explanation of the effect of stock liquidity on investment efficiency. That is, higher stock liquidity is more beneficial to firms facing financing constraints that are more likely to suffer from information asymmetry problems. Collectively, the results indicate that higher stock liquidity is more effective in improving investment efficiency in young firms, which is consistent with the view that high stock liquidity is more valuable in alleviating information asymmetry problems in these firms. On the other hand, the beneficial effect of stock liquidity is lacking or less pronounced for mature firms, consistent with the view that these firms possess a more transparent information environment.

### 7.1.2 Stock liquidity, business risk, and investment efficiency

In this section, I examine the extent to which stock liquidity improves investment efficiency for firms with high business risk (or business uncertainty), as measured in operating income volatility (Fang et al. 2009). Firms with higher business risk are likely to experience uncertainty in their future cash flow. These firms tend to exhibit greater opacity in their information environment (Zhang 2006; Fang et al. 2009), which incentivises managers to act opportunistically by investing suboptimally. Further, due to the lack of information on managers' decisions, investors may be reluctant to invest in these firms for fear that they would be disadvantaged (Myers and Majluf 1984). This could lead to firms being unable to raise enough funds for financing positive net present value projects and in turn result in lower investments. On the other hand, information asymmetry also can prevent investors from assessing firm value correctly, thus causing temporary mispricing. If these firms are overvalued, managers are incentivised to over-invest using the excessive funds obtained from temporary stock mispricing (Baker et al. 2003). Conversely, if these firms are undervalued, managers may have to forego investment with a positive NPV opportunity due to the inability to raise enough external capital, thus resulting in under-investment.

Given that stock prices of firms with liquid stock are more informative, the information environment of firms with higher income volatility (higher business risk) is likely to improve if their stocks are more liquid. Specifically, the problems of moral hazard and adverse selection in these firms can be mitigated by increased transparency and the feedback effect that high stock liquidity brings. An increase in stock liquidity enables stock prices to more closely track a firm’s fundamental value (O'Hara 1995; Subrahmanyam and Titman 2001; Khanna and Sonti 2004). The resulting informative stock price increases transparency and managerial investment decisions become more visible to investors. Agency literature argues that managers subjected to close market scrutiny would have incentives to invest in value-enhancing projects and withdraw from value-decreasing projects so as to align their interests with those of shareholders. Hence, high stock liquidity can enhance investment efficiency to a greater extent in high business risk firms through increasing transparency.

Furthermore, information-laden stock prices can accelerate market feedback to firm managers on their investment decisions if their firm's stock liquidity is greater, influencing them to take value-increasing investment decisions. The feedback effects from stock prices to managers become more important when their firms' information environment is more opaque. Subrahmanyam and Titman (2001) argue that feedback is more valuable to firms with high cash flow uncertainty with respect to existing projects. In a similar vein, Fang et al. (2009) document that the feedback effect of stock liquidity on firm performance (as measured by firm market-to-book ratio) is stronger in firms with higher operating income volatility, as these firms exhibit greater uncertainty in their information environment. They argue that stock price feedback to managers is more valuable for firms when their businesses are hard to value.

In sum, it is plausible to argue that high stock liquidity is particularly more beneficial to firms inflicted with information opacity such as firms with high business risk, as it can reduce information asymmetry and agency costs by incorporating greater private information into stock price and accelerating feedback from stock prices to managers. When the market is more informed as a result of an increase in stock liquidity, it can influence managers of firms with high business risk to improve investment efficiency. In contrast, firms with low business risk have a relatively more transparent environment because of the stability of historical earnings and predictability of future profits. As such, these firms are likely to be less afflicted by moral hazard and adverse selection problems, resulting in stock liquidity having a lower impact on investment efficiency in these firms. Thus, I expect the effect of stock liquidity on investment efficiency to be (more) less pronounced in firms with high (low) business risk.

#### *7.1.2.1 Empirical results*

Following Fang et al. (2009), I use operating income volatility (*IncVol*) as a proxy for business risk or uncertainty where *IncVol* is defined as the standard deviation of quarterly operating income before depreciation divided by quarterly book value of assets. *IncVol* is measured over 20 quarters prior to the end of fiscal year *t* with a minimum of eight quarterly observations. I divide the sample firms into two subgroups based on the median value of *IncVol* with the group with higher (lower) *IncVol* values categorised as high (low) business risk firms. Table 17 presents that the differences between mean values of stock liquidity proxies and other variables from two subgroups of business risk. The *t*-test results reveal statistical differences (at the 1 percent level) between the mean values of the stock liquidity proxies and other firm characteristics across the two groups.

Specifically, the high business risk (BR) firms invest more (*INV*), are smaller (*LogAsset*) and younger (*Firm_Age*). The high BR group also exhibits higher volatility in sales (*σ(Sale)*), operating cash flows (*σ(CFO)*) and investments (*σ(INV)*), as well as greater operating cycle (*OCycle*), but a lower ratio of CFO to sales (*CFOsale*). Firms with high business risk tend to carry more cash *Slack*) but hold lower tangible assets (*Tangibility*). These firms also have higher market-to-book value (*MB*) but lower leverage (*Ind_Kstruct*) as well as lower likelihood of bankruptcy (*Z_Score*). Thirty-nine percent of high BR group firms experience losses (*Loss*), compared to 15 percent in low BR group. High BR group has lower financial reporting quality (*AQ*), institutional ownership (*IO*) and analyst following (*Analyst*), but higher investor protection right (*G_Score*). Ninety-one percent firms in the high BR group do not have a *G-score* value (*G_Dummy*), compared to 85 percent of firms in the low BR group. The results for the liquidity measures are also inconsistent, whereby high business risk firms exhibit lower *LIQFHT, LIQZERO,* and *LIQindex* values but higher *LIQTURN* values. These firms also have a higher likelihood of over-investing (*OverFirm*). In conclusion, it appears that the high and low business risk firms are significantly different in firm characteristics, highlighting the importance of gaining an understanding of how stock liquidity affects investment efficiency across high and low business risk firms separately.[73]

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Tables 18 and 19 report the estimates from regressing investment levels (*INV*) on *LIQ, OverFirm*, the interaction *LIQ* x *OverFirm*, and control variables separately for firms with high business risk (Table 18) and those with low business risk (Table 19). The models have an adjusted R-squared of between 15.0 percent and 29.5 percent, with a higher explanatory power witnessed for firms with high business risk. Within the setting of under-investing firms (H1a), results from Columns (1) through (4) of Table 18 for the high BR group show that the coefficients on all four *LIQ* proxies (i.e., *LIQFHT, LIQZERO, LIQTURN*, and *LIQindex*) are positive and statistically significant (at the 10 percent level or better) and are also larger in magnitude relative to the comparative coefficients reported in Columns (1) through (4) of Table 19 for the low BR group (coefficients = 1.35, 7.92, 1.47, 1.26 for the high BR group *vs.* 0.76, -2.55, 0.80, 0.29 for the low BR group). Also, only the coefficient on *LIQFHT* proxy is statistically significant for the low BR group. Turning to the economic significance, my findings suggest that a one percent increment in stock liquidity across the *LIQFHT, LIQZERO, LIQTURN*, and *LIQindex* proxies results in a 9.40 percent, 4.01 percent, 4.39 percent, and 6.51 percent increase in investment levels for under-investing firms in the high BR group respectively, whereas smaller/negative changes of 5.02 percent, -1.37 percent, 2.96 percent, and 1,78 percent are observed in the low BR group for the corresponding *LIQ* proxies. The results thus far suggest that in terms of both statistical and economical significance, the effect of stock liquidity appears to be more pronounced when under-investing firms exhibit greater business risk, suggesting that high stock liquidity is more beneficial in improving investment efficiency when under-investing firms experience greater information asymmetry.

[73] I repeat the two-sample test using non-parametric Mann-Whitney-Wilcoxon test for medians and find that the results are consistent with *t*-test results.

When comparing the results across high and low business risk groups within the setting of over-investing firms, the coefficients on the joint significance test (H1b) in the high BR group are larger in magnitude and significantly ($p$<.01) negative for three out of four *LIQ* proxies (i.e., *LIQFHT*, *LIQZERO* and *LIQindex*), whereas the corresponding coefficients in the low BR group are smaller in magnitude and significantly ($p$<.05) negative in three out of four *LIQ* proxies (i.e., *LIQFHT*, *LIQZERO* and *LIQindex*). In terms of economic significance, the results suggest that a one percent increment in the *LIQFHT, LIQZERO* and *LIQindex* proxies results in a 15.66 percent, 14.06 percent, and 11.61 percent decrease in investment levels for over-investing firms in the high BR group, whereas the low BR group experiences smaller decrements of 7.19 percent, 6.54 percent and 5.47 percent in investment levels based on the corresponding *LIQ* proxies. Again, these results are consistent with the conjecture that the beneficial effect of liquidity on reducing over-investment appears to be more pronounced in over-investing firms with high business risk.

Results from Chow tests confirm that there are significant differences between the regression coefficients on the liquidity proxies and their interactions with *OverFirm* across the two subsamples of low and high business risk firms at the 10 percent level or better, except *LIQTURN* which is insignificant (F-statistics reported in Table 19). In sum, my findings show that the impact of stock liquidity on investment efficiency is stronger in firms with high business risk, suggesting that stock liquidity plays important informational and feedback roles in mitigating information asymmetry to a larger extent in these firms. My results are consistent with prior empirical findings (e.g., Fang et al. 2009) on the role of stock liquidity in making prices more informative to shareholders by stimulating greater informed trading.

<<<INSERT TABLES 18 AND 19 ABOUT HERE>>>

Figure 4 provides visual evidence in support of the multivariate results reported in Tables 18 and 19 by depicting how the stock liquidity (*LIQ*) slopes change with increasing values of *OverFirm* for high (Panel A) and low (Panel B) business risk firms, respectively.

The adjusted mean investment levels (*INV*) for low and high stock liquidity (*LIQ*) are graphed with *LIQ* on the *x* axis and with separate lines for the likelihood of under- and over-investment (*OverFirm*). The slope of the gradient indicates the extent to which investment efficiency is affected by stock liquidity among the subsample of firms with high and low business risk. The graphs indicate that the *LIQ* slopes are more positive (negative) for under-investing (over-investing) firms with high business risk (Panel A of Figure 4) relative to firms with low business risk (Panel B of Figure 4), implying that the beneficial effect of high stock liquidity is more pronounced for firms with high business risk. In other words, the positive and stronger effect of stock liquidity on investment efficiency is concentrated among firms with high business risk possibly because it potentially improves the quality and quantity of information for firms plagued by information asymmetry.

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#### *7.1.2.2 Conclusion*

Overall, the results reported in this section are consistent with the capital market-based explanation of the effect of stock liquidity on investment efficiency by showing that higher stock liquidity is more beneficial to firms with higher business risk or uncertainty, which are more likely to suffer from information asymmetry problems. Collectively, the results suggest that higher stock liquidity is more effective in improving investment efficiency in firms with high business risk, indicating that high stock liquidity is more likely to mitigate information asymmetry problems manifested in these firms. On the other hand, the beneficial effect of stock liquidity is lacking or less pronounced for firms with low business risk, suggesting that these firms may exhibit a more transparent information environment, which renders high stock liquidity less useful.

## 7.2 Stock liquidity, corporate governance, and investment efficiency

As discussed earlier, I identify two types of possible explanations of the association of stock liquidity and investment efficiency, namely the capital market-based and corporate governance-based explanations. Prior literature suggests that these two explanations are not necessarily mutually exclusive. This section formally investigates the corporate governance-based explanation of my findings by evaluating whether the effect of stock liquidity on investment efficiency is more pronounced in the presence of monitoring institutional investors.

### 7.2.1 Stock liquidity, monitoring institutions, and investment efficiency

Prior studies suggest that the governance role of large institutional investors can be enhanced through an increase in stock liquidity that facilitates voice (Maug 1998; Edmans et al. 2013) as well as exit threats (Edmans 2009; Bharath et al. 2013; Edmans et al. 2013). These studies in general do not distinguish monitoring from non-monitoring institutions.[74] As the trading objectives differ between these two types of institutions, stock liquidity may have a differential impact on investment efficiency in firms with different proportions of monitoring institutions (e.g., Porter 1992, Edmans 2009). Hence, I test whether the effects of stock liquidity on investment efficiency vary with different types of institutional investors.

According to Bushee (1998) and Ramalingegowda and Yu (2012), institutional investors differ in terms of their trading styles, incentives, and capabilities for monitoring. Institutions that have long investment horizons, concentrated shareholdings, and independence from management are characterised as monitoring institutions (Ramalingegowda and Yu 2012). They are more likely to monitor managers because they represent long-term shareholders who seek to benefit from their monitoring activities. As

[74] An exception is Fang et al. (2014) who differentiate between dedicated and non-dedicated institutional investors based on Bushee's (1998, 2001) institutional investor classification scheme, and find a positive relationship between stock liquidity and non-dedicated institutional investors, using decimalization as an exogenous shock to liquidity.

such, their monitoring efforts are likely to increase investment efficiency in firms. In contrast, institutions that engage in momentum trading and have high portfolio turnover are characterised as non-monitoring institutions (Ramalingegowda and Yu 2012). These institutions include transient investors and quasi-indexers whose trading behaviours mainly focus on short-term profit maximization and short investment horizons. Monitoring is not central to their investment strategies and they are likely to exit a firm at the first sign of reported low earnings. As a result, their trading strategies are likely to encourage short-term investments by firms (Bushee 1998). The above views raise an important question of whether the positive effect of stock liquidity on investment efficiency will be more pronounced for firms with a high proportion of monitoring institutions because stock liquidity may allow these institutions to exercise their governance through voice and exit threats.

High stock liquidity makes it easier for monitoring institutions to increase holdings, which enables them to effectively apply voice threats (Maug 1998). Given that monitoring institutions have incentives to monitor managers, the possibility of accumulating larger stakes as a result of high stock liquidity provides even greater incentives to increase their efforts in direct monitoring (Grossman and Hart 1980; Schleifer and Vishny 1986; Admati et al. 1994; Kahn and Winton 1998). Further, because monitoring institutions are willing to collect costly information related to managerial long-term investment decisions, they can profit from informed trading through liquid stock, and thus make prices more informative (Admati and Pfleiderer 2009; Edmans 2009). As a result, managers of high-stock-liquidity firms may be willing to invest efficiently due to increased transparency arising from greater price efficiency and better monitoring.

On the other hand, high stock liquidity through voice threats plays a lesser role in firms with high proportion of non-monitoring institutions (i.e., low proportion of monitoring institutions), as direct intervention is not their overriding strategy. Instead, these firms are more likely to face greater pressure to fixate on near-term earnings, as non-monitoring institutions are only interested in buying and keeping stocks with short-term performance. As such, due to lower trading costs, high stock liquidity allows non-monitoring institutions to exacerbate managerial short-termism by discouraging long-term investment behaviours (Porter 1992; Bhide 1993; Bushee 1998). Because long-term investments may temporarily depress stock prices due to initial cash outlays and earnings disappointment, managers of these firms are likely to sacrifice long-term investments (like investment in R&D). As such, non-monitoring institutions are less likely to promote firm investment efficiency (Bushee 1998). Bhide (1993) argues that high stock liquidity can encourage short-termism among firms with higher non-monitoring institutions as high stock liquidity makes it easier for large-scaled institutional owners to sell in response to low quarterly earnings. Fang et al. (2014) provide evidence that high stock liquidity impedes firm investment in innovation (measured by patents and citations per patent) and high stock liquidity also attracts a greater presence of non-dedicated institutional investors such as transient shareholders and quasi-indexers. They argue that an increase in non-dedicated institutions may influence managers to focus on short-term profit by foregoing value-enhancing investment. Hence, the effect of stock liquidity on investment efficiency is expected to be weaker among firms with a greater proportion of non-monitoring institutions.

#### *7.2.1.1 Empirical results*

To test how the effect on stock liquidity on investment efficiency differs between firms with high and low proportions of monitoring institutional ownership (hereafter, monitoring IO), I first divide my full sample into two groups based on the median proportion of monitoring IO in firms and then reestimate my main regression (Equation (1)) for each subsample separately. The fraction of monitoring IO (*MonIO*) is measured as the percentage of monitoring IO scaled by the total of monitoring IO and non-monitoring IO for each firm in fiscal year. Observations with *MonIO* below (above) the median are classified as low (high) monitoring IO firms. Following Ramalingegowda and Yu (2012), monitoring institutions are defined as dedicated institutions with long investment horizons and concentrated holdings (as defined by Bushee (2001)) and those that are independent from corporate management (as defined by Brickley et al. (1998)).[75] Non-monitoring institutions include Bushee's transient institutions, Bushee's quasi-indexing institutions, and Bushee's dedicated institutions that are also classified as non-independent by Brickley et al. (1998). Non-monitoring institutions that by virtue of owning diverse shares and being short-term in focus have little incentives to monitor and are more likely to pressure managers to focus on short-term earnings. Dedicated non-independent institutions such as bank trusts and insurance companies are less likely to engage in monitoring because of their non-independent nature.

Summary statistics for the subsamples of high and low monitoring IO firms, stratified by the median monitoring IO value of 10.7 percent, are presented in Table 20. Firms with monitoring IO greater than 10.7 percent are categorised as high monitoring IO firms whereas those below 10.7 percent as low monitoring IO firms, respectively. The distribution of investment levels (*INV*) appears to be comparable between the high and low group: the mean and median values of *INV* are 15.52 (14.99), and 10.55 (9.94) for high (low) monitoring IO group, respectively. The mean and median values of propensity to over-invest (*OverFirm*) are also quite similar across both groups: 0.53 (0.54), and 0.56 (0.56) for high (low) group, respectively. On average, stock liquidity values (*LIQ*) are lower for the high monitoring IO group, in comparison to the low monitoring IO group (at the 1 percent level, based on *t*-test). The mean and median percentages of monitoring IO (*MonIO*) for the high (low) monitoring IO group are 24 percent (4 percent) and 20 percent (4 percent), respectively.

<<<INSERT TABLE 20 ABOUT HERE>>>

[75] Professor Brian Bushee's institutional investor classification data are obtained from http://acct.wharton.upenn.edu/faculty/bushee/IIclass.html. Institutions are classified as dedicated, quasi-indexer or transient. The data also comes with the codes assigned to each institutional investor for the legal type. Following Brickley et al. (1988), I assign type 3 (investment companies), type 4 (independent investment advisors), and type 5 (public pension funds) as institutions independence from management; while type 1 (bank trusts), type 2 (insurance companies) and type 5 (Others - excluding public pension funds) are classified as institutions that are non-independence from management.

Tables 21 and 22 report the results from the regression analyses that assess the impact of stock liquidity on investment efficiency for firms with high (Table 21) and low (Table 22) monitoring IO. I estimate the regression models for high and low monitoring IO separately rather than using three-way interactions to allow the parameter estimates on my control variables to also vary across the two subsamples of firms and to simplify the interpretation of the empirical results.

Consistent with hypothesis H1a, I find that stock liquidity is positively and significantly (at the 10 percent level or better) associated with investment levels using the *LIQFHT*, *LIQTURN*, and *LIQindex* proxies for both high and low monitoring IO firms in firms with a higher propensity to under-invest. By comparing the magnitude of the coefficients on *LIQ* (*LIQFHT, LIQTURN*, *LIQindex*) across high and low monitoring IO group, the coefficients appear to be slightly larger in magnitude (2.28, 2.49, 1.43 in Table 21) for the high monitoring IO group, relative to those (1.01, 2.03, 0.81 in Table 22) for the low monitoring IO group, indicating that the effect of stock liquidity increasing investment levels in under-investing firms appears to be larger when there is greater ownership by monitoring institutions. In terms of economic significance, my statistically significant results suggest that a one percent increment in stock liquidity using *LIQFHT* proxy (*LIQTURN*, *LIQindex*) is associated with an increase of 10.48 percent (7.64 percent, 8.01 percent) in the investment levels of under-investing firms with high monitoring IO. A corresponding increment of 4.01 percent (6.43 percent, 4.18 percent) is observed in the investment levels of under-investing firms with low monitoring IO. Overall, my results suggest that for firms with greater propensity to under-invest, the effect of stock liquidity on promoting investments is economically greater for high monitoring IO firms than for low monitoring IO firms.

Turning to the setting of over-investing firms, I find that stock liquidity is negatively and significantly (at the 10 percent level or better) associated with investment levels using *LIQFHT*, *LIQZERO*, and *LIQindex* proxies for both high and low monitoring IO firms, as indicated by the joint significance tests (H1b). Again, the magnitude of the coefficients on the joint tests (*LIQFHT, LIQZERO*, *LIQindex*) appear to be larger for the high monitoring IO firms (-3.40, -21.90, -1.74 in Table 21), relative to those (-1.73, -14.41, -1.01 in Table 22) for the low monitoring IO group, suggesting that the decreasing effect of stock liquidity on the investment levels of over-investing firms is accentuated within firms with larger proportion of monitoring IO. In terms of economic significance, a one percent increment in stock liquidity using *LIQFHT* proxy (*LIQZERO*, *LIQindex*) is associated with a reduction of 15.64 percent (10.16 percent, 9.73 percent) in the investment levels of over-investing firms with high monitoring IO. The corresponding effect observed in low monitoring IO firms is a decrement of 6.87 percent (6.25 percent, 5.21 percent) in investment levels. Thus, the effect of liquidity appears to be more economically significant in over-investing firms with high monitoring IO, relative to over-investing firms with low monitoring IO.

Results from Chow tests confirm that there are significant differences between the regression coefficients on the liquidity proxies and their interactions with *OverFirm* across the two subsamples of firms with low and high monitoring institutions at the 5 percent level or better (F-statistics reported in Table 22), except *LIQindex* which is insignificant. Overall, my findings reported in Tables 21 and 22 show that the effects of stock liquidity on investment efficiency generally appear to be more pronounced in firms with high proportion of monitoring IO. My evidence is consistent with the view that high stock liquidity enhances the monitoring efforts of monitoring IO through voice threats, resulting in greater investment efficiency.

<<<INSERT TABLES 21 AND 22 ABOUT HERE>>>

Next, I expand on my analyses in Tables 21 and 22 by rerunning the analyses after segregating the full sample into tertiles based on the level of monitoring institutional ownership (*MonIO*) and then replicating my regression analyses for observations in the top (*MonIO* >= 16.3 percent) and the bottom tertile (*MonIO* < 5.9 percent) of *MonIO*. The results in Tables 23 and 24 continue to show that the coefficients on the stock liquidity proxies are bigger in magnitude and mostly significant for the top monitoring IO group (Table 23), while the associations between stock liquidity and investment efficiency are no longer significant in the bottom monitoring IO group (Table 24). Specifically, among firms with the top tertile of monitoring IO, stock liquidity appears to have an increasing effect on investment levels for under-investing firms (at the 10 percent level or better using *LIQFHT*, *LIQTURN*, and *LIQindex*); and a decreasing effect for over-investing firms (at the 1 percent level using *LIQFHT*, *LIQZERO*, and *LIQindex*). For firms with the bottom tertile of monitoring IO, there is no evidence that stock liquidity has an impact on investment efficiency (all coefficients on *LIQ* and its interactions with *OverFirm* are insignificant except coefficient on joint test using *LIQZERO*). Results from Chow tests indicate that there are significant differences between the regression coefficients on the liquidity proxies and their interactions with *OverFirm* across the two subsamples of firms with bottom and top tertile monitoring institutions at the 10 percent level or better (F-statistics reported in Table 24). These results further support the view that the association between stock liquidity and investment efficiency is more likely to be driven by firms with higher proportion of monitoring IO.

<<<INSERT TABLES 23 AND 24 ABOUT HERE>>>

Figure 5 provides visual evidence in support of the multivariate results reported in Tables 21 and 22 based on the median proportion of monitoring IO, depicting how the stock liquidity (*LIQ*) slopes change with increasing values of *OverFirm* across subsample firms with high (Panel A) and low (Panel B) proportion of monitoring IO, respectively. The adjusted mean investment levels (*INV*) for low and high stock liquidity (*LIQ*) are graphed with *LIQ* on the *x* axis and with separate lines for the likelihood of under- and over-investment (*OverFirm*). The slope of the gradient indicates the extent of investment efficiency among subsample firms (high and low proportion of monitoring IO firms, respectively) are attributable to stock liquidity. The graphs show that the *LIQ* slopes are more positive (negative) for under-investing (over-investing) firms in high monitoring IO subsample (Panel A of Figure 5) than in the low monitoring IO subsample (Panel B of Figure 5). The results suggest that the stronger effect of stock liquidity on investment efficiency is predominantly among firms with higher monitoring IO. These effects are more visible when comparing firms in the top tertile of monitoring IO (Panel A of Figure 6) and the bottom tertile of monitoring IO (Panel B of Figure 6). The slopes are far steeper for the top tertile of monitoring IO firms (Panel A of Figure 6) than for the bottom tertile group (Panel B of Figure 6), confirming that stock liquidity has a greater effect on investment efficiency in firms with higher monitoring IO.

<<<INSERT FIGURES 5 AND 6 ABOUT HERE>>>

#### *7.2.1.2 Conclusion*

This section investigates whether the effect of stock liquidity on investment efficiency is driven by the higher ownership of monitoring institutions in publicly held firms. Consistent with the corporate governance-based explanation, the beneficial effect of stock liquidity on investment efficiency is concentrated in firms with a higher proportion of monitoring institutions. That is, for firms with high monitoring institutions, over-investing firms invest less and under-investing firms invest more when their stock liquidity is higher. My results are consistent with the view that higher stock liquidity allows monitoring institutions to exert stronger governance by increasing their voice threats, thereby resulting in greater investment efficiency. On the other hand, the beneficial effect of stock liquidity is lacking or smaller for firms with low monitoring institutions (i.e., high non-monitoring institutions). In sum, I find evidence that stock liquidity enhances firm investment efficiency to a greater extent in firms with high monitoring institutions relative to firms with high non-monitoring institutions.

# Chapter 8: Conclusions

## 8.1 Introduction

This chapter concludes my thesis by reviewing the research questions in Section 8.2, summarising the research design and findings in Section 8.3, and highlighting its limitations and suggestions for future research in Section 8.4.

## 8.2 Review of the research question and hypotheses

There has been much academic focus on the impact of stock liquidity on managerial decisions and firm performance. One stream of literature has focused on the informational role of stock liquidity, arguing that high stock liquidity can improve the informational content of stock prices by encouraging more informed trading. An increase in stock liquidity incorporates more private information into stock prices, and thereby reduces information asymmetry and facilitates more effective assessment of the firm's decisions (Wurgler 2000; Durnev et al. 2003). In addition, high stock liquidity also speeds up market feedback to firm managers on the quality of their decisions by producing more informative stock prices. Hence, managers are incentivised to take corrective actions to improve firm performance based on information inferred from stock prices (Subrahmanyam and Titman 2001; Khanna and Sonti 2004; Bond et al. 2010).

Another stream of research expounds the governance role of stock liquidity. This literature links stock liquidity and firm performance through the effects of direct intervention (e.g., voice threats) and the effects of exit threats that can be considered as forms of governance. This literature argues that an increase in stock liquidity enables investors to easily accumulate a larger equity ownership, thereby inducing better direct monitoring (Maug 1998), and hence leading to better firm performance. Further, given that higher stock liquidity also enables unhappy investors to quickly liquidate a large position, firm managers are incentivised to improve firm performance because the exit of large investors can depress stock prices (Admati and Pfleiderer 2009; Edmans 2009).

It is not a surprise to find mixed empirical evidence on the benefits of stock liquidity given that the stock liquidity literature has provided conflicting predictions about the role of stock liquidity in firm performance. While some prior studies find strong evidence consistent with theoretical predictions on the beneficial effect of stock liquidity on firm performance (Fang et al. 2009; Bharath et al. 2013), others document results supporting the claims that high stock liquidity is detrimental to firm performance (Fang et al. 2014). My thesis seeks to contribute to the ongoing debate on whether stock liquidity leads to lower or higher firm performance, by evaluating the impact of stock liquidity on investment efficiency.

As part of my additional tests, I investigate whether the effect of stock liquidity on investment efficiency is more pronounced for young firms and high business risk firms, respectively, which are expected to be inflicted with information asymmetry problems. I argue that high stock liquidity is more beneficial to these firms as it can increase transparency and feedback effect to these firms, thereby improving investment efficiency. I also test for whether the effect of stock liquidity on investment efficiency is more pronounced for firms with high monitoring institutions, drawing upon the arguments that high stock liquidity can help monitoring institutions to monitor effectively by enhancing the power of their voice threats.

In the following subsection, I describe how these research questions are addressed in my thesis and summarise the main findings.

## 8.3 Summary of research design and empirical findings

My research question examines whether stock liquidity is positively associated with investment efficiency. Hypothesis 1a predicts that stock liquidity is positively associated with under-investment, whereas hypothesis 1b predicts that stock liquidity is negatively associated with over-investment. I examine the impact of stock liquidity on firm's real investment decisions using the framework of Biddle et al. (2009).

Specifically, I regress the investment levels on stock liquidity conditional on a given firm's likelihood of over-investing or under-investing (proxied by an aggregated measure of cash balance and leverage) and other relevant covariates. Given that stock liquidity constitutes several dimensions of attributes, I employ four measures of stock liquidity: (1) cost of trading as a percentage of prices, (2) zero-return days, (3) share turnover, and (4) a composite measure of stock liquidity that I develop by standardising and aggregating the three individual measures of stock liquidity to capture various aspects of stock liquidity's attributes.

My results for tests of H1a show that stock liquidity is positively and statistically associated with investments among firms with higher likelihood of under-investing, thereby supporting the view that high stock liquidity improves investment efficiency in under-investing firms. My results for tests of H1b show that the overall effect of stock liquidity on investments among firms with higher likelihood of over-investing is negative and significant, thereby supporting the view that high stock liquidity improves investment efficiency in over-investing firms.

I perform a battery of robustness and sensitivity tests to rule out alternative explanations and spurious relationships. The results broadly remain the same when I: (1) include informative stock price as a control variable to determine whether stock liquidity is of incremental value in explaining investment efficiency; (2) use two-stage least squares and change regression specifications to eliminate the possibility that stock liquidity and investment efficiency are endogenously related; (3) run regressions after year exclusions and industry exclusions to rule out the possibility that a particular year or industry drives the main results, and (4) employ alternative proxies of stock liquidity and investment. The results from these tests generally substantiate my main findings.

My main results demonstrate that high stock liquidity leads to improvements in investment efficiency. These observed patterns are further analysed by investigating whether the stock liquidity-investment efficiency relationship is stronger for firms: (1) classified as having poor information environment, and (2) with greater ownership of institutional investors who have a long-term focus. These form my additional tests concerning whether higher stock liquidity is more beneficial to firms inflicted with information asymmetry and to firms with higher monitoring institutional ownership.

To gain insight into the informational role of stock liquidity, I test whether the beneficial effect of stock liquidity on firm investment efficiency is more pronounced in two settings where information asymmetry is more acute: young firms (proxied by firm age), and high business risk firms (proxied by operating income volatility). In each analysis, I split the sample firms into two subsamples based on the median values of the variable of interest (i.e., firm age, and operating income volatility). I then re-estimate my main analyses (Equation (1)) separately for each subsample for each context. My results indicate that the association between stock liquidity and investment efficiency is stronger among young firms and also high business risk firms. These results are consistent with stock liquidity having a greater beneficial effect on investment efficiency for firms inflicted with information asymmetry problems.

To shed light on the governance role of stock liquidity, I test whether the beneficial effect of stock liquidity on firm investment efficiency is stronger in firms with higher monitoring institutions. I rerun the conditional regression (Equation (1)) separately for two subsamples representing firms with high and low proportions of monitoring institutional ownership. Overall, my results show that the effects of stock liquidity on investment efficiency are more pronounced among firms with a high proportion of monitoring institutions, whereas the effect is smaller or lacking for firms with a high proportion of non-monitoring institutions (i.e., low monitoring institutions). Hence, my findings support the view that high stock liquidity enhances the ability of monitoring institutions to intervene directly (i.e., voice threats) to mitigate managers' opportunistic behaviours, thereby improving investment efficiency.

Collectively, these findings highlight the critical role of stock liquidity in affecting managers' investment decisions, particularly when firms' information environment is opaque and the proportion of monitoring institutions is greater. Young firms and high business risk firms inflicted with information opacity are more likely to benefit from more liquid stock as it helps increase the information content of stock prices, improve transparency, and enhance feedback effect, thus, leading to better managers' investment decisions. My findings also suggest that high stock liquidity is more beneficial to firms with a high proportion of monitoring ownership in the sense that it enhances the institutions' monitoring roles by facilitating voice threats.

My results have a number of important implications for regulators and investors. First, my finding that stock liquidity plays an important role in promoting investment efficiency may provide insights to regulators as they continue to assess the effectiveness of regulatory reforms that increase liquidity in stock markets. Second, my finding that supports the view that higher stock liquidity enhances the governance role of monitoring institutional investors may help institutional investors understand the moderating effect of their levels of ownership as they vary their trading strategies. Finally, my finding that higher stock liquidity plays as a curative device may increase investors' confidence in capital markets as they make economic decisions.

## 8.4 Limitations and future research opportunities

My study suffers from several limitations. First, there is no single proxy developed to date that can perfectly capture all three elements of stock liquidity, namely depth (the number of shares that can be traded at given bid and ask prices), breadth (the size of market participants who are unable to exercise significant market power regardless of their size), and resiliency (how quickly prices return to previous levels after experiencing price changes) (Hasbrouck 2007). The stock liquidity constructs employed in my study are derived following the methodologies used in prior studies and are intended to measure various aspects of stock liquidity. Although my main liquidity proxies have been shown to be highly correlated with liquidity benchmarks computed from high-frequency (intraday) stock data (Fong, et al. 2014), each of my liquidity proxies is subject to its own limitations in perfectly capturing stock liquidity. As such, although I conduct regression tests using an extensive set of other alternative measures of stock liquidity, I cannot reject the possibility that my results are subject to measurement errors as stock liquidity is not directly observable and not easily operationalized.

A second limitation is that my findings do not necessarily imply a causal relationship between stock liquidity and investment efficiency, but instead provide evidence of associations. My findings are robust to a wide range of additional tests such as controlling for endogeneity, using different measures of stock liquidity and specific measures of investment, but I cannot completely rule out the possibility of my findings being driven by omitted variables. Hence, my empirical results should be interpreted with some caution. Future research might address these methodology weaknesses and employ an alternative research design to confirm a causal relationship between stock liquidity and investment efficiency.

My thesis demonstrates that the relationship between stock liquidity and investment efficiency is more pronounced when firm's information asymmetry is greater and monitoring institutional ownership is higher. Future research can extend my thesis by investigating the mediating effect of other potential mechanisms on the relationship between stock liquidity and investment efficiency. One such area that can be explored is to examine how the interplay between internal monitoring (e.g., proxied by internal quality control systems) and external monitoring (e.g., proxied by stock liquidity) affects investment efficiency.

## References


Admati, A. R., and P. Pfleiderer. 1988. A theory of intraday patterns: Volume and price variability. *Review of Financial Studies* 1 (1).

———. 2009. The "Wall Street Walk" and shareholder activism: Exit as a form of voice. *Review of Financial Studies* 22 (7):2645-85.

Admati, A. R., P. Pfleiderer, and J. Zechner. 1994. Large shareholder activism, risk sharing, and financial market equilibrium. *Journal of Political Economy* 102 (6):1097.

Aggarwal, R., I. Erel, M. Ferreira, and P. Matos. 2011. Does governance travel around the world? Evidence from institutional investors. *Journal of Financial Economics* 100 (1):154-81.

Akerlof, G. A. 1970. The market for "lemons": Quality uncertainty and the market mechanism. *Quarterly Journal of Economics* 84 (3):488-500.

Almeida, H., and M. Campello. 2007. Financial constraints, asset tangibility, and corporate investment. *Review of Financial Studies* 20 (5):1429-60.

Amihud, Y. 2002. Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets* 5 (1):31-56.

Amihud, Y., and H. Mendelson. 1986. Asset pricing and the bid-ask spread. *Journal of Financial Economics* 17 (2):223-49.

———. 1989. The effects of beta, bid-ask spread, residual risk, and size on stock returns. *Journal of Finance* 44 (2):479-86.

———. 2012. Liquidity, the value of the firm, and corporate finance. *Journal of Applied Corporate Finance* 24 (1):17-32.

Amihud, Y., H. Mendelson, and L. H. Pedersen. 2005. Liquidity and asset prices. *Foundations & Trends in Finance* 1 (4):269-364.

Armour, J., B. Black, B. Cheffins, and R. Nolan. 2009. Private enforcement of corporate law: An empirical comparison of the United Kingdom and the United States. *Journal of Empirical Legal Studies* 6 (4):687-722.

Ashbaugh-Skaife, H., J. Gassen, and R. LaFond. 2006. *Does stock price synchronicity represent firm-specific information? The international evidence*. Working paper, Massachusetts Institute of Technology. Available at http://ssrn.com/abstract=768024.

Asquith, P., and D. W. Mullins Jr. 1986. Equity issues and offering dilution. *Journal of Financial Economics* 15 (1/2):61-89.

Atkins, A. B., and E. A. Dyl. 1997. Transactions costs and holding periods for common stocks. *Journal of Finance* 52 (1):309-25.

Attig, N., W.-M. Fong, Y. Gadhoum, and L. H. P. Lang. 2006. Effects of large shareholding on information asymmetry and stock liquidity. *Journal of Banking & Finance* 30 (10):2875-92.

Avery, C., J. A. Chevalier, and S. Schaefer. 1998. Why do managers undertake acquisitions? An analysis of internal and external rewards for acquisitiveness. *Journal of Law, Economics & Organization* 14 (1):24.

Baker, M., and J. C. Stein. 2004. Market liquidity as a sentiment indicator. *Journal of Financial Markets* 7 (3):271-99.

Baker, M., J. C. Stein, and J. Wurgler. 2003. When does the market matter? Stock prices and the investment of equity-dependent firms. *Quarterly Journal of Economics* 118 (3):969-1005.

Bakke, T.-E., and T. M. Whited. 2010. Which firms follow the market? An analysis of corporate investment decisions. *Review of Financial Studies* 23 (5):1941-80.

Balakrishnan, K., M. B. Billings, B. Kelly, and A. Ljungqvist. 2014a. Shaping liquidity: On the causal effects of voluntary disclosure. *Journal of Finance* 69 (5):2237-78.

Balakrishnan, K., J. E. Core, and R. S. Verdi. 2014b. The relation between reporting quality and financing and investment: Evidence from changes in financing capacity. *Journal of Accounting Research* 52 (1):1-36.

Banerjee, S., V. A. Gatchev, and P. A. Spindt. 2007. Stock market liquidity and firm dividend policy. *Journal of Financial & Quantitative Analysis* 42 (2):369-97.

Barber, B. M. 2007. Monitoring the monitor: Evaluating CalPERS' activism. *Journal of Investing* 16 (4):66-80.

Bates, T. W. 2005. Asset sales, investment opportunities, and the use of proceeds. *Journal of Finance* 60 (1):105-35.

Beatty, A., W. Scott Liao, and J. Weber. 2010. The effect of private information and monitoring on the role of accounting quality in investment decisions. *Contemporary Accounting Research* 27 (1):17-47.

Bebchuk, L. A., and L. A. Stole. 1993. Do short-term objectives lead to under- or overinvestment in long term projects? *Journal of Finance* 48 (2):719-29.

Becht, M., J. Franks, C. Mayer, and S. Rossi. 2009. Returns to shareholder activism: Evidence from a clinical study of the Hermes UK focus fund. *Review of Financial Studies* 22 (8):3093-129.

Becker-Blease, J. R., and D. L. Paul. 2006. Stock liquidity and investment opportunities: Evidence from index additions. *Financial Management* 35 (3):35-51.

Bertrand, M., and S. Mullainathan. 2003. Enjoying the quiet life? Corporate governance and managerial preferences. *Journal of Political Economy* 111 (5):1043-75.

Bessembinder, H. 2003. Trade execution costs and market quality after decimalization. *Journal of Financial & Quantitative Analysis* 38 (4):747-77.

Bharath, S., P. Pasquariello, and G. Wu. 2009. Does asymmetric information drive capital structure decisions? *Review of Financial Studies* 22 (8):3211-43.

Bharath, S. T., S. Jayaraman, and V. Nagar. 2013. Exit as governance: An empirical analysis. *Journal of Finance* 68 (6):2515-47.

Bhide, A. 1993. The hidden costs of stock market liquidity. *Journal of Financial Economics* 34 (1):31-51.

Biddle, G. C., and G. Hilary. 2006. Accounting quality and firm-level capital investment. *Accounting Review* 81 (5):963-82.

Biddle, G. C., G. Hilary, and R. S. Verdi. 2009. How does financial reporting quality relate to investment efficiency? *Journal of Accounting & Economics* 48 (2/3):112-31.

Black, B. S. 1990. Shareholder passivity reexamined. *Michigan Law Review* 89 (3):520-20.

Blanchard, O. J., F. Lopez-de-Silanes, and A. Shleifer. 1994. What do firms do with cash windfalls? *Journal of Financial Economics* 36 (3):337-60.

Boehmer, E., and E. K. Kelley. 2009. Institutional investors and the informational efficiency of prices. *Review of Financial Studies* 22 (9):3563-94.

Bond, P., I. Goldstein, and E. S. Prescott. 2010. Market-based corrective actions. *Review of Financial Studies* 23 (2):781-820.

Bond, S., and C. Meghir. 1994. Dynamic investment models and the firm's financial policy. *Review of Economic Studies* 61 (207):197.

Brennan, M. J., and A. Subrahmanyama. 1996. Market microstructure and asset pricing: On the compensation for illiquidity in stock returns. *Journal of Financial Economics* 41 (3):441-64.

Brickley, J. A., R. C. Lease, and C. W. Smith Jr. 1988. Ownership structure and voting on antitakeover amendments. *Journal of Financial Economics* 20 (0):267-91.

Brown, J. R., S. M. Fazzari, and B. C. Petersen. 2009. Financing external innovation and growth: Cash flow, equity, and the 1990s R&D boom. *The Journal of Fiance* 64 (1):151-85.

Brown, J. R., G. Martinsson, and B. C. Petersen. 2012. Do financing constraints matter for R&D? *European Economic Review* 56 (8):1512-29.

Burns, N., S. Kedia, and M. Lipson. 2010. Institutional ownership and monitoring: Evidence from financial misreporting. *Journal of Corporate Finance* 16 (4):443-55.

Bushee, B. J. 1998. The influence of institutional investors in myopic R&D investment behavior. *Accounting Review* 73 (3):305.

———. 2001. Do institutional investors prefer near-term earnings over long-run value? *Contemporary Accounting Research* 18 (2):207-46.

Bushman, R. M., J. D. Piotroski, and A. J. Smith. 2011. Capital allocation and timely accounting recognition of economic losses. *Journal of Business Finance & Accounting* 38 (1/2):1-33.

Busse, J. A., T. Clifton Green, and N. Jegadeesh. 2012. Buy-side trades and sell-side recommendations: Interactions and information content. *Journal of Financial Markets* 15 (2):207-32.

Butler, A. W., G. Grullon, and J. P. Weston. 2005. Stock market liquidity and the cost of issuing equity. *Journal of Financial & Quantitative Analysis* 40 (2):331-48.

Calomiris, C. W., and R. G. Hubbard. 1995. Internal finance and investment: Evidence from the undistributed profits tax of 1936-37. *Journal of Business* 68 (4):443.

Carpenter, R. E., S. M. Fazzari, and B. C. Petersen. 1994. Inventory investment, internal-finance fluctuations, and the business cycle. *Brookings Papers on Economic Activity* (2):75-138.

Chaney, T., D. Sraer, and D. Thesmar. 2012. The collateral channel: How real estate shocks affect corporate investment. *American Economic Review* 102 (6):2381-409.

Chen, F., O.-K. Hope, Q. Li, and X. Wang. 2011. Financial reporting quality and investment efficiency of private firms in emerging markets. *Accounting Review* 86 (4):1255-88.

Chen, Q., I. Goldstein, and W. Jiang. 2007a. Price informativeness and investment sensitivity to stock price. *Review of Financial Studies* 20 (3):619-50.

Chen, X., J. Harford, and K. Li. 2007b. Monitoring: Which institutions matter? *Journal of Financial Economics* 86 (2):279-305.

Chen, Y., S. G. Rhee, M. Veeraraghavan, and L. Zolotoy. 2015. Stock liquidity and managerial short-termism. *Journal of Banking & Finance* 60:44-59.

Cheng, M., D. Dhaliwal, and Y. Zhang. 2013. Does investment efficiency improve after the disclosure of material weaknesses in internal control over financial reporting? *Journal of Accounting and Economics* 56 (1):1-18.

Chirinko, R. S., and H. Schaller. 1995. Why does liquidity matter in investment equations? *Journal of Money, Credit & Banking* 27 (2):527-48.

Chordia, T., R. Roll, and A. Subrahmanyam. 2008. Liquidity and market efficiency. *Journal of Financial Economics* 87 (2):249-68.

Chung, D., and K. Hrazdil. 2010. Liquidity and market efficiency: A large sample study. *Journal of Banking and Finance* 34 (10):2346-57.

Chung, H. 2006. Investor protection and the liquidity of cross-listed securities: Evidence from the ADR market. *Journal of Banking & Finance* 30 (5):1485-505.

Chung, K. H., J. Elder, and J.-C. Kim. 2010. Corporate governance and liquidity. *Journal of Financial & Quantitative Analysis* 45 (2):265-91.

Chung, K. H., and H. Zhang. 2011. Corporate governance and institutional ownership. *Journal of Financial & Quantitative Analysis* 46 (1):247-73.

———. 2014. A simple approximation of intraday spreads using daily data. *Journal of Financial Markets* 17 (0):94-120.

Coffee, J. C., Jr. 1991. Liquidity versus control: The institutional investor as corporate monitor. *Columbia Law Review* 91 (6):1277-368.

Committee on Capital Markets Regulation. 2009. The global financial crisis: A plan for regulatory reform.

Corwin, S. A., and P. Schultz. 2012. A simple way to estimate bid-ask spreads from daily high and low prices. *Journal of Finance* 67 (2):719-60.

Crawford, S. S., D. T. Roulstone, and E. C. So. 2012. Analyst initiations of coverage and stock return synchronicity. *Accounting Review* 87 (5):1527-53.

Dass, N., V. Nanda, and S. C. Xiao. 2012. *Do firms choose their stock liquidity? A study of innovative firms and their stock liquidity*. Working paper, Georgia Institute of Technology. Available at http://ssrn.com/abstract=2023882.

Demiralp, I., R. D'Mello, F. P. Schlingemann, and V. Subramaniam. 2011. Are there monitoring benefits to institutional ownership? Evidence from seasoned equity offerings. *Journal of Corporate Finance* 17 (5):1340-59.

Dharwadkar, R., M. Goranova, P. Brandes, and R. Khan. 2008. Institutional ownership and monitoring effectiveness: It's not just how much but what else you own. *Organization Science* 19 (3):419-40.

Diamond, D. W. 1985. Optimal release of information by firms. *Journal of Finance* 40 (4):1071-94.

Diamond, D. W., and R. E. Verrecchia. 1991. Disclosure, liquidity, and the cost of capital. *Journal of Finance* 46 (4):1325-59.

Dow, J., and G. Gorton. 1995. Profitable informed trading in a simple general equilibrium model of asset pricing. *Journal of Economic Theory* 67 (2):327-69.

———. 1997. Stock market efficiency and economic efficiency: Is there a connection? *Journal of Finance* 52 (3):1087-129.

Dow, J., and R. Rahi. 2003. Informed trading, investment, and welfare. *Journal of Business* 76 (3):439-54.

Durnev, A., R. Morck, and B. Yeung. 2001. *Does firm-specific information in stock prices guide capital allocation?* Working paper, National Bureau of Economic Research. Available at http://www.nber.org/papers/w8093.

———. 2004. Value-enhancing capital budgeting and firm-specific stock return variation. *Journal of Finance* 59 (1):65-105.

Durnev, A., R. Morck, B. Yeung, and P. Zarowin. 2003. Does greater firm-specific return variation mean more or less informed stock pricing? *Journal of Accounting Research* 41 (5):797-836.

Easley, D., S. Hvidkjaer, and M. O'Hara. 2002. Is information risk a determinant of asset returns? *Journal of Finance* 57 (5):2185-221.

Easley, D., N. M. Kiefer, and M. O'Hara. 1997. One day in the life of a very common stock. *Review of Financial Studies* 10 (3).

Easley, D., and M. O'Hara. 2003. Microstructure and asset pricing (chapter 17) In *Handbook of the economics of finance*, edited by M. H. G.M. Constantinides and R. M. Stulz: Elsevier, 1021-51.

———. 2004. Information and the cost of capital. *Journal of Finance* 59 (4):1553-83.

Edmans, A. 2009. Blockholder trading, market efficiency, and managerial myopia. *Journal of Finance* 64 (6):2481-513.

Edmans, A., V. W. Fang, and E. Zur. 2013. The effect of liquidity on governance. *Review of Financial Studies* 26 (6):1443-82.

Edmans, A., and G. Manso. 2011. Governance through trading and intervention: A theory of multiple blockholders. *Review of Financial Studies* 24 (7):2395-428.

Elyasiani, E., S. Hauser, and B. Lauterbach. 2000. Market response to liquidity improvements: Evidence from exchange listings. *Financial Review* 35 (1):1.

Fairfield, P. M., J. S. Whisenant, and T. L. Yohn. 2003. Accrued earnings and growth: Implications for future profitability and market mispricing. *Accounting Review* 78 (1):353.

Fama, E. F. 1980. Agency problems and the theory of the firm. *Journal of Political Economy* 88 (2):288-307.

Fama, E. F., and K. R. French. 1997. Industry costs of equity. *Journal of Financial Economics* 43 (2):153-93.

Fama, E. F., and M. C. Jensen. 1983. Separation of ownership and control. *Journal of Law & Economics* 26 (2):301-26.

Fang, V. W., T. H. Noe, and S. Tice. 2009. Stock market liquidity and firm value. *Journal of Financial Economics* 94 (1):150-69.

Fang, V. W., X. Tian, and S. Tice. 2014. Does stock liquidity enhance or impede firm innovation? *Journal of Finance* 69 (5):2085-125.

Fazzari, S. M., R. G. Hubbard, and B. C. Petersen. 1988. Financing constraints and corporate investment. *Brookings Papers on Economic Activity* (1):141-206.

Fee, C. E., C. J. Hadlock, and J. R. Pierce. 2009. Investment, financing constraints, and internal capital markets: Evidence from the advertising expenditures of multinational firms. *Review of Financial Studies* 22 (6):2361-92.

Ferreira, D., M. A. Ferreira, and C. C. Raposo. 2011. Board structure and price informativeness. *Journal of Financial Economics* 99 (3):523-45.

Fong, K., C. Holden, and C. Trzcinka. 2014. *What are the best liquidity proxies for global research?* Working paper, Indiana University. Available at http://dx.doi.org/10.2139/ssrn.1558447.

Fos, V. 2017. The disciplinary effects of proxy contests. *Management Science* 63 (3):655-671.

Francis, J., R. LaFond, P. Olsson, and K. Schipper. 2005. The market pricing of accruals quality. *Journal of Accounting & Economics* 39 (2):295-327.

Francis, J. R., and X. Martin. 2010. Acquisition profitability and timely loss recognition. *Journal of Accounting & Economics* 49 (1/2):161-78.

Fraser Federal Reserve Archive. 2013. Appendix b: Statistical tables relating to income, employment, and production.

Frederickson, J. R., and G. Hilary. 2010. *Disclosure quality and capital investment*. Working paper, University of Melbourne. Available at https://works.bepress.com/james_frederickson/1/.

Furfine, C. H. 2003. Decimalization and market liquidity. *Economic Perspectives* 27 (4):2-12.

Gaspar, J.-M., M. Massa, and P. Matos. 2005. Shareholder investment horizons and the market for corporate control. *Journal of Financial Economics* 76 (1):135-65.

Gillan, S. L., and L. T. Starks. 2000. Corporate governance proposals and shareholder activism: The role of institutional investors. *Journal of Financial Economics* 57 (2):275-305.

———. 2007. The evolution of shareholder activism in the United States. *Journal of Applied Corporate Finance* 19 (1):55-73.

Glosten, L. R., and P. R. Milgrom. 1985. Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of Financial Economics* 14 (1):71-100.

Gompers, P., J. Ishii, and A. Metrick. 2003. Corporate governance and equity prices. *Quarterly Journal of Economics* 118 (1):107.

Gompers, P. A. 1995. Optimal investment, monitoring, and the staging of venture capital. *Journal of Finance* 50 (5):1461-89.

Gompers, P. A., and A. Metrick. 2001. Institutional investors and equity prices. *Quarterly Journal of Economics* 116 (1):229-59.

Goyenko, R. Y., C. W. Holden, and C. A. Trzcinka. 2009. Do liquidity measures measure liquidity? *Journal of Financial Economics* 92 (2):153-81.

Gregoriou, A., and N. D. Nguyen. 2010. Stock liquidity and investment opportunities: New evidence from FTSE 100 index deletions. *Journal of International Financial Markets, Institutions and Money* 20 (3):267-74.

Grossman, S. J., and O. D. Hart. 1980. Takeover bids, the free-rider problem, and the theory of the corporation. *Bell Journal of Economics* 11 (1):42-64.

———. 1986. The costs and benefits of ownership: A theory of vertical and lateral integration. *Journal of Political Economy* 94 (4):691-719.

Grossman, S. J., and J. E. Stiglitz. 1980. On the impossibility of informationally efficient markets. *American Economic Review* 70 (3):393.

Grullon, G., G. Kanatas, and J. P. Weston. 2004. Advertising, breadth of ownership, and liquidity. *Review of Financial Studies* 17 (2):439-61.

Gujarati, D. 2003. *Basic Econometrics*. 4th ed. New York, NY: McGraw-Hill.

Hadlock, C. J., and J. R. Pierce. 2010. New evidence on measuring financial constraints: Moving beyond the KZ index. *Review of Financial Studies* 23 (5):1909-40.

Hall, B. 1992. *Investment and research and development at the firm level: Does the source of financing matter?* Working paper, National Bureau of Economic Research. Available at http://www.nber.org/papers/w4096.

Harford, J. 1999. Corporate cash reserves and acquisitions. *Journal of Finance* 54 (6):1969-97.

Harris, L. 1990. Statistical properties of the Roll serial covariance bid/ask spread estimator. *Journal of Finance* 45 (2):579-90.

Harris, L. 2003. *Trading and exchanges: Market microstructure for practitioners*. New York: Oxford University Press.

Hartzell, J. C., and L. T. Starks. 2003. Institutional investors and executive compensation. *Journal of Finance* 58 (6):2351-74.

Hasbrouck, J. 2007. *Empirical Market Microstructure: The Institutions, Economics and Econometrics of Securities Trading*. Oxford; New York: Oxford University Press.

Hayek, F. A. 1945. The use of knowledge in society. *American Economic Review* 35 (4):519-30.

He, W., D. Li, J. Shen, and B. Zhang. 2013. Large foreign ownership and stock price informativeness around the world. *Journal of International Money and Finance* 36:211-30.

He, W., and J. Shen. 2014. Do foreign investors improve informational efficiency of stock prices? Evidence from Japan. *Pacific-Basin Finance Journal* 27:32-48.

Healy, P. M., A. P. Hutton, and K. G. Palepu. 1999. Stock performance and intermediation changes surrounding sustained increases in disclosure. *Contemporary Accounting Research* 16 (3):485-520.

Heaton, J. B. 2002. Managerial optimism and corporate finance. *Financial Management* 31 (2):33.

Himmelberg, C. P., and B. C. Petersen. 1994. R&D and internal finance: A panel study of small firms in high-tech industries. *Review of Economics & Statistics* 76 (1):38.

Holderness, C. G. 2009. The myth of diffuse ownership in the United States. *Review of Financial Studies* 22 (4):1377-408.

Holmström, B. 1999. Managerial incentive problems: A dynamic perspective. *Review of Economic Studies* 66 (226):169-82.

Holmström, B., and J. Tirole. 1993. Market liquidity and performance monitoring. *Journal of Political Economy* 101 (4):678.

Hoshi, T., and A. Kashyap. 1991. Corporate structure, liquidity, and investment: Evidence from Japanese industrial groups. *Quarterly Journal of Economics* 106 (1):33-60.

Hubbard, R. G. 1998. Capital-market imperfections and investment. *Journal of Economic Literature* 36 (1):193-225.

———. 2007. An action plan for US capital markets. *International Finance* 10 (1):91-99.

Hubbard, R. G., A. K. Kashyap, and T. M. Whited. 1995. Internal finance and firm investment. *Journal of Money, Credit & Banking* 27 (3):683-701.

Jayaraman, S., and T. T. Milbourn. 2012. The role of stock liquidity in executive compensation. *Accounting Review* 87 (2):537-63.

Jensen, M. C. 1986. Agency costs of free cash flow, corporate finance, and takeovers. *American Economic Review* 76 (2):323.

Jensen, M. C., and W. H. Meckling. 1976. Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics* 3 (4):305-60.

Kadlec, G. B., and J. J. McConnell. 1994. The effect of market segmentation and illiquidity on asset prices: Evidence from exchange listings. *Journal of Finance* 49 (2):611-36.

Kahn, C., and A. Winton. 1998. Ownership structure, speculation, and shareholder intervention. *Journal of Finance* 53 (1):99-129.

Kashyap, A. K., and O. A. Lamont. 1994. Credit conditions and the cyclical behavior of inventories. *Quarterly Journal of Economics* 109 (3):565.

Kau, J. B., J. S. Linck, and P. H. Rubin. 2008. Do managers listen to the market? *Journal of Corporate Finance* 14 (4):347-62.

Kelly, B., and A. Ljungqvist. 2012. Testing asymmetric-information asset pricing models. *Review of Financial Studies* 25 (5):1366-413.

Khanna, N., and R. Sonti. 2004. Value creating stock manipulation: Feedback effect of stock prices on firm value. *Journal of Financial Markets* 7 (3):237-70.

Kim, Y., H. Li, and S. Li. 2012. Does eliminating the form 20-F reconciliation from IFRS to U.S. GAAP have capital market consequences? *Journal of Accounting and Economics* 53 (1–2):249-70.

Kumar, P., N. Langberg, and K. Sivaramakrishnan. 2012. Voluntary disclosures, corporate control, and investment. *Journal of Accounting Research* 50 (4):1041-76.

Kyle, A. S. 1985. Continuous auctions and insider trading. *Econometrica* 53 (6):1315-35.

Kyle, A. S., and J.-L. Vila. 1991. Noise trading and takeovers. *RAND Journal of Economics* 22 (1):54-71.

La Porta, R., F. Lopez-de-Silanes, and A. Shleifer. 1999. Corporate ownership around the world. *Journal of Finance* 54 (2):471-517.

Lambert, R., C. Leuz, and R. E. Verrecchia. 2007. Accounting information, disclosure, and the cost of capital. *Journal of Accounting Research* 45 (2):385-420.

Lamont, O. A. 2000. Investment plans and stock returns. *Journal of Finance* 55 (6):2719-45.

Lang, L., and E. Ofek. 1996. Leverage, investment, and firm growth. *Journal of Financial Economics* 40 (1):3-29.

Lang, M., K. V. Lins, and M. Maffett. 2012. Transparency, liquidity, and valuation: International evidence on when transparency matters most. *Journal of Accounting Research* 50 (3):729-74.

Lang, M., and R. Lundholm. 1993. Cross-sectional determinants of analyst ratings of corporate disclosures. *Journal of Accounting Research* 31 (2):246-71.

Lee, D. W., and M. H. Liu. 2011. Does more information in stock price lead to greater or smaller idiosyncratic return volatility? *Journal of Banking and Finance* 35 (6):1563-80.

Leland, H. E. 1992. Insider trading: Should it be prohibited? *Journal of Political Economy* 100 (4):859.

Lesmond, D. A., P. F. O'Connor, and L. W. Senbet. 2008. *Capital structure and equity liquidity*. Working paper, University of Maryland. Available at http://ssrn.com/abstract=1107660.

Lesmond, D. A., J. P. Ogden, and C. A. Trzcinka. 1999. A new estimate of transaction costs. *Review of Financial Studies* 12 (5).

Leuz, C., and R. E. Verrecchia. 2000. The economic consequences of increased disclosure. *Journal of Accounting Research* 38 (3):91-124.

Lipson, M., and S. Mortal. 2009. *Liquidity and capital structure*. Working paper, University of Virginia. Available at http://ssrn.com/abstract=887413.

Lo, A. W., and W. Jiang. 2000. Trading volume: Definitions, data analysis, and implications of portfolio theory. *Review of Financial Studies* 13 (2).

Loughran, T., and P. Schultz. 2005. Liquidity: Urban versus rural firms. *Journal of Financial Economics* 78 (2):341-74.

Luo, Y. 2005. Do insiders learn from outsiders? Evidence from mergers and acquisitions. *Journal of Finance* LX (4):1951-82.

Madhavan, A. 2000. Market microstructure: A survey. *Journal of Financial Markets* 3 (3):205-58.

Malmendier, U., and G. Tate. 2008. Who makes acquisitions? CEO overconfidence and the market's reaction. *Journal of Financial Economics* 89 (1):20-43.

Masulis, R. W., and A. N. Korwar. 1986. Seasoned equity offerings: An empirical investigation. *Journal of Financial Economics* 15 (1/2):91-118.

Maug, E. 1998. Large shareholders as monitors: Is there a trade-off between liquidity and control? *Journal of Finance* 53 (1):65-98.

McCahery, J. A., Z. Sautner, and L. T. Starks. 2016. Behind the scenes: The corporate governance preferences of institutional investors. *Journal of Finance* 71 (6):2905-32.

McNichols, M. F., and S. R. Stubben. 2008. Does earnings management affect firms' investment decisions? *Accounting Review* 83 (6):1571-603.

Merton, H. M., and F. Modigliani. 1961. Dividend policy, growth, and the valuation of shares. *The Journal of Business* 34 (4):411-33.

Mikkelson, W. H., and M. M. Partch. 1986. Valuation effects of security offerings and the issuance process. *Journal of Financial Economics* 15 (1/2):31-60.

Modigliani, F., and M. H. Miller. 1958. The cost of capital, corporation finance, and the theory of investment. *American Economic Review* 48 (3):261.

Mohanram, P., and S. Rajgopal. 2009. Is PIN priced risk? *Journal of Accounting and Economics* 47 (3):226-43.

Morck, R., A. Shleifer, and R. W. Vishny. 1990. Do managerial objectives drive bad acquisitions? *Journal of Finance* 45 (1):31-48.

Myers, S. C. 1977. Determinants of corporate borrowing. *Journal of Financial Economics* 5 (2):147-75.

Myers, S. C., and N. S. Majluf. 1984. Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics* 13 (2):187-221.

Narayanan, M. P. 1985. Managerial incentives for short-term results. *Journal of Finance* 40 (5):1469-84.

Ng, J. 2011. The effect of information quality on liquidity risk. *Journal of Accounting & Economics* 52 (2/3):126-43.

O'Hara, M. 1995. *Market Microstructure Theory*. Cambridge, MA: Blackwell.

———. 2003. Presidential address: Liquidity and price discovery. *Journal of Finance* 58 (4):1335-54.

Opler, T., L. Pinkowitz, R. Stulz, and R. Williamson. 1999. The determinants and implications of corporate cash holdings. *Journal of Financial Economics* 52 (1):3-46.

Pang, J., and H. Wu. 2009. Financial markets, financial dependence, and the allocation of capital. *Journal of Banking & Finance* 33 (5):810-18.

Petersen, M. A. 2009. Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies* 22 (1):435-80.

Porter, M. E. 1992. Capital disadvantage: America's failing capital investment system. *Harvard Business Review* 70 (5):65-82.

Qi, C., I. Goldstein, and J. Wei. 2007. Price informativeness and investment sensitivity to stock price. *Review of Financial Studies* 20 (3):619-50.

Rajan, R. G., and L. Zingales. 1998. Financial dependence and growth. *American Economic Review* 88 (3):559-86.

Ramalingegowda, S., and Y. Yu. 2012. Institutional ownership and conservatism. *Journal of Accounting & Economics* 53 (1/2):98-114.

Rauh, J. D. 2006. Investment and financing constraints: Evidence from the funding of corporate pension plans. *Journal of Finance* 61 (1):33-71.

Richardson, S. 2006. Over-investment of free cash flow. *Review of Accounting Studies* 11 (2/3):159-89.

Roll, R. 1984. A simple implicit measure of the effective bid-ask spread in an efficient market. *Journal of Finance* 39 (4):1127-39.

———. 1986. The hubris hypothesis of corporate takeovers. *Journal of Business* 59 (2):197-216.

———. 1988. $R^2$. *Journal of Finance* 43 (3):541-66.

Roosenboom, P., F. P. Schlingemann, and M. Vasconcelos. 2014. Does stock liquidity affect incentives to monitor? Evidence from corporate takeovers. *Review of Financial Studies* 27 (8):2392-433.

Sadka, R. 2011. Liquidity risk and accounting information. *Journal of Accounting & Economics* 52 (2/3):144-52.

Sadka, R., and A. Scherbina. 2007. Analyst disagreement, mispricing, and liquidity. *Journal of Finance* 62 (5):2367-403.

Schaller, H. 1993. Asymmetric information, liquidity constraints, and Canadian investment. *Canadian Journal of Economics* 26 (3):552.

Scharfstein, D. S., and J. C. Stein. 1990. Herd behavior and investment. *American Economic Review* 80 (3):465.

Schleifer, A., and R. W. Vishny. 1986. Large shareholders and corporate control. *Journal of Political Economy* 94 (3):461-88.

Shleifer, A., and R. W. Vishny. 1997. A survey of corporate governance. *Journal of Finance* 52 (2):737-83.

Stein, J. C. 1988. Takeover threats and managerial myopia. *Journal of Political Economy* 96 (1):61.

———. 2003. Agency, information and corporate investment. In *Handbook of the economics of finance*, edited by G. Constantinides, M. Harris and R. Stulz: Elsevier, 111-65.

Stiglitz, J. E., and A. Weiss. 1981. Credit rationing in markets with imperfect information. *American Economic Review* 71 (3):393.

Stoll, H. R. 2000. Friction. *Journal of Finance* 55 (4):1478-514.

Stulz, R. M. 1990. Managerial discretion and optimal financing policies. *Journal of Financial Economics* 26 (1):3-27.

Subrahmanyam, A., and S. Titman. 1999. The going-public decision and the development of financial markets. *Journal of Finance* 54 (3):1045-82.

———. 2001. Feedback from stock prices to cash flows. *Journal of Finance* 56 (6):2389-413.

Titman, S., K. C. J. Wei, and X. Feixue. 2004. Capital investments and stock returns. *Journal of Financial & Quantitative Analysis* 39 (4):677-700.

Tobin, J. 1969. A general equilibrium approach to monetary theory. *Journal of Money, Credit & Banking* 1 (1):15-29.

———. 1987. On the efficiency of the financial system. In *Policies for Prosperity: Essays in a Keynesian Mode*, edited by P. M. Jackson. Brighton, Sussex: Wheatsheaf Books, 282-96.

Tong, L., and H. Sapra. 2009. Auditor conservatism and investment efficiency. *Accounting Review* 84 (6):1933-58.

Velury, U., and D. S. Jenkins. 2006. Institutional ownership and the quality of earnings. *Journal of Business Research* 59 (9):1043-51.

Verdi, R. S. 2006. *Financial reporting quality and investment efficiency*. Working paper, Massachusetts Institute of Technology. Available at https://ssrn.com/abstract=930922.

Wang, J. 1993. A model of intertemporal asset prices under asymmetric information. *Review of Economic Studies* 60 (2):249-382.

Welker, M. 1995. Disclosure policy, information asymmetry, and liquidity in equity markets. *Contemporary Accounting Research* 11 (2):801-27.

Whited, T. M. 1992. Debt, liquidity constraints and corporate investment: Evidence from panel data. *Journal of Finance* 47 (4):1425-60.

Williamson, O. 1985. *The Economic Institutions of Capitalism: Firms, Markets, Relational Contracting*. New York: Free Press.

Wurgler, J. 2000. Financial markets and the allocation of capital. *Journal of Financial Economics* 58 (1/2):187-214.

Yan, X., and Z. Zhang. 2009. Institutional investors and equity returns: Are short-term institutions better informed? *Review of Financial Studies* 22 (2):893-924.

Zhang, X. F. 2006. Information uncertainty and stock returns. *Journal of Finance* 61 (1):105-36.

# Appendix A: Notations and Definitions of Variable

| Variables | Definition | Source |
|---|---|---|
| **Dependent variable** | | |
| *INV* | The sum of research and development (R & D), capital expenditure, and acquisition expenditure less cash receipts from sale of property, plant, and equipment multiplied by 100 and scaled by lagged total assets. | *Compustat* |
| **Independent variables** | | |
| ***i. Stock liquidity:*** | | |
| *LIQFHT* | The cost of trading as a percentage of stock price, measured as a function of return volatility and proportion of zero returns (Fong et al. 2014). This measure is multiplied by negative 100. The higher (lower) values of this measure indicate higher (lower) stock liquidity. | *CRSP* |
| *LIQZERO* | The number of zero-return trading days over the firm's fiscal year divided by the total trading days of the fiscal year; multiplied by -1. The higher (lower) values of this measure indicate higher (lower) stock liquidity. | *CRSP* |
| *LIQTURN* | The natural logarithm of one plus the ratio of total shares traded annually divided by share outstanding. The higher (lower) values of this measure indicate higher (lower) stock liquidity. | *CRSP* |
| *LIQindex* | Composite score of stock liquidity, a continuous variable computed as the standardized average of *LIQFHT, LIQZERO*, and *LIQTURN*. The higher (lower) values of this measure indicate higher (lower) stock liquidity. | |
| ***ii. Proxy for over- and under-investment:*** | | |
| *OverFirm* | A decile ranked variable used to distinguish between settings where over- or under-investment is more likely; *OverFirm* is increasing in the likelihood of over-investment (it is the average of ranked values of two partitions variables, i.e., *cash balance* and *leverage (multiplied by minus one)* which are used as ex-ante firm-specific characteristics that are likely to affect the likelihood that a firm will over- or under-invest). | *Compustat* |
| ***iii. Control variables:*** | | |
| *AQ* | Standard deviation of the firm-level residuals from Francis, LaFond, Olsson, and Schipper (2005) model (which is adapted from Dechow and Dichev (2002)) during the years *t-5* to *t-1* and multiplied by negative one. The model is a regression model of total current accruals on lagged, current, and future cash flows, plus the change in revenues, PPE for firm *i* at year *t*. All variables are scaled by average total assets. The model is estimated cross-sectionally for each industry with at least 20 observations in a given year based on the Fama & French (1997) 48-industry classification. | *Compustat* |
| *IO* | The percentage of firm shares held by institutional investors. | *Thomson Reuters 13F* |
| *Analyst* | The number of analysts following the firm. | *IBES* |
| *G_Score* | The measure of investor protection rights created by Gompers et al. (2003), multiplied by minus one.<br>http://faculty.som.yale.edu/andrewmetrick/data.html | Andrew Metrick's website |
| *G_Dummy* | An indicator variable that takes the value of one if *G_Score* is missing, and zero otherwise. | |

| | | |
|---|---|---|
| *LogAsset* | The log of total assets. | *Compustat* |
| *MB* | The ratio of the market value to the book value of total assets. | *Compustat* |
| *σ(CFO)* | Standard deviation of the cash flow from operations deflated by average total assets from year *t-5* to *t-1*. | *Compustat* |
| *σ(Sales)* | Standard deviation of the sales deflated by average total assets from year *t-5* to *t-1*. | *Compustat* |
| *σ(INV)* | Standard deviation of investment deflated by average total assets from year *t-5* to *t-1*. | *Compustat* |
| *Z_Score* | A measure of distress computed following the methodology in Altman (1968). | *Compustat* |
| *Tangibility* | Tangibility is the ratio of PPE to total assets. | *Compustat* |
| *Kstruct* | K-structure is a measure of market leverage computed as the ratio of long-term debt to the sum of long-term debt to the market value of equity. | *Compustat* |
| *Ind_Kstruct* | The mean K-structure for firms in the same SIC 3-digit industry. | *Compustat* |
| *CFOsale* | The ratio of CFO to sales. | *Compustat* |
| *DIV* | Dividend is an indicator variable that takes the value of one if the firm paid a dividend, and zero otherwise. | *Compustat* |
| *Firm_Age* | The difference between the first year when the firm appears in CRSP and the current year. | *CRSP* |
| *OCycle* | Operating cycle is the log of receivables to sales plus inventory to COGS multiplied by 360. | *Compustat* |
| *Loss* | An indicator variable that takes the value of one if net income before extraordinary item is negative, and zero otherwise. | *Compustat* |
| *Slack* | The ratio of cash to PPE. | *Compustat* |
| *IND* | Industry fixed effects based on the Fame-French (1997) 48 industry classifications. | Kenneth French's website |

***iv. Alternative stock liquidity proxies***

| | | |
|---|---|---|
| *LIQAM* | -1 x (the natural logarithm of one plus firm *i*'s Amihud (2002) illiquidity ratio), where the Amihud illiquidity ratio is calculated as the daily ratio of absolute value of stock returns to dollar volume, averaged over firm *i*'s fiscal year *t*. Stock included in the computation meets 3 criteria: (1) it has at least 200 days of return and volume data, (2) stock price > $5 at the end of fiscal year, and (3) it is required to be listed at the end of its fiscal year. | *CRSP* |
| *LIQBAS* | The closing percent quoted spread (*LIQBAS*) developed by Chung and Zhang (2014), measured as the yearly average of daily closing bid-ask spread scaled by the mean of daily closing bid and closing ask prices. This measure is multiplied by negative 100 and is excluded from analyses if: (1) daily negative bid-ask spreads (crossed quotes) for which the ask price is smaller than the bid price (Balakrishnan et al. 2014); or (2) daily bid-ask spread that is greater than 50% of the quote midpoint for which the bid-ask spread is unreasonably larger than the mean of ask and bid price (Chung and Zhang 2014). The higher (lower) values of this measure indicate higher (lower) stock liquidity. | *CRSP* |
| *LIQHL* | The price-based spread proxy developed by Corwin and Schultz (2012), multiplied by negative one. The higher (lower) values of this measure indicate higher (lower) stock liquidity. The data can be downloaded from | Professor Shane A. Corwin's |

| | | |
|---|---|---|
| | *http://www3.nd.edu/~scorwin/.* | website |
| *LIQROLL* | The bid-ask spread estimated by the serial covariance in price changes, a measure derived by Roll (1984). This measure is multiplied by negative 100. The higher (lower) values of this measure indicate higher (lower) stock liquidity. | *CRSP* |
| *LIQindex6* | A composite stock liquidity index (*LIQindex6*) by standardising the three additional measures of liquidity (*LIQBAS, LIQHL, LIQROLL*) and the three liquidity measures from the main analyses (*LIQFHT, LIQZERO, LIQTURN*) and then calculating the unweighted mean of these six standardised measures. | |
| ***v. Alternative investment proxies*** | | |
| *Capex* | Capital expenditure, computed as the capital expenditure in year *t*+1 scaled by lagged total assets. | *Compustat* |
| *Non-Capex* | Non capital expenditure, calculated as the sum of R&D expenditures and acquisitions in year *t*+1 scaled by lagged total assets. | *Compustat* |
| ***vi. Variables used in additional tests*** | | |
| *Firm_Age* | The difference between the first year when the firm appears in CRSP and the current year. | *CRSP* |
| *IncVol* | Operating income volatility (*IncVol*), measured as the standard deviation of quarterly operating income before depreciation divided by quarterly book value of assets. *IncVol* is measured over 20 quarters prior to the end of fiscal year *t* with a minimum of eight quarterly observations. | *Compustat* |
| *MonIO* | The proportion of monitoring institutional ownership (IO), measured as the percentage of monitoring IO scaled by the total of monitoring IO and non-monitoring IO in a firm. Following Ramalingegowde and Yu (2012), monitoring institutions are defined as dedicated institutions with long investment horizons and concentrated holdings (as defined by Bushee (2001)) and those that are independent from corporate management (as defined by Brickley et al. (1998)).<br>Professor Brian Bushee's institutional investor classification data are obtained from http://acct.wharton.upenn.edu/faculty/bushee/IIclass.html. | *Thomson Reuters 13F* |

# Table of Results

**TABLE 1**
**Sample Selection and Distribution**

**Panel A: Sample Selection**

| | Observations |
|---|---|
| Compustat data for years between 1989 and 2012 | 247,541 |
| Less: firms not traded on NYSE, AMEX, or Nasdaq | (99,858) |
| | 147,683 |
| Less: firms operating in Financial industries (SIC 6000-6999) | (42,331) |
| | 105,352 |
| Less: firm-year data before 1995 after constructing variables of interest | (33,279) |
| | 72,073 |
| Less: missing data after merging with data from CRSP, IBES, and Thomson Reuters 13F | (29,618) |
| Final firm-year data for years between 1995 and 2012 | 42,455 |

**Panel B: Industry Membership of Sample Firms**

| Fama and French Industry Name | Number of Firms | % of Sample |
|---|---|---|
| Business Services | 5,571 | 13.12 |
| Electronic Equipment | 3,361 | 7.92 |
| Pharmaceutical Products | 2,849 | 6.71 |
| Retail | 2,719 | 6.40 |
| Petroleum & Natural Gas | 1,977 | 4.66 |
| Computers | 1,953 | 4.60 |
| Medical Equipment | 1,942 | 4.57 |
| Machinery | 1,879 | 4.43 |
| Utilities | 1,858 | 4.38 |
| Wholesale | 1,656 | 3.90 |
| Measuring & Control Equipment | 1,376 | 3.24 |
| Communication | 1,346 | 3.17 |
| Chemicals | 1,142 | 2.69 |
| Transportation | 1,128 | 2.66 |
| 14 Industries | 30,757 | 72.45 |
| 26 Other Industries | 11,698 | 27.55 |
| Total Sample | 42,455 | 100.00 |

**Panel C: Year Distribution of Sample Firms**

| Year | Number of Firms | % of Sample |
|---|---|---|
| 1995 | 2,308 | 5.44 |
| 1996 | 2,400 | 5.65 |
| 1997 | 2,378 | 5.60 |
| 1998 | 2,355 | 5.55 |
| 1999 | 2,471 | 5.82 |
| 2000 | 2,509 | 5.91 |
| 2001 | 2,528 | 5.95 |
| 2002 | 2,672 | 6.29 |
| 2003 | 2,611 | 6.15 |
| 2004 | 2,554 | 6.02 |
| 2005 | 2,454 | 5.78 |
| 2006 | 2,370 | 5.58 |
| 2007 | 2,361 | 5.56 |
| 2008 | 2,358 | 5.55 |
| 2009 | 2,335 | 5.50 |
| 2010 | 2,289 | 5.39 |
| 2011 | 2,252 | 5.30 |
| 2012 | 1,250 | 2.94 |
| Total Sample | 42,455 | 100.00 |

This table presents sample selection procedure (Panel A), industry distribution of sample firms (Panel B) and year distribution of sample firms (Panel C).

**TABLE 2**
**Descriptive Statistics**

| | n | Mean | Std. Dev. | Min. | Median | Max. |
|---|---|---|---|---|---|---|
| *INV* | 42,455 | 14.813 | 16.307 | -0.293 | 9.717 | 96.971 |
| *LIQFHT* | 42,455 | -0.717 | 1.064 | -5.793 | -0.281 | 0.000 |
| *LIQZERO* | 42,455 | -0.072 | 0.084 | -0.370 | -0.036 | 0.000 |
| *LIQTURN* | 42,455 | 0.815 | 0.487 | 0.073 | 0.743 | 2.203 |
| *LIQindex* | 42,455 | 0.000 | 0.833 | -3.274 | 0.193 | 1.460 |
| *OverFirm* | 42,455 | 0.510 | 0.224 | 0.000 | 0.500 | 1.000 |
| *Total Assets* | 42,455 | 2,993.846 | 11516.130 | 0.805 | 368.506 | 333795.000 |
| *logAsset* | 42,455 | 5.995 | 1.991 | -0.217 | 5.909 | 12.718 |
| *MB* | 42,455 | 1.972 | 1.472 | 0.604 | 1.478 | 9.217 |
| *σ(Sales)* | 42,455 | 0.285 | 0.274 | 0.013 | 0.200 | 1.536 |
| *σ(CFO)* | 42,455 | 0.073 | 0.064 | 0.008 | 0.054 | 0.370 |
| *σ(INV)* | 42,455 | 14.057 | 23.019 | 0.396 | 6.421 | 154.992 |
| *Z_Score* | 42,455 | 1.271 | 1.338 | -4.190 | 1.345 | 4.677 |
| *Tangibility* | 42,455 | 0.278 | 0.231 | 0.010 | 0.204 | 0.890 |
| *kstruc* | 42,455 | 0.171 | 0.203 | 0.000 | 0.095 | 0.828 |
| *Ind_Kstruct* | 42,455 | 0.167 | 0.118 | 0.028 | 0.134 | 0.504 |
| *CFOsale* | 42,455 | -0.035 | 0.808 | -6.545 | 0.083 | 0.612 |
| *Slack* | 42,455 | 3.126 | 8.003 | 0.001 | 0.442 | 56.667 |
| *DIV* | 42,455 | 0.389 | 0.488 | 0.000 | 0.000 | 1.000 |
| *Firm_Age* | 42,455 | 19.403 | 16.660 | 1.000 | 14.000 | 88.000 |
| *OCycle* | 42,455 | 4.611 | 0.749 | 2.093 | 4.688 | 6.292 |
| *Loss* | 42,455 | 0.274 | 0.446 | 0.000 | 0.000 | 1.000 |
| *AQ* | 42,455 | -0.056 | 0.052 | -0.480 | -0.041 | -0.003 |
| *IO* | 42,455 | 0.523 | 0.291 | 0.005 | 0.552 | 1.000 |
| *Analyst* | 42,455 | 6.366 | 7.003 | 0.000 | 4.000 | 53.000 |
| *G_Score* | 42,455 | -1.104 | 3.118 | -18.000 | 0.000 | 0.000 |
| *G_Dummy* | 42,455 | 0.879 | 0.326 | 0.000 | 1.000 | 1.000 |

This table presents descriptive statistics for the variables used in the analyses. Investment is a measure of total investment scaled by lagged total assets. The main test variables include *LIQFHT, LIQZERO, LIQTURN,* and *LIQindex*. *LIQFHT* formulated by Fong et al. (2014) implies the cost of trading as a percentage of stock price. *LIQZERO* captures the effects of transaction costs from measuring the proportion of annual zero-return trading days (Lesmond et al. 1999). Both *LIQFHT* and *LIQZERO* are multiplied by -1 so that higher values indicate greater stock liquidity. *LIQTURN* is defined as the natural logarithm of the ratio of total shares traded annually divided by total number of shares outstanding per fiscal year. *LIQindex* is a continuous variable computed as the standardized average of *LIQFHT, LIQZERO*, and *LIQTURN*. *OverFirm* is a ranked variable based on the average of a ranked (deciles) measure of cash and leverage, multiplied by -1. *LogAsset* is the log of total assets. *MB* is the ratio of the market value to the book value of total assets. *σ(Sales), σ(CFO) and σ(INV)* is the standard deviation of sales, CFO and investment respectively. *Z_Score* is a measure of distress computed following the methodology in Altman(1968). *Tangibility* is the ratio of PPE to total assets. *Kstruc* is a measure of market leverage computed as the ratio of long-term debt to the sum of long-term debt to the market value of equity. *Ind_ Kstruc* is the mean K-structure for firms in the same SIC 3-digit industry. *CFOsale* is the ratio of CFO to sales. *Slack* is the ratio of cash to PPE. *DIV* is an indicator variable that takes the value of one if the firm paid a dividend, and zero otherwise. *Firm_Age* is the difference between the first year when the firm appears in CRSP and the current year. *OCycle* is a measure of the log of operating cycle of the firm. *Loss* is an indicator variable that takes the value of one if net income before extraordinary item is negative, and zero otherwise. *AQ* (accruals quality) is the standard deviation of the firm-level residuals based on Francis et al. (2005) during the years *t-5* to *t-1* and multiplied by negative one. *IO* is the percentage of firm shares held by institutional investors. *Analyst* is the number of analysts following the firm. *G_Score* is the measure of investor protection rights created by Gompers et al. (2003), multiplied by minus one. *G_Dummy* is an indicator variable that takes the value of one if *G_Score* is missing, and zero otherwise.

**TABLE 3**

**Pearson Correlation Matrix**

| | *INV* | *LIQFHT* | *LIQZERO* | *LIQTURN* | *LIQindex* | *OverFirm* | *logAsset* | *MB* | *σ(Sales)* | *σ(CFO)* | *σ(INV)* | *Z_Score* | *Tangibility* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *LIQFHT* | **-0.022** | | | | | | | | | | | | |
| *LIQZERO* | 0.007 | **0.834** | | | | | | | | | | | |
| *LIQTURN* | **0.118** | **0.317** | **0.473** | | | | | | | | | | |
| *LIQindex* | **0.041** | **0.861** | **0.923** | **0.716** | | | | | | | | | |
| *OverFirm* | **0.113** | **0.281** | **0.278** | **0.322** | **0.352** | | | | | | | | |
| *logAsset* | **-0.184** | **0.538** | **0.467** | **0.274** | **0.512** | **0.237** | | | | | | | |
| *MB* | **0.357** | **0.095** | **0.149** | **0.217** | **0.185** | **0.277** | **-0.153** | | | | | | |
| *σ(Sales)* | **-0.012** | **-0.113** | **-0.067** | **0.108** | **-0.029** | **0.012** | **-0.158** | **0.077** | | | | | |
| *σ(CFO)* | **0.277** | **-0.176** | **-0.052** | **0.135** | **-0.037** | **0.088** | **-0.422** | **0.372** | **0.282** | | | | |
| *σ(INV)* | **0.172** | **-0.079** | 0.005 | **0.102** | **0.011** | **-0.067** | **-0.124** | **0.108** | **0.129** | **0.260** | | | |
| *Z_Score* | **-0.254** | **0.097** | **-0.016** | **-0.074** | 0.003 | **0.076** | **0.129** | **-0.115** | **0.346** | **-0.240** | **-0.304** | | |
| *Tangibility* | **-0.025** | 0.005 | **-0.091** | **-0.128** | **-0.086** | **-0.319** | **0.239** | **-0.215** | **-0.169** | **-0.252** | **-0.051** | **-0.016** | |
| *Kstruc* | **-0.227** | **-0.082** | **-0.117** | **-0.094** | **-0.117** | **-0.563** | **0.311** | **-0.394** | **-0.100** | **-0.285** | **0.045** | **-0.082** | **0.388** |
| *Ind_Kstruct* | **-0.222** | **0.016** | **-0.066** | **-0.169** | **-0.088** | **-0.351** | **0.319** | **-0.338** | **-0.099** | **-0.298** | **-0.080** | **0.031** | **0.545** |
| *CFOsale* | **-0.236** | **0.087** | **0.021** | **-0.033** | **0.030** | **-0.012** | **0.227** | **-0.223** | **0.072** | **-0.297** | **-0.185** | **0.452** | **0.156** |
| *Slack* | **0.148** | **0.018** | **0.073** | **0.124** | **0.086** | **0.265** | **-0.221** | **0.229** | **-0.100** | **0.333** | **0.119** | **-0.241** | **-0.370** |
| *DIV* | **-0.160** | **0.189** | **0.055** | **-0.170** | **0.030** | 0.001 | **0.390** | **-0.112** | **-0.166** | **-0.299** | **-0.183** | **0.192** | **0.247** |
| *Firm_Age* | **-0.159** | **0.195** | **0.120** | **-0.103** | **0.085** | **0.045** | **0.420** | **-0.146** | **-0.211** | **-0.277** | **-0.225** | **0.120** | **0.165** |
| *OCycle* | -0.005 | **-0.052** | **-0.042** | -0.009 | **-0.041** | **0.047** | **-0.105** | **0.047** | **-0.105** | **0.026** | **-0.066** | **-0.071** | **-0.341** |
| *Loss* | **0.092** | **-0.217** | **-0.078** | **0.039** | **-0.103** | **-0.076** | **-0.264** | **0.035** | **-0.017** | **0.247** | **0.217** | **-0.547** | **-0.119** |
| *AQ* | **-0.120** | **0.210** | **0.096** | **-0.025** | **0.113** | **0.026** | **0.374** | **-0.172** | **-0.257** | **-0.494** | **-0.172** | **0.135** | **0.276** |
| *IO* | **-0.050** | **0.579** | **0.569** | **0.501** | **0.660** | **0.297** | **0.623** | 0.007 | **-0.102** | **-0.247** | **-0.098** | **0.138** | **-0.017** |
| *Analyst* | **0.018** | **0.380** | **0.360** | **0.385** | **0.450** | **0.359** | **0.702** | **0.156** | **-0.044** | **-0.157** | **-0.053** | **0.062** | **0.123** |
| *G_Score* | **0.033** | **-0.142** | **-0.122** | **-0.026** | **-0.116** | **-0.100** | **-0.251** | -0.002 | **0.047** | **0.105** | **0.058** | **-0.057** | **-0.055** |
| *G_Dummy* | **0.032** | **-0.144** | **-0.126** | **-0.042** | **-0.125** | **-0.115** | **-0.248** | **-0.011** | **0.039** | **0.098** | **0.054** | **-0.056** | **-0.049** |

(This table is continued on the next page)

**TABLE 3 (Continued)**

**Pearson Correlation Matrix**

| | *Kstruc* | *Ind_Kstruct* | *CFOsale* | *Slack* | *DIV* | *Firm_Age* | *OCycle* | *Loss* | *AQ* | *IO* | *Analyst* | *G_Score* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *LIQFHT* | | | | | | | | | | | | |
| *LIQZERO* | | | | | | | | | | | | |
| *LIQTURN* | | | | | | | | | | | | |
| *LIQindex* | | | | | | | | | | | | |
| *OverFirm* | | | | | | | | | | | | |
| *logAsset* | | | | | | | | | | | | |
| *MB* | | | | | | | | | | | | |
| σ*(Sales)* | | | | | | | | | | | | |
| σ*(CFO)* | | | | | | | | | | | | |
| σ*(INV)* | | | | | | | | | | | | |
| *Z_Score* | | | | | | | | | | | | |
| *Tangibility* | | | | | | | | | | | | |
| *Kstruc* | | | | | | | | | | | | |
| *Ind_Kstruct* | **0.590** | | | | | | | | | | | |
| *CFOsale* | **0.095** | **0.144** | | | | | | | | | | |
| *Slack* | **-0.251** | **-0.275** | **-0.297** | | | | | | | | | |
| *DIV* | **0.122** | **0.277** | **0.139** | **-0.198** | | | | | | | | |
| *Firm_Age* | **0.116** | **0.208** | **0.110** | **-0.159** | **0.462** | | | | | | | |
| *OCycle* | **-0.174** | **-0.272** | **-0.048** | **0.010** | **-0.039** | **0.046** | | | | | | |
| *Loss* | **0.061** | **-0.105** | **-0.320** | **0.178** | **-0.276** | **-0.200** | 0.008 | | | | | |
| *AQ* | **0.170** | **0.227** | **0.171** | **-0.200** | **0.233** | **0.193** | **-0.057** | **-0.207** | | | | |
| *IO* | **0.039** | **0.032** | **0.158** | **-0.063** | **0.123** | **0.131** | **-0.045** | **-0.203** | **0.262** | | | |
| *Analyst* | **-0.018** | **0.030** | **0.127** | **-0.075** | **0.187** | **0.216** | **-0.062** | **-0.191** | **0.238** | **0.487** | | |
| *G_Score* | **-0.026** | **-0.060** | **-0.056** | **0.071** | **-0.151** | **-0.162** | -0.008 | **0.098** | **-0.097** | **-0.173** | **-0.202** | |
| *G_Dummy* | **-0.017** | **-0.049** | **-0.057** | **0.067** | **-0.129** | **-0.131** | -0.008 | **0.094** | **-0.096** | **-0.177** | **-0.211** | **0.955** |

This table presents the Pearson correlation matrix for variables used in the main tests of H1a and H1b. Correlations significant at the 5 percent level or lower (two-tailed) are bolded. See Appendix A for variable definitions.

**TABLE 4**
**Conditional Relation between Investment and Stock Liquidity (2-way clustering): Main Tests**

| Variable | Pred. Sign | *LIQFHT(1)* | *LIQZERO(2)* | *LIQTURN(3)* | *LIQindex(4)* |
|---|---|---|---|---|---|
| *LIQ (1)* ***$H_{1a}$: under-invest*** | + | 1.201*** | 4.396 | 1.476** | 1.012** |
| | | (5.273) | (0.978) | (1.705) | (2.171) |
| *LIQ* x *OverFirm (2)* | - | -3.230*** | -25.303*** | -2.261** | -2.910*** |
| | | (-6.486) | (-3.197) | (-1.904) | (-4.123) |
| *(1)+(2)* ***$H_{1b}$: over-invest*** | - | -2.030*** | -20.910*** | -0.785* | -1.898*** |
| | | (-5.531) | (-4.778) | (-1.313) | (-4.995) |
| *IO* | + | 3.523*** | 4.115*** | 3.114*** | 3.781*** |
| | | (4.600) | (5.606) | (4.334) | (5.536) |
| *Analyst* | + | 0.130*** | 0.118*** | 0.123*** | 0.134*** |
| | | (5.701) | (5.192) | (5.292) | (6.121) |
| *G_Score* | + | -0.294*** | -0.294*** | -0.306*** | -0.292*** |
| | | (-5.166) | (-5.067) | (-5.369) | (-5.080) |
| *G_Dummy* | ? | 2.649*** | 2.671*** | 2.761*** | 2.675*** |
| | | (4.016) | (4.154) | (3.904) | (4.010) |
| *OverFirm* | + | 1.766** | 1.828*** | 5.469*** | 3.777*** |
| | | (2.324) | (2.361) | (4.645) | (4.703) |
| *logAsset* | - | -1.399*** | -1.309*** | -1.466*** | -1.411*** |
| | | (-9.264) | (-8.908) | (-10.107) | (-9.147) |
| *MB* | + | 2.426*** | 2.462*** | 2.385*** | 2.431*** |
| | | (16.075) | (16.134) | (16.766) | (15.966) |
| *σ(Sales)* | - | 0.744 | 0.758 | 0.713 | 0.836* |
| | | (1.196) | (1.229) | (1.127) | (1.326) |
| *σ(CFO)* | + | 13.973*** | 14.789*** | 13.976*** | 14.549*** |
| | | (5.135) | (5.678) | (4.871) | (5.374) |
| *σ(INV)* | + | 0.032*** | 0.032*** | 0.031*** | 0.032*** |
| | | (3.765) | (3.787) | (3.625) | (3.770) |
| *Z_Score* | - | -2.007*** | -2.054*** | -2.022*** | -2.035*** |
| | | (-9.954) | (-10.344) | (-9.837) | (-10.100) |
| *Tangibility* | + | 9.840*** | 9.626*** | 9.910*** | 9.832*** |
| | | (10.048) | (10.108) | (10.040) | (10.205) |
| *Ind_Kstruct* | - | -11.027*** | -11.475*** | -10.979*** | -11.135*** |
| | | (-5.613) | (-6.191) | (-5.551) | (-5.631) |
| *CFOsale* | - | -1.373*** | -1.396*** | -1.393*** | -1.382*** |
| | | (-5.273) | (-5.355) | (-5.296) | (-5.320) |
| *DIV* | - | -0.905*** | -0.957*** | -0.854*** | -0.985*** |
| | | (-3.271) | (-3.386) | (-2.981) | (-3.486) |
| *Firm_Age* | - | -0.026*** | -0.026*** | -0.027*** | -0.028*** |
| | | (-3.454) | (-3.477) | (-3.605) | (-3.650) |
| *OCycle* | - | -1.628*** | -1.667*** | -1.615*** | -1.632*** |
| | | (-6.637) | (-6.946) | (-6.547) | (-6.730) |
| *Loss* | - | -3.741*** | -3.765*** | -3.798*** | -3.758*** |
| | | (-14.376) | (-14.973) | (-15.265) | (-14.705) |
| *AQ* | + | 5.428 | 9.651* | 11.558** | 9.376* |
| | | (0.887) | (1.609) | (1.928) | (1.539) |
| *AQ* x *OverFirm* | - | -1.852 | -10.466 | -13.464* | -9.643 |
| | | (-0.191) | (-1.054) | (-1.367) | (-0.969) |
| Constant | | 25.303*** | 24.353*** | 23.920*** | 24.457*** |
| | | (11.147) | (10.665) | (10.717) | (10.744) |
| Industry FE | | Yes | Yes | Yes | Yes |
| Firm & Year clusters | | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ (%) | | 26.45 | 26.39 | 26.29 | 26.37 |
| $R^2_{old}$ (%) | | 26.37 | 26.37 | 26.37 | 26.37 |
| $R^2_{new}$ (%) | | 26.55 | 26.50 | 26.39 | 26.47 |
| Gujarati (2003) Δ $R^2$ *F*-statistic | | 52.019*** | 37.543*** | 5.767*** | 28.868*** |
| Sample size | | 42,455 | 42,455 | 42,455 | 42,455 |

This table presents the results of regression estimates for models that examine the relation between stock liquidity and investment levels. *LIQFHT* formulated by Fong et al. (2014) implies the cost of trading as a percentage of stock price. *LIQZERO* captures the effects of transaction costs from measuring the proportion of annual zero-return trading days (Lesmond et al. 1999). Both *LIQFHT* and *LIQZERO* are multiplied by -1 so that higher values indicate greater stock liquidity. *LIQTURN* is defined as the natural logarithm of the ratio of total shares traded annually divided by total number of shares outstanding per fiscal year. *LIQindex* is a continuous variable computed as the standardized average of *LIQFHT, LIQZERO*, and *LIQTURN.* The first row reports the coefficient estimate and the second row reports the two-way clustered *t*-statistic based on standard error clustered by firm and year (in parentheses). Industry fixed effect based on Fama and French's classification scheme is included in all regressions but the coefficients are not reported. The Gujarati (2003) $\Delta$ $R^2$ *F*-statistics test the null hypothesis that the inclusion of *LIQ* and *LIQ* x *OverFirm* as explanatory variables do not affect the explanatory power of the regression analyses. The *F*-statistic is given by:

$$\frac{(R^2_{new}-R^2_{old})/n}{(1-R^2_{new})/df},$$

where $R^2_{new}$ ($R^2_{old}$) is the $R^2$ value of the regression model with the inclusion (exclusion) of *LIQ* and *LIQ* x *OverFirm*, *n* equals the number of new regressors being considered (two [i.e., *LIQ* and *LIQ* x *OverFirm*]), and *df* is the number of observations minus the number of parameters in the regression model that includes *LIQ* and *LIQ* x *OverFirm* (Gujarati 2003, 260–264). ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively, based on one-tailed tests if the coefficient has a predicted sign, and two-tailed tests otherwise. See Appendix A for other variable definitions.

**TABLE 5**
**Conditional Relation between Investment and Stock Liquidity: Explicitly Controlling for Price Informativeness (*PIN*)**

| Variable | Pred. Sign | *LIQFHT(1)* | *LIQZERO(2)* | *LIQTURN(3)* | *LIQindex(4)* |
|---|---|---|---|---|---|
| *LIQ (1)* ***$H_{1a}$: under-invest*** | + | 1.266*** | 3.754 | 1.278* | 0.933** |
| | | (6.207) | (0.928) | (1.507) | (2.226) |
| *LIQ x OverFirm (2)* | - | -3.541*** | -28.496*** | -2.436** | -3.355*** |
| | | (-7.408) | (-3.675) | (-2.065) | (-4.801) |
| *(1)+(2)* ***$H_{1b}$: over-invest*** | - | -2.275*** | -24.74*** | -1.158** | -2.422*** |
| | | (-5.955) | (-5.371) | (-1.731) | (-5.725) |
| *IO* | + | 3.133*** | 3.674*** | 2.895*** | 3.550*** |
| | | (4.280) | (5.050) | (4.200) | (5.169) |
| *Analyst* | + | 0.126*** | 0.110*** | 0.122*** | 0.130*** |
| | | (5.174) | (4.528) | (5.039) | (5.591) |
| *G_Score* | ? | -0.294*** | -0.295*** | -0.305*** | -0.290*** |
| | | (-3.876) | (-3.884) | (-4.010) | (-3.815) |
| *G_Dummy* | ? | 2.750*** | 2.767*** | 2.884*** | 2.767*** |
| | | (3.796) | (3.819) | (3.859) | (3.818) |
| *OverFirm* | + | 1.172* | 1.118 | 5.330*** | 3.489*** |
| | | (1.417) | (1.265) | (4.430) | (4.149) |
| *logAsset* | - | -1.605*** | -1.544*** | -1.678*** | -1.638*** |
| | | (-9.053) | (-9.170) | (-9.857) | (-9.534) |
| *MB* | + | 2.312*** | 2.330*** | 2.271*** | 2.312*** |
| | | (14.529) | (14.821) | (14.741) | (14.759) |
| *σ(Sales)* | - | 0.538 | 0.511 | 0.585 | 0.633 |
| | | (0.839) | (0.813) | (0.898) | (0.983) |
| *σ(CFO)* | + | 13.778*** | 14.648*** | 14.070*** | 14.533*** |
| | | (4.736) | (5.283) | (4.635) | (5.054) |
| *σ(INV)* | + | 0.031*** | 0.031*** | 0.030*** | 0.031*** |
| | | (3.473) | (3.486) | (3.361) | (3.493) |
| *Z_Score* | - | -1.896*** | -1.943*** | -1.926*** | -1.927*** |
| | | (-8.585) | (-8.887) | (-8.744) | (-8.786) |
| *Tangibility* | + | 10.130*** | 9.854*** | 10.203*** | 10.062*** |
| | | (9.856) | (9.877) | (9.907) | (9.990) |
| *Ind_Kstruct* | - | -11.287*** | -11.695*** | -11.275*** | -11.423*** |
| | | (-5.971) | (-6.772) | (-6.041) | (-6.213) |
| *CFOsale* | - | -1.454*** | -1.474*** | -1.477*** | -1.463*** |
| | | (-5.143) | (-5.218) | (-5.167) | (-5.201) |
| *DIV* | - | -0.768*** | -0.838*** | -0.748*** | -0.887*** |
| | | (-2.599) | (-2.770) | (-2.524) | (-2.954) |
| *Firm_Age* | - | -0.027*** | -0.028*** | -0.030*** | -0.030*** |
| | | (-3.417) | (-3.481) | (-3.646) | (-3.711) |
| *OCycle* | - | -1.656*** | -1.707*** | -1.634*** | -1.670*** |
| | | (-6.553) | (-6.869) | (-6.454) | (-6.676) |
| *Loss* | - | -3.867*** | -3.884*** | -3.917*** | -3.883*** |
| | | (-14.416) | (-14.989) | (-15.294) | (-14.744) |
| *AQ* | + | 6.242 | 11.037** | 13.169** | 10.933** |
| | | (1.015) | (1.808) | (2.153) | (1.790) |
| *AQ x OverFirm* | - | -0.711 | -10.532 | -14.088* | -10.032 |
| | | (-0.069) | (-1.026) | (-1.362) | (-0.973) |
| *PIN* | ? | 6.471*** | 8.523*** | 6.118*** | 8.036*** |
| | | (4.074) | (5.560) | (3.238) | (5.240) |
| *Constant* | | 27.608*** | 27.338*** | 26.047*** | 27.139*** |
| | | (11.556) | (11.685) | (10.935) | (11.788) |
| Industry FE | | Yes | Yes | Yes | Yes |
| Firm & Year clusters | | Yes | Yes | Yes | Yes |
| Adjusted R2 | | 0.261 | 0.261 | 0.259 | 0.260 |
| Sample size | | 37,403 | 37,403 | 37,403 | 37,403 |

This table presents the results of regression estimates for models that examine the relation between stock liquidity and investment levels, explicitly controlling for stock price informativeness (*PIN*). *PIN* is the probability of informed trading based on the extended version of Easley's et al. (1997). *PIN* is multiplied by -1 to measure the extent of stock price informativeness so that higher values indicate greater price informativeness. *LIQFHT* formulated by Fong et al. (2014) implies the cost of trading as a percentage of stock price. *LIQZERO* captures the effects of transaction costs from measuring the proportion of annual zero-return trading days (Lesmond et al. 1999). Both *LIQFHT* and *LIQZERO* are multiplied by -1 so that higher values indicate greater stock liquidity. *LIQTURN* is defined as the natural logarithm of the ratio of total shares traded annually divided by total number of shares outstanding per fiscal year. *LIQindex* is a continuous variable computed as the standardized average of *LIQFHT, LIQZERO*, and *LIQTURN*. The first row reports the coefficient estimate and the second row reports the two-way clustered t-statistic based on standard error clustered by firm and year (in parentheses). Industry fixed effect based on Fama and French's classification scheme is included in all regressions but the coefficients are not reported. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively, based on one-tailed tests if the coefficient has a predicted sign, and two-tailed tests otherwise. See Appendix A for other variable definitions.

**TABLE 6**

**Endogeneity and Reverse Causality: Two-Stage Least Squares Regressions**

**Stage 1: Dependent Variable = *LIQ***

| Variable | Pr. Sign | *LIQFHT (1)* | *LIQZERO (2)* | *LIQTURN (3)* | *LIQindex (4)* |
|---|---|---|---|---|---|
| *LagLIQ* | + | 48.771*** | 0.539*** | 0.693*** | 0.621*** |
| | | (16.799) | (20.224) | (36.413) | (29.908) |
| *TwoLIQ* | + | 0.383*** | 0.349*** | 0.116*** | 0.250*** |
| | | (14.513) | (14.415) | (5.673) | (21.550) |
| *IO* | + | 0.177*** | 0.013*** | 0.207*** | 0.258*** |
| | | (3.653) | (3.952) | (5.856) | (6.558) |
| *Analyst* | + | -0.003*** | -0.000*** | 0.002** | 0.000 |
| | | (-3.881) | (-3.073) | (2.172) | (0.319) |
| *G_Score* | ? | -0.000 | 0.000 | 0.001 | 0.001 |
| | | (-0.106) | (0.551) | (0.933) | (0.436) |
| *G_Dummy* | ? | 0.031 | 0.000 | -0.005 | 0.009 |
| | | (1.245) | (0.057) | (-0.345) | (0.432) |
| *OverFirm* | + | -0.008 | -0.000 | -0.026* | -0.021 |
| | | (-0.218) | (-0.010) | (-1.485) | (-0.781) |
| *logAsset* | - | 0.001 | 0.001 | 0.003 | 0.006* |
| | | (0.183) | (1.115) | (0.896) | (1.330) |
| *MB* | + | 0.024*** | 0.003*** | 0.028*** | 0.040*** |
| | | (3.912) | (5.646) | (10.723) | (10.189) |
| *σ(Sales)* | - | -0.070*** | 0.001 | 0.033*** | 0.007 |
| | | (-3.616) | (0.684) | (3.001) | (0.423) |
| *σ(CFO)* | + | 0.047 | 0.008 | 0.149*** | 0.185*** |
| | | (0.489) | (1.208) | (3.494) | (2.751) |
| *σ(INV)* | + | 0.000** | 0.000** | 0.000** | 0.000*** |
| | | (1.657) | (1.748) | (1.977) | (3.202) |
| *Z_Score* | - | 0.037*** | 0.001** | -0.000 | 0.011*** |
| | | (5.342) | (2.242) | (-0.090) | (2.425) |
| *Tangibility* | + | -0.002 | 0.000 | -0.010 | -0.018 |
| | | (-0.050) | (0.012) | (-0.634) | (-0.757) |
| *Ind_Kstruct* | - | -0.188* | -0.010 | -0.053 | -0.153* |
| | | (-1.416) | (-0.888) | (-0.770) | (-1.386) |
| *CFOsale* | - | -0.013* | -0.001* | -0.008** | -0.011** |
| | | (-1.496) | (-1.378) | (-2.258) | (-2.040) |
| *DIV* | - | -0.000 | -0.002** | -0.041*** | -0.047*** |
| | | (-0.015) | (-2.212) | (-6.958) | (-5.358) |
| *Firm_Age* | - | 0.000** | -0.000 | -0.001*** | -0.000** |
| | | (1.660) | (-0.603) | (-5.694) | (-1.895) |
| *OCycle* | - | 0.004 | 0.001*** | 0.004* | 0.006* |
| | | (0.593) | (3.068) | (1.570) | (1.639) |
| *Loss* | - | -0.126*** | -0.004*** | -0.009 | -0.058*** |
| | | (-5.816) | (-6.528) | (-1.124) | (-7.322) |
| *AQ* | + | 0.687*** | 0.019* | 0.045 | 0.260** |
| | | (2.333) | (1.628) | (0.621) | (1.882) |
| *AQ* x *OverFirm* | - | -1.357*** | -0.047*** | -0.443*** | -0.903*** |
| | | (-2.951) | (-2.484) | (-2.890) | (-4.055) |
| Constant | | -0.199** | -0.018*** | -0.023 | -0.219*** |
| | | (-2.195) | (-3.240) | (-0.534) | (-3.688) |
| Industry FE | | Yes | Yes | Yes | Yes |
| Firm & Year clusters | | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | | 0.803 | 0.844 | 0.737 | 0.841 |
| Sample size | | 42,109 | 42,109 | 42,109 | 42,109 |

This table presents the first-stage regression analysis results with stock liquidity (*LIQ*) as dependent variable. Two instrumental variables are employed: lag stock liquidity (*LagLIQ*), and the mean stock liquidity of the two firms in firm *i*'s industry that have the closest size (market value of equity) to firm *i* (*TwoLIQ*). The first row reports the coefficient estimate and the second row reports the two-way clustered *t*-statistic based on standard error clustered by firm and year (in parentheses). Industry fixed effect based on Fama and French's classification scheme is included in all regressions but the coefficients are not reported. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively, based on one-tailed tests if the coefficient has a predicted sign, and two-tailed tests otherwise. See Appendix A for other variable definitions.

**TABLE 7**
**Endogeneity and Reverse Causality: Two-Stage Least Squares Regressions**
**Stage 2: Dependent Variable = *INV***

| Variable | Pr. Sign | *LIQFHT (1)* | *LIQZERO (2)* | *LIQTURN (3)* | *LIQindex (4)* |
|---|---|---|---|---|---|
| ***PrLIQ (1)*** | + | 1.000*** | 0.360 | 1.393* | 0.427 |
| | | (3.005) | (0.072) | (1.354) | (0.728) |
| *PrLIQ* x *OverFirm (2)* | - | -4.005*** | -34.012*** | -4.191*** | -4.027*** |
| | | (-6.428) | (-3.790) | (-2.862) | (-4.732) |
| **joint significance (1)+(2)** | - | -3.006*** | -33.650*** | -2.798*** | -3.600*** |
| | | (-7.441) | (-7.065) | (-3.958) | (-9.326) |
| *IO* | + | 4.279*** | 5.067*** | 3.929*** | 5.335*** |
| | | (5.943) | (6.952) | (4.916) | (7.587) |
| *Analyst* | + | 0.124*** | 0.112*** | 0.144*** | 0.137*** |
| | | (5.726) | (5.038) | (6.610) | (6.340) |
| *G_Score* | ? | -0.287*** | -0.289*** | -0.293*** | -0.277*** |
| | | (-3.876) | (-3.905) | (-3.949) | (-3.739) |
| *G_Dummy* | ? | 2.600*** | 2.621*** | 2.722*** | 2.602*** |
| | | (3.681) | (3.713) | (3.849) | (3.684) |
| *OverFirm* | + | 1.212 | 1.075 | 7.024*** | 3.764*** |
| | | (1.538) | (1.267) | (5.296) | (4.298) |
| *logAsset* | - | -1.283*** | -1.174*** | -1.474*** | -1.256*** |
| | | (-8.768) | (-8.648) | (-10.328) | (-8.641) |
| *MB* | + | 2.520*** | 2.563*** | 2.448*** | 2.562*** |
| | | (16.883) | (17.692) | (17.172) | (17.346) |
| *σ(Sales)* | - | 0.599 | 0.666 | 0.876* | 0.871* |
| | | (0.941) | (1.066) | (1.340) | (1.340) |
| *σ(CFO)* | + | 14.085*** | 15.436*** | 14.673*** | 15.579*** |
| | | (5.199) | (5.990) | (5.179) | (5.885) |
| *σ(INV)* | + | 0.032*** | 0.033*** | 0.032*** | 0.033*** |
| | | (3.793) | (3.918) | (3.739) | (3.926) |
| *Z_Score* | - | -1.974*** | -2.065*** | -2.039*** | -2.051*** |
| | | (-9.721) | (-10.377) | (-9.940) | (-10.212) |
| *Tangibility* | + | 9.827*** | 9.392*** | 9.929*** | 9.655*** |
| | | (10.139) | (10.217) | (10.215) | (10.407) |
| *Ind_Kstruct* | - | -11.512*** | -11.910*** | -11.060*** | -11.834*** |
| | | (-6.069) | (-7.038) | (-5.820) | (-6.559) |
| *CFOsale* | - | -1.444*** | -1.457*** | -1.448*** | -1.453*** |
| | | (-5.472) | (-5.547) | (-5.472) | (-5.546) |
| *DIV* | - | -0.911*** | -1.046*** | -1.029*** | -1.140*** |
| | | (-3.228) | (-3.707) | (-3.630) | (-4.037) |
| *Firm_Age* | - | -0.025*** | -0.025*** | -0.029*** | -0.028*** |
| | | (-3.270) | (-3.324) | (-3.681) | (-3.666) |
| *Ocycle* | - | -1.672*** | -1.736*** | -1.625*** | -1.696*** |
| | | (-6.939) | (-7.394) | (-6.643) | (-7.164) |
| *Loss* | - | -3.829*** | -3.730*** | -3.716*** | -3.753*** |
| | | (-14.799) | (-15.187) | (-14.659) | (-14.989) |
| *AQ* | + | 5.303 | 9.283* | 12.247** | 9.655** |
| | | (0.894) | (1.614) | (2.112) | (1.651) |
| *AQ* x *OverFirm* | - | -2.721 | -11.284 | -16.400* | -11.982 |
| | | (-0.275) | (-1.148) | (-1.640) | (-1.204) |
| Constant | | 24.216*** | 23.094*** | 23.308*** | 22.871*** |
| | | (10.748) | (10.602) | (10.497) | (10.411) |
| Industry FE | | Yes | Yes | Yes | Yes |
| Firm & Year clusters | | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | | 0.267 | 0.268 | 0.265 | 0.267 |
| Sample size | | 42,109 | 42,109 | 42,109 | 42,109 |

This table presents the second-stage regression analysis results with investment levels (*INV*) as dependent variable. *PrLIQ* and (*PrLIQ* x *OverFirm*) are the predicted values from the first-stage regressions reported in Panel A of Table 5. The first row reports the coefficient estimate and the second row reports the two-way clustered *t*-statistic based on standard error clustered by firm and year (in parentheses). Industry fixed effect based on Fama and French's classification scheme is included in all regressions but the coefficients are not reported. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively, based on one-tailed tests if the coefficient has a predicted sign, and two-tailed tests otherwise. See Appendix A for other variable definitions.

## TABLE 8
## Endogeneity and Reverse Causality: Intertemporal Relations (Three-Year)

| Variable | Pr. Sign | *LIQFHT (1)* | *LIQZERO (2)* | *LIQTURN (3)* | *LIQindex (4)* |
|---|---|---|---|---|---|
| *ΔLIQ* | + | 1.595*** | 16.717*** | 1.380* | 2.492*** |
| | | (4.966) | (2.619) | (1.385) | (5.175) |
| *ΔLIQ* x *OverFirm* | - | -1.507** | -13.611 | -2.344** | -2.753*** |
| | | (-1.647) | (-1.274) | (-1.712) | (-2.627) |
| ***joint significance*** | - | 0.0878 | 3.107 | -0.964* | -0.262 |
| | | (0.116) | (0.368) | (-1.537) | (-0.312) |
| *ΔIO* | + | 3.095** | 3.086** | 3.391** | 2.635** |
| | | (2.077) | (2.027) | (2.187) | (1.803) |
| *ΔAnalyst* | + | 0.138*** | 0.139*** | 0.134*** | 0.135*** |
| | | (3.663) | (3.796) | (3.556) | (3.553) |
| *ΔG_Score* | ? | -0.097** | -0.100** | -0.108*** | -0.106** |
| | | (-2.061) | (-2.176) | (-2.488) | (-2.230) |
| *G_Dummy* | ? | 1.193** | 1.326*** | 1.407*** | 1.353*** |
| | | (2.161) | (2.898) | (2.668) | (2.631) |
| *OverFirm* | + | 7.595*** | 7.622*** | 6.998*** | 7.844*** |
| | | (10.881) | (8.676) | (10.151) | (10.818) |
| *ΔlogAsset* | - | -10.158*** | -10.090*** | -9.881*** | -10.160*** |
| | | (-14.030) | (-14.029) | (-15.005) | (-14.181) |
| *ΔMB* | + | 2.053*** | 2.061*** | 2.128*** | 2.044*** |
| | | (9.986) | (10.283) | (11.093) | (10.143) |
| *Δσ(Sales)* | - | -1.362*** | -1.387*** | -1.316*** | -1.462*** |
| | | (-2.515) | (-2.563) | (-2.424) | (-2.696) |
| *Δσ(CFO)* | + | 2.954 | 2.985 | 3.410 | 3.005 |
| | | (1.117) | (1.135) | (1.253) | (1.151) |
| *Δσ(INV)* | + | -0.093*** | -0.095*** | -0.094*** | -0.094*** |
| | | (-6.960) | (-6.936) | (-6.945) | (-6.948) |
| *ΔZ_Score* | - | 0.788*** | 0.862*** | 0.887*** | 0.822*** |
| | | (3.705) | (4.164) | (4.309) | (3.904) |
| *ΔTangibility* | + | -2.610* | -2.578* | -2.752* | -2.538 |
| | | (-1.313) | (-1.292) | (-1.377) | (-1.273) |
| *ΔInd_Kstruct* | - | -22.117*** | -23.381*** | -23.478*** | -22.769*** |
| | | (-9.175) | (-10.119) | (-10.661) | (-9.506) |
| *ΔCFOsale* | - | -0.921*** | -0.939*** | -0.959*** | -0.925*** |
| | | (-3.231) | (-3.290) | (-3.368) | (-3.245) |
| *DIV* | - | -0.174 | -0.252 | -0.247 | -0.249 |
| | | (-0.653) | (-0.966) | (-0.956) | (-0.932) |
| *Firm_Age* | - | -0.002 | -0.002 | -0.004 | -0.003 |
| | | (-0.319) | (-0.250) | (-0.532) | (-0.400) |
| *ΔOCycle* | - | 0.542 | 0.572 | 0.516 | 0.552 |
| | | (1.146) | (1.200) | (1.092) | (1.155) |
| *Loss* | - | -4.004*** | -4.012*** | -4.081*** | -4.004*** |
| | | (-10.983) | (-10.738) | (-11.130) | (-10.997) |
| *ΔAQ* | + | -9.672 | -10.061* | -10.792* | -10.087* |
| | | (-1.249) | (-1.304) | (-1.397) | (-1.301) |
| *ΔAQ* x *OverFirm* | - | 32.505** | 33.139** | 33.609** | 32.949** |
| | | (2.203) | (2.249) | (2.316) | (2.247) |
| Constant | | -2.221 | -2.415 | -1.895 | -2.472 |
| | | (-1.113) | (-1.233) | (-0.951) | (-1.246) |
| Industry FE | | Yes | Yes | Yes | Yes |
| Firm & Year clusters | | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | | 0.171 | 0.171 | 0.170 | 0.171 |
| Sample size | | 28,797 | 28,797 | 28,797 | 28,797 |

This table presents the results from tests that regress firm-specific changes in investment levels on the firm-specific changes in stock liquidity and in the other control variables. I use three-year periods to compute changes (Δ) for all variables except dummy variables and variables that have little changes over the years. The first row reports the coefficient estimate and the second row reports the two-way clustered *t*-statistic based on standard error clustered by firm and year (in parentheses). Industry fixed effect based on Fama and French's classification scheme is included in all regressions but the coefficients are not reported. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively, based on one-tailed tests if the coefficient has a predicted sign, and two-tailed tests otherwise. See Appendix A for variable definitions.

**TABLE 9**
**Regression by Year Exclusions: Robustness Tests**

| Year excluded | *LIQFHT* (1) *H1a* | *LIQFHT* (1) *H1b* | *LIQZERO* (2) *H1a* | *LIQZERO* (2) *H1b* | *LIQTURN* (3) *H1a* | *LIQTURN* (3) *H1b* | *LIQindex* (4) *H1a* | *LIQindex* (4) *H1b* |
|---|---|---|---|---|---|---|---|---|
| 1995 | 1.321*** | -2.196*** | 7.253* | -25.04*** | 1.585** | -1.100** | 1.231*** | -2.147*** |
| 1996 | 1.249*** | -1.954*** | 6.074 | -21.31*** | 1.461** | -0.897* | 1.135** | -1.873*** |
| 1997 | 1.232*** | -2.070*** | 5.572 | -20.82*** | 1.661** | -0.911* | 1.122** | -1.925*** |
| 1998 | 1.135*** | -1.958*** | 3.073 | -20.17*** | 1.503** | -0.702 | 0.912** | -1.801*** |
| 1999 | 1.186*** | -1.959*** | 3.504 | -20.60*** | 1.256* | -0.638 | 0.913** | -1.806*** |
| 2000 | 1.121*** | -2.213*** | 2.735 | -21.74*** | 1.352* | -0.649 | 0.819** | -1.990*** |
| 2001 | 1.138*** | -1.950*** | 3.446 | -19.61*** | 0.963* | -0.637 | 0.849** | -1.816*** |
| 2002 | 1.216*** | -1.977*** | 4.689 | -20.43*** | 1.316* | -0.833* | 1.020** | -1.890*** |
| 2003 | 1.137*** | -1.952*** | 3.534 | -20.17*** | 1.433* | -0.948* | 0.929** | -1.909*** |
| 2004 | 1.201*** | -1.901*** | 3.979 | -19.86*** | 1.487* | -0.679 | 1.006** | -1.770*** |
| 2005 | 1.198*** | -2.059*** | 4.022 | -21.21*** | 1.575** | -0.676 | 0.998** | -1.883*** |
| 2006 | 1.193*** | -1.981*** | 3.733 | -20.57*** | 1.364* | -0.787 | 0.963** | -1.892*** |
| 2007 | 1.209*** | -2.011*** | 4.356 | -20.72*** | 1.513* | -0.795* | 1.029** | -1.899*** |
| 2008 | 1.303*** | -2.096*** | 6.226* | -21.17*** | 2.018*** | -0.712 | 1.259*** | -1.877*** |
| 2009 | 1.196*** | -2.049*** | 4.777 | -20.48*** | 1.640** | -0.726 | 1.054** | -1.862*** |
| 2010 | 1.222*** | -2.052*** | 4.692 | -20.96*** | 1.479* | -0.790 | 1.042** | -1.922*** |
| 2011 | 1.208*** | -2.058*** | 4.372 | -20.95*** | 1.619** | -0.752 | 1.036** | -1.898*** |
| 2012 | 1.196*** | -2.013*** | 4.371 | -20.39*** | 1.390* | -0.817* | 0.998** | -1.893*** |
| Main results (Table 4) | 1.201*** | -2.030*** | 4.396 | -20.91*** | 1.476** | -0.785* | 1.012** | -1.898*** |

This table presents the results of robustness checks on the relation between stock liquidity and investment efficiency. Each regression is performed by excluding one fiscal firm year at a time from my full sample, with standard error clustered by firm and year. Industry fixed effect based on Fama and French's classification scheme is included in all regressions. For brevity, only coefficients for H1a (under-invest) and H1b (over-invest) are reported. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively, based on one-tailed tests.

**TABLE 10**
**Regression by Industry Exclusions: Robustness Tests**

| Industry excluded | *LIQFHT* (1) | | *LIQZERO* (2) | | *LIQTURN* (3) | | *LIQindex* (4) | |
|---|---|---|---|---|---|---|---|---|
| | *H1a* | *H1b* | *H1a* | *H1b* | *H1a* | *H1b* | *H1a* | *H1b* |
| Aircraft | 1.197*** | -1.998*** | 4.367 | -20.84*** | 1.477** | -0.763 | 1.010** | -1.873*** |
| Agriculture | 1.198*** | -2.040*** | 4.339 | -21.01*** | 1.458** | -0.785* | 1.003** | -1.908*** |
| Automobiles and Trucks | 1.207*** | -1.976*** | 4.557 | -20.49*** | 1.497** | -0.770 | 1.034** | -1.849*** |
| Beer & Liquor | 1.213*** | -2.037*** | 4.613 | -21.09*** | 1.498** | -0.816* | 1.034** | -1.919*** |
| Construction Materials | 1.225*** | -2.049*** | 4.550 | -20.92*** | 1.542** | -0.813* | 1.047** | -1.908*** |
| Printing and Publishing | 1.209*** | -2.101*** | 4.485 | -21.54*** | 1.560** | -0.794* | 1.026** | -1.949*** |
| Shipping Containers | 1.199*** | -2.029*** | 4.329 | -20.81*** | 1.420* | -0.749 | 0.998** | -1.885*** |
| Business Services | 1.026*** | -1.840*** | 2.133 | -20.56*** | 1.394* | -1.267** | 0.793** | -2.006*** |
| Chemicals | 1.172*** | -2.056*** | 4.244 | -20.98*** | 1.554** | -0.766 | 0.994** | -1.901*** |
| Electronic Equipment | 1.144*** | -2.052*** | 3.330 | -21.09*** | 1.277* | -1.090** | 0.894** | -2.078*** |
| Apparel | 1.218*** | -2.044*** | 4.865 | -21.50*** | 1.504** | -0.741 | 1.044** | -1.908*** |
| Construction | 1.205*** | -2.027*** | 4.409 | -20.95*** | 1.477** | -0.792* | 1.016** | -1.898*** |
| Computers | 1.156*** | -1.878*** | 3.564 | -19.36*** | 1.317* | -0.787* | 0.940** | -1.792*** |
| Pharmaceutical Products | 1.071*** | -1.907*** | 3.688 | -17.76*** | 1.590** | -0.398 | 0.922** | -1.544*** |
| Electrical Equipment | 1.188*** | -1.990*** | 3.790 | -20.40*** | 1.361* | -0.732 | 0.963** | -1.852*** |
| Fabricated Products | 1.212*** | -2.054*** | 4.560 | -21.23*** | 1.473** | -0.787* | 1.022** | -1.921*** |
| Food Products | 1.208*** | -2.010*** | 4.505 | -21.16*** | 1.435* | -0.813* | 1.016** | -1.912*** |
| Entertainment | 1.275*** | -2.055*** | 5.242 | -21.54*** | 1.420** | -0.774* | 1.086*** | -1.927*** |
| Precious Metals | 1.202*** | -2.034*** | 4.469 | -20.96*** | 1.509** | -0.805* | 1.021** | -1.909*** |
| Healthcare | 1.225*** | -2.120*** | 4.701 | -21.42*** | 1.539** | -0.785* | 1.037** | -1.947*** |
| Consumer Goods | 1.218*** | -2.072*** | 4.687 | -21.07*** | 1.513** | -0.815* | 1.039** | -1.928*** |
| Measuring & Control Equip't | 1.189*** | -1.979*** | 3.905 | -19.96*** | 1.422** | -0.777 | 0.984** | -1.837*** |
| Machinery | 1.267*** | -2.008*** | 5.326 | -20.76*** | 1.693** | -0.995** | 1.147*** | -1.948*** |
| Restaurants, Hotels, Motels | 1.198*** | -2.055*** | 4.457 | -21.05*** | 1.512** | -0.771 | 1.017** | -1.906*** |
| Medical Equipment | 1.218*** | -2.121*** | 4.094 | -21.18*** | 1.279* | -0.589 | 0.957** | -1.872*** |
| Non-Metallic & Industrial Metal Mining | 1.214*** | -2.018*** | 4.699 | -20.94*** | 1.518** | -0.864* | 1.046** | -1.923*** |
| Petroleum and Natural Gas | 1.183*** | -2.063*** | 4.190 | -20.47*** | 1.452** | -0.656 | 0.979** | -1.848*** |
| Almost Nothing | 1.223*** | -2.113*** | 4.757 | -21.71*** | 1.439** | -0.795* | 1.026** | -1.967*** |
| Business Supplies | 1.213*** | -2.036*** | 4.480 | -20.83*** | 1.455** | -0.721 | 1.020** | -1.873*** |
| Personal Services | 1.179*** | -1.994*** | 4.107 | -20.30*** | 1.463** | -0.754 | 0.985** | -1.848*** |
| Retail | 1.174*** | -2.003*** | 3.888 | -20.27*** | 1.439* | -0.573 | 0.970** | -1.792*** |
| Rubber and Plastic Products | 1.219*** | -2.038*** | 4.913 | -20.99*** | 1.523** | -0.759* | 1.053** | -1.886*** |
| Candy & Soda | 1.201*** | -2.029*** | 4.390 | -20.90*** | 1.475** | -0.785* | 1.011** | -1.898*** |
| Steel Works Etc | 1.224*** | -2.026*** | 4.799 | -21.03*** | 1.545** | -0.750 | 1.058** | -1.884*** |
| Communication | 1.216*** | -2.027*** | 5.584 | -21.26*** | 1.732** | -0.806* | 1.112*** | -1.891*** |
| Recreation | 1.217*** | -2.069*** | 4.776 | -21.26*** | 1.547** | -0.837* | 1.047** | -1.942*** |
| Transportation | 1.224*** | -2.066*** | 4.739 | -21.64*** | 1.601** | -0.903* | 1.060** | -1.981*** |
| Textiles | 1.200*** | -2.031*** | 4.392 | -20.91*** | 1.468** | -0.777* | 1.010** | -1.897*** |
| Utilities | 1.223*** | -2.002*** | 3.609 | -21.64*** | 1.244* | -0.667 | 0.961** | -1.901*** |
| Wholesale | 1.237*** | -2.052*** | 5.072 | -21.25*** | 1.389* | -0.856* | 1.051** | -1.955*** |
| Main results (Table 4) | 1.201*** | -2.030*** | 4.396 | -20.91*** | 1.476** | -0.785* | 1.012** | -1.898*** |

This table presents the results of robustness checks on the relation between stock liquidity and investment efficiency. Each regression is performed by excluding one industry at a time from my full sample, with standard error clustered by firm and year. Industry fixed effect based on Fama and French's classification scheme is included in all regressions. For brevity, only coefficients for H1a (under-invest) and H1b (over-invest) are reported. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively, based on one-tailed tests.

**TABLE 11**
**Conditional Relation between Investment and Stock Liquidity: Alternative Stock liquidity Measures**

| Variable | Pred. Sign | *LIQAM* (1) | *LIQBAS* (2) | *LIQHL* (3) | *LIQROLL* (4) | *LIQindex6* (5) |
|---|---|---|---|---|---|---|
| *LIQ (1)* ***$H_{1a}$: under-invest*** | + | 7.524*** | 0.516*** | 1.575*** | 4.196*** | 1.675*** |
| | | (2.960) | (5.184) | (6.458) | (8.159) | (3.950) |
| *LIQ x OverFirm (2)* | - | -21.007*** | -1.162*** | -2.068*** | -5.215*** | -3.757*** |
| | | (-2.373) | (-5.794) | (-3.989) | (-4.806) | (-4.894) |
| *(1)+(2)* ***$H_{1b}$: over-invest*** | - | -13.480** | -0.646*** | -0.493 | -1.019* | -2.082*** |
| | | (-1.745) | (-3.991) | (-1.216) | (-1.302) | (-3.762) |
| *IO* | + | 1.198* | 3.151*** | 2.755*** | 2.657*** | 3.244*** |
| | | (1.496) | (4.310) | (3.390) | (3.359) | (4.078) |
| *Analyst* | + | 0.112*** | 0.143*** | 0.136*** | 0.134*** | 0.139*** |
| | | (3.514) | (6.584) | (5.954) | (6.099) | (6.156) |
| *G_Score* | ? | -0.185** | -0.271*** | -0.299*** | -0.298*** | -0.291*** |
| | | (-2.194) | (-3.638) | (-4.027) | (-4.018) | (-3.930) |
| *G_Dummy* | ? | 1.726** | 2.463*** | 2.723*** | 2.713*** | 2.637*** |
| | | (2.041) | (3.469) | (3.849) | (3.785) | (3.729) |
| *OverFirm* | + | 3.747*** | 2.340*** | 1.448* | -1.120 | 4.288*** |
| | | (3.089) | (2.888) | (1.587) | (-1.002) | (5.469) |
| *logAsset* | - | -1.654*** | -1.450*** | -1.590*** | -1.589*** | -1.486*** |
| | | (-7.517) | (-9.076) | (-9.599) | (-10.542) | (-8.963) |
| *MB* | + | 1.956*** | 2.421*** | 2.322*** | 2.327*** | 2.369*** |
| | | (6.447) | (15.988) | (15.664) | (16.066) | (15.079) |
| *σ(Sales)* | - | 1.482* | 0.763 | 0.937* | 0.758 | 0.857* |
| | | (1.537) | (1.195) | (1.506) | (1.226) | (1.324) |
| *σ(CFO)* | + | 10.572** | 14.424*** | 14.180*** | 14.010*** | 14.284*** |
| | | (1.847) | (5.148) | (5.083) | (5.105) | (5.235) |
| *σ(INV)* | + | 0.062*** | 0.033*** | 0.033*** | 0.031*** | 0.033*** |
| | | (4.014) | (3.908) | (3.782) | (3.617) | (3.883) |
| *Z_Score* | - | -0.158 | -2.038*** | -2.075*** | -2.032*** | -2.048*** |
| | | (-0.406) | (-9.918) | (-10.324) | (-9.969) | (-9.880) |
| *Tangibility* | + | 10.516*** | 8.460*** | 10.148*** | 9.889*** | 10.100*** |
| | | (7.319) | (7.794) | (9.583) | (9.976) | (9.858) |
| *Ind_Kstruct* | - | -10.190*** | -14.973*** | -10.672*** | -10.090*** | -11.073*** |
| | | (-4.934) | (-8.794) | (-5.592) | (-5.785) | (-5.389) |
| *CFOsale* | - | 9.615*** | -1.538*** | -1.325*** | -1.373*** | -1.304*** |
| | | (4.022) | (-5.870) | (-5.247) | (-5.253) | (-5.105) |
| *DIV* | - | -0.979*** | -1.218*** | -0.974*** | -0.972*** | -0.928*** |
| | | (-2.819) | (-4.145) | (-3.637) | (-3.524) | (-3.372) |
| *Firm_Age* | - | -0.005 | -0.026*** | -0.025*** | -0.026*** | -0.026*** |
| | | (-0.659) | (-3.561) | (-3.373) | (-3.465) | (-3.476) |
| *OCycle* | - | 0.134 | -1.536*** | -1.646*** | -1.614*** | -1.644*** |
| | | (0.394) | (-7.150) | (-6.887) | (-6.649) | (-6.885) |
| *Loss* | - | -2.875*** | -3.494*** | -3.576*** | -3.520*** | -3.775*** |
| | | (-6.321) | (-13.841) | (-13.123) | (-14.066) | (-13.523) |
| *AQ* | + | -24.727** | 6.607 | 3.395 | 5.217 | 3.784 |
| | | (-1.928) | (1.054) | (0.522) | (0.854) | (0.556) |
| *AQ x OverFirm* | - | 54.919*** | -5.037 | 1.108 | -2.462 | 0.824 |
| | | (2.638) | (-0.504) | (0.107) | (-0.244) | (0.079) |
| Constant | | 17.155*** | 21.745*** | 27.662*** | 29.796*** | 24.934*** |
| | | (5.996) | (7.730) | (11.624) | (12.646) | (10.205) |
| Industry FE | | Yes | Yes | Yes | Yes | Yes |
| Firm & Year clusters | | Yes | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ (%) | | 0.204 | 0.260 | 0.267 | 0.266 | 0.266 |
| Sample size | | 15,708 | 42,392 | 41,770 | 42,404 | 41,381 |

This table presents regression analysis results with additional proxies of stock liquidity as test variables. *LIQAM* is the price impact measure introduced by Amihud (2001). *LIQBAS* is a measure of the closing percent quoted spread developed by Chung and Zhang (2014). *LIQHL* is the price-based spread proxy employed by Corwin and Schultz (2012). *LIQROLL* is the serial correlation-based measure derived by Roll (1984). *LIQindex6* is a composite liquidity index computed by standardising the three additional measures of liquidity (*LIQBAS, LIQHL, LIQROLL*) and the three liquidity measures from the main analysis (*LIQFHT, LIQZERO, LIQTURN*) and then calculating the unweighted mean of these six standardised measures. The first row reports the coefficient estimate and the second row reports the two-way clustered *t*-statistic based on standard error clustered by firm and year (in parentheses). Industry fixed effect based on Fama and French's classification scheme is included in all regressions but the coefficients are not reported. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively, based on one-tailed tests if the coefficient has a predicted sign, and two-tailed tests otherwise. See Appendix A for other variable definitions.

**TABLE 12**
**Conditional Relation between Investment and Stock Liquidity: Alternative Investment Measures**
**Dependent Variable: *Capex***

| Variable | Pred. Sign | *LIQFHT (1)* | *LIQZERO (2)* | *LIQTURN (3)* | *LIQindex (4)* |
|---|---|---|---|---|---|
| *LIQ (1)* ***$H_{1a}$: under-invest*** | + | 0.004*** | 0.017 | 0.011*** | 0.004** |
| | | (3.212) | (0.879) | (3.016) | (2.006) |
| *LIQ x OverFirm (2)* | - | -0.011*** | -0.100*** | -0.014*** | -0.011*** |
| | | (-6.049) | (-3.274) | (-3.183) | (-3.987) |
| *(1)+(2)* ***$H_{1b}$: over-invest*** | - | -0.008*** | -0.084*** | -0.003* | -0.007*** |
| | | (-6.448) | (-4.862) | (-1.335) | (-4.313) |
| *IO* | + | 0.005** | 0.007*** | 0.001 | 0.005** |
| | | (2.103) | (2.866) | (0.309) | (2.243) |
| *Analyst* | + | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| | | (3.415) | (3.136) | (3.000) | (3.691) |
| *G_Score* | ? | 0.000 | 0.000 | 0.000 | 0.000 |
| | | (0.381) | (0.371) | (0.200) | (0.386) |
| *G_Dummy* | ? | -0.000 | -0.000 | 0.000 | -0.000 |
| | | (-0.068) | (-0.053) | (0.046) | (-0.038) |
| *OverFirm* | + | 0.009*** | 0.008** | 0.026*** | 0.015*** |
| | | (2.503) | (2.233) | (5.124) | (4.459) |
| *logAsset* | - | -0.004*** | -0.003*** | -0.004*** | -0.004*** |
| | | (-5.907) | (-5.746) | (-6.550) | (-6.139) |
| *MB* | + | 0.008*** | 0.009*** | 0.008*** | 0.008*** |
| | | (14.111) | (14.101) | (14.336) | (13.718) |
| *σ(Sales)* | - | 0.007*** | 0.007*** | 0.007*** | 0.008*** |
| | | (3.007) | (3.077) | (2.816) | (3.173) |
| *σ(CFO)* | + | 0.049*** | 0.052*** | 0.047*** | 0.051*** |
| | | (5.657) | (5.991) | (5.389) | (5.838) |
| *σ(INV)* | + | 0.000** | 0.000** | 0.000** | 0.000** |
| | | (2.239) | (2.274) | (2.029) | (2.273) |
| *Z_Score* | - | 0.003*** | 0.003*** | 0.003*** | 0.003*** |
| | | (5.200) | (4.909) | (5.077) | (4.958) |
| *Tangibility* | + | 0.167*** | 0.167*** | 0.168*** | 0.168*** |
| | | (20.130) | (20.086) | (20.040) | (20.067) |
| *Ind_Kstruct* | - | -0.057*** | -0.059*** | -0.056*** | -0.057*** |
| | | (-6.475) | (-6.798) | (-6.041) | (-6.325) |
| *CFOsale* | - | 0.002*** | 0.002*** | 0.002*** | 0.002*** |
| | | (2.815) | (2.752) | (2.816) | (2.849) |
| *DIV* | - | -0.006*** | -0.007*** | -0.006*** | -0.007*** |
| | | (-5.534) | (-5.851) | (-5.128) | (-5.887) |
| *Firm_Age* | - | -0.000*** | -0.000*** | -0.000*** | -0.000*** |
| | | (-3.652) | (-3.667) | (-3.713) | (-3.829) |
| *OCycle* | - | 0.004*** | 0.004*** | 0.004*** | 0.004*** |
| | | (5.415) | (5.362) | (5.483) | (5.490) |
| *Loss* | - | -0.012*** | -0.012*** | -0.012*** | -0.012*** |
| | | (-10.102) | (-10.209) | (-10.219) | (-10.159) |
| *AQ* | + | 0.018 | 0.030 | 0.038* | 0.029 |
| | | (0.658) | (1.126) | (1.434) | (1.070) |
| *AQ x OverFirm* | - | 0.016 | -0.010 | -0.020 | -0.006 |
| | | (0.385) | (-0.221) | (-0.473) | (-0.145) |
| Constant | | -0.003 | -0.006 | -0.009 | -0.005 |
| | | (-0.503) | (-0.848) | (-1.186) | (-0.716) |
| Industry FE | | Yes | Yes | Yes | Yes |
| Firm & Year clusters | | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ (%) | | 0.448 | 0.448 | 0.447 | 0.448 |
| Sample size | | 42,443 | 42,443 | 42,443 | 42,443 |

This table presents regression analysis results with *Capex* investment as dependent variables. *Capex* is a measure of capital expenditure scaled by lagged total assets. The first row reports the coefficient estimate and the second row reports the two-way clustered *t*-statistic based on standard error clustered by firm and year (in parentheses). Industry fixed effect based on Fama and French's classification scheme is included in all regressions but the coefficients are not reported. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively, based on one-tailed tests if the coefficient has a predicted sign, and two-tailed tests otherwise. See Appendix A for other variable definitions.

**TABLE 13**
**Conditional Relation between Investment and Stock Liquidity: Alternative Investment Measures**
**Dependent Variable: *Non-Capex***

| Variable | Pred. Sign | *LIQFHT (1)* | *LIQZERO (2)* | *LIQTURN (3)* | *LIQindex (4)* |
|---|---|---|---|---|---|
| *LIQ (1)* ***$H_{1a}$: under-invest*** | + | 0.008*** | 0.016 | 0.005 | 0.005* |
| | | (3.940) | (0.477) | (0.707) | (1.416) |
| *LIQ x OverFirm (2)* | - | -0.020*** | -0.140** | -0.012 | -0.018*** |
| | | (-4.471) | (-2.284) | (-1.039) | (-2.813) |
| *(1)+(2)* ***$H_{1b}$: over-invest*** | - | -0.0123*** | -0.124*** | -0.007 | -0.013*** |
| | | (-3.820) | (-3.461) | (-1.162) | (-3.390) |
| *IO* | + | 0.030*** | 0.034*** | 0.030*** | 0.033*** |
| | | (4.667) | (5.520) | (4.839) | (5.351) |
| *Analyst* | + | 0.001*** | 0.001*** | 0.001*** | 0.001*** |
| | | (5.300) | (4.766) | (5.022) | (5.396) |
| *G_Score* | ? | -0.003*** | -0.003*** | -0.003*** | -0.003*** |
| | | (-4.463) | (-4.465) | (-4.522) | (-4.421) |
| *G_Dummy* | ? | 0.025*** | 0.025*** | 0.025*** | 0.025*** |
| | | (3.902) | (3.926) | (4.001) | (3.917) |
| *OverFirm* | + | 0.007 | 0.008 | 0.028*** | 0.019*** |
| | | (0.936) | (1.126) | (2.766) | (2.634) |
| *logAsset* | - | -0.010*** | -0.010*** | -0.011*** | -0.010*** |
| | | (-9.446) | (-8.622) | (-10.042) | (-9.060) |
| *MB* | + | 0.015*** | 0.015*** | 0.015*** | 0.015*** |
| | | (13.078) | (13.042) | (13.207) | (13.150) |
| *σ(Sales)* | - | 0.001 | 0.001 | 0.002 | 0.002 |
| | | (0.265) | (0.277) | (0.337) | (0.383) |
| *σ(CFO)* | + | 0.082*** | 0.087*** | 0.084*** | 0.087*** |
| | | (3.295) | (3.617) | (3.272) | (3.500) |
| *σ(INV)* | + | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| | | (3.490) | (3.502) | (3.401) | (3.498) |
| *Z_Score* | - | -0.022*** | -0.023*** | -0.023*** | -0.023*** |
| | | (-13.036) | (-13.347) | (-13.005) | (-13.169) |
| *Tangibility* | + | -0.063*** | -0.064*** | -0.063*** | -0.063*** |
| | | (-9.742) | (-9.904) | (-9.724) | (-9.779) |
| *Ind_Kstruct* | - | -0.051*** | -0.054*** | -0.051*** | -0.052*** |
| | | (-3.483) | (-3.906) | (-3.596) | (-3.639) |
| *CFOsale* | - | -0.017*** | -0.017*** | -0.017*** | -0.017*** |
| | | (-6.817) | (-6.872) | (-6.834) | (-6.862) |
| *DIV* | - | -0.003 | -0.003 | -0.003 | -0.003 |
| | | (-1.033) | (-1.138) | (-1.049) | (-1.273) |
| *Firm_Age* | - | -0.000** | -0.000** | -0.000** | -0.000** |
| | | (-1.857) | (-1.874) | (-2.039) | (-2.030) |
| *OCycle* | - | -0.021*** | -0.021*** | -0.021*** | -0.021*** |
| | | (-8.555) | (-8.762) | (-8.541) | (-8.633) |
| *Loss* | - | -0.024*** | -0.024*** | -0.024*** | -0.024*** |
| | | (-10.906) | (-11.069) | (-11.089) | (-11.048) |
| *AQ* | + | 0.029 | 0.057 | 0.068 | 0.055 |
| | | (0.553) | (1.069) | (1.277) | (1.040) |
| *AQ x OverFirm* | - | -0.040 | -0.096 | -0.115 | -0.091 |
| | | (-0.438) | (-1.052) | (-1.254) | (-0.999) |
| Constant | | 0.257*** | 0.250*** | 0.249*** | 0.250*** |
| | | (11.862) | (11.204) | (11.580) | (11.461) |
| Industry FE | | Yes | Yes | Yes | Yes |
| Firm & Year clusters | | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ (%) | | 0.296 | 0.295 | 0.295 | 0.295 |
| Sample size | | 42,443 | 42,443 | 42,443 | 42,443 |

This table presents the regression analysis results with *Non-Capex* investment as dependent variables. *Non-Capex* is calculated as the sum of R&D expenditures and acquisitions scaled by lagged total assets. The first row reports the coefficient estimate and the second row reports the two-way clustered *t*-statistic based on standard error clustered by firm and year (in parentheses). Industry fixed effect based on Fama and French's classification scheme is included in all regressions but the coefficients are not reported. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively, based on one-tailed tests if the coefficient has a predicted sign, and two-tailed tests otherwise. See Appendix A for other variable definitions.

**TABLE 14**
**Univariate Analyses for Young vs Mature Firms**

| Variable | Young Firms (*Firm_Age* <= 13) n=20,603 Mean | Median | Std. Dev. | Mature Firms (*Firm_Age* > 13) n=21,852 Mean | Median | Std. Dev. | Test of Differences t-statistic |
|---|---|---|---|---|---|---|---|
| *INV* | 17.142 | 11.471 | 18.230 | 12.616 | 8.501 | 13.907 | 28.858*** |
| *LIQFHT* | -0.879 | -0.405 | 1.169 | -0.564 | -0.197 | 0.930 | -30.827*** |
| *LIQZERO* | -0.078 | -0.044 | 0.085 | -0.067 | -0.028 | 0.084 | -14.069*** |
| *LIQTURN* | 0.875 | 0.812 | 0.503 | 0.758 | 0.681 | 0.464 | 24.930*** |
| *LIQindex* | -0.033 | 0.157 | 0.878 | 0.031 | 0.219 | 0.788 | -7.917*** |
| *overfirm* | 0.512 | 0.500 | 0.234 | 0.508 | 0.500 | 0.214 | 1.869* |
| *Total assets* | 1281.416 | 236.960 | 5332.448 | 4608.398 | 651.418 | 15016.207 | -30.065*** |
| *logAsset* | 5.506 | 5.468 | 1.741 | 6.457 | 6.479 | 2.100 | -50.590*** |
| *MB* | 2.181 | 1.586 | 1.689 | 1.776 | 1.399 | 1.201 | 28.618*** |
| *σ(Sales)* | 0.338 | 0.244 | 0.308 | 0.235 | 0.168 | 0.226 | 39.540*** |
| *σ(CFO)* | 0.089 | 0.067 | 0.073 | 0.058 | 0.044 | 0.051 | 51.359*** |
| *σ(INV)* | 19.309 | 9.141 | 28.550 | 9.105 | 4.760 | 14.506 | 46.809*** |
| *Z_Score* | 1.058 | 1.184 | 1.509 | 1.472 | 1.471 | 1.116 | -32.287*** |
| *Tangibility* | 0.248 | 0.166 | 0.227 | 0.305 | 0.239 | 0.232 | -25.606*** |
| *Ind_Kstruct* | 0.153 | 0.108 | 0.114 | 0.181 | 0.155 | 0.120 | -25.097*** |
| *CFOsale* | -0.131 | 0.072 | 1.020 | 0.056 | 0.091 | 0.518 | -23.942*** |
| *Slack* | 4.272 | 0.762 | 9.299 | 2.046 | 0.298 | 6.365 | 28.923*** |
| *DIV* | 0.206 | | | 0.562 | | | |
| *Firm_Age* | 7.555 | 7.000 | 3.175 | 30.573 | 26.000 | 16.511 | -196.702*** |
| *OCycle* | 4.552 | 4.620 | 0.815 | 4.666 | 4.738 | 0.676 | -15.768*** |
| *Loss* | 0.361 | | | 0.192 | | | |
| *AQ* | -0.065 | -0.047 | 0.060 | -0.048 | -0.037 | 0.043 | -32.777*** |
| *IO* | 0.496 | 0.496 | 0.302 | 0.548 | 0.592 | 0.278 | -18.586*** |
| *Analyst* | 5.634 | 4.000 | 6.119 | 7.056 | 4.000 | 7.682 | -21.029*** |
| *G_Score* | -0.760 | 0.000 | 2.468 | -1.429 | 0.000 | 3.595 | 22.235*** |
| *G_Dummy* | 0.906 | | | 0.853 | | | |

This table presents the descriptive statistics of variables used in regression analyses for subsamples of young and mature firms. A firm is defined as young if its average age (*Firm_Age*) is 13 years or less, and as mature if it is more than 13 years. Young firms are characterised as financially constrained whereas mature firms are likely to be non-financially constrained. Univariate analysis results for comparing the means of variables of these two subsamples are reported. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively. See Appendix A for other variable definitions.

**TABLE 15**

**Conditional Relation between Investment and Stock Liquidity: Young Firms (*Firm_Age* <= 13)**

| Variable | Pred. Sign | *LIQFHT(1)* | *LIQZERO(2)* | *LIQTURN(3)* | *LIQindex 4)* |
|---|---|---|---|---|---|
| *LIQ (1)* ***$H_{1a}$: under-invest*** | + | 1.642*** | 8.474* | 2.327*** | 1.662*** |
| | | (6.289) | (1.472) | (2.122) | (3.013) |
| *LIQ x OverFirm (2)* | - | -3.710*** | -37.058*** | -3.978** | -4.139*** |
| | | (-5.809) | (-3.451) | (-2.463) | (-4.451) |
| *(1)+(2)* ***$H_{1b}$: over-invest*** | - | -2.069*** | -28.58*** | -1.651** | -2.478*** |
| | | (-4.134) | (-4.522) | (-2.051) | (-4.248) |
| *IO* | + | 3.733*** | 4.577*** | 3.558*** | 4.040*** |
| | | (4.378) | (5.706) | (4.374) | (5.032) |
| *Analyst* | + | 0.140*** | 0.128*** | 0.128*** | 0.149*** |
| | | (3.948) | (3.621) | (3.375) | (4.299) |
| *G_Score* | ? | -0.211* | -0.203* | -0.201* | -0.192 |
| | | (-1.395) | (-1.336) | (-1.322) | (-1.268) |
| *G_Dummy* | ? | 2.448** | 2.378** | 2.438** | 2.331** |
| | | (1.846) | (1.802) | (1.791) | (1.751) |
| *OverFirm* | + | 0.308 | 0.209 | 6.310*** | 3.068*** |
| | | (0.274) | (0.176) | (4.027) | (2.853) |
| *logAsset* | - | -1.883*** | -1.690*** | -1.878*** | -1.849*** |
| | | (-9.607) | (-8.802) | (-10.460) | (-9.561) |
| *MB* | + | 2.408*** | 2.467*** | 2.397*** | 2.435*** |
| | | (13.251) | (13.590) | (13.616) | (13.332) |
| *σ(Sales)* | - | 0.149 | 0.129 | 0.116 | 0.221 |
| | | (0.201) | (0.176) | (0.155) | (0.298) |
| *σ(CFO)* | + | 11.058*** | 12.079*** | 11.224*** | 11.622*** |
| | | (3.620) | (3.934) | (3.633) | (3.770) |
| *σ(INV)* | + | 0.026*** | 0.026*** | 0.025*** | 0.026*** |
| | | (2.928) | (2.929) | (2.763) | (2.931) |
| *Z_Score* | - | -1.955*** | -2.013*** | -1.970*** | -1.977*** |
| | | (-8.219) | (-8.608) | (-8.202) | (-8.362) |
| *Tangibility* | + | 10.195*** | 9.900*** | 10.235*** | 10.189*** |
| | | (8.540) | (8.471) | (8.532) | (8.609) |
| *Ind_Kstruct* | - | -14.202*** | -14.876*** | -14.076*** | -14.331*** |
| | | (-5.909) | (-6.536) | (-5.740) | (-5.862) |
| *CFOsale* | - | -1.222*** | -1.254*** | -1.248*** | -1.231*** |
| | | (-4.578) | (-4.701) | (-4.659) | (-4.640) |
| *DIV* | - | -0.683* | -0.778** | -0.658* | -0.772** |
| | | (-1.566) | (-1.763) | (-1.515) | (-1.764) |
| *OCycle* | - | -1.756*** | -1.802*** | -1.750*** | -1.761*** |
| | | (-6.246) | (-6.393) | (-6.185) | (-6.247) |
| *Loss* | - | -3.983*** | -4.039*** | -4.101*** | -4.040*** |
| | | (-11.126) | (-11.463) | (-11.623) | (-11.330) |
| *AQ* | + | 9.549 | 14.136** | 16.725** | 13.502** |
| | | (1.196) | (1.825) | (2.153) | (1.732) |
| *AQ x OverFirm* | - | -8.795 | -17.835* | -22.168** | -16.336 |
| | | (-0.663) | (-1.363) | (-1.677) | (-1.235) |
| *Constant* | | 27.918*** | 26.248*** | 24.603*** | 26.304*** |
| | | (8.675) | (8.177) | (8.133) | (8.269) |
| Industry FE | | Yes | Yes | Yes | Yes |
| Firm & Year clusters | | Yes | Yes | Yes | Yes |
| Adjusted R2 | | 0.281 | 0.280 | 0.279 | 0.280 |
| Sample size | | 20,603 | 20,603 | 20,603 | 20,603 |

This table presents the regression analysis results for young firms (financially constrained) where the firm age (*Firm_Age*) is less than or equal to 13. *Firm_Age* is measured as the number of years since the firm first appears in Compustat with a stock price. The first row reports the coefficient estimate and the second row reports the two-way clustered t-statistic based on standard error clustered by firm and year (in parentheses). Industry fixed effect based on Fama and French's classification scheme is included in all regressions but the coefficients are not reported. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively, based on one-tailed tests if the coefficient has a predicted sign, and two-tailed tests otherwise. See Appendix A for other variable definitions.

**TABLE 16**

**Conditional Relation between Investment and Stock Liquidity: Mature Firms (*Firm_Age* > 13)**

| Variable | Pred. Sign | *LIQFHT(1)* | *LIQZERO(2)* | *LIQTURN(3)* | *LIQindex(4)* |
|---|---|---|---|---|---|
| *LIQ (1)* ***$H_{1a}$: under-invest*** | + | 0.776*** | 1.174 | 0.068 | 0.355 |
| | | (2.616) | (0.278) | (0.078) | (0.733) |
| *LIQ x OverFirm (2)* | - | -2.304*** | -12.208** | 0.610 | -1.139** |
| | | (-3.734) | (-1.748) | (0.508) | (-1.697) |
| *(1)+(2)* ***$H_{1b}$: over-invest*** | - | -1.528*** | -11.03*** | 0.678 | -0.784** |
| | | (-3.179) | (-2.780) | (0.866) | (-1.951) |
| *IO* | + | 3.634*** | 3.999*** | 3.164*** | 3.729*** |
| | | (3.993) | (4.443) | (3.837) | (4.439) |
| *Analyst* | + | 0.126*** | 0.118*** | 0.118*** | 0.127*** |
| | | (4.668) | (4.329) | (4.440) | (4.668) |
| *G_Score* | ? | -0.217** | -0.221** | -0.225** | -0.221** |
| | | (-2.182) | (-2.214) | (-2.239) | (-2.218) |
| *G_Dummy* | ? | 1.553** | 1.616** | 1.586** | 1.617** |
| | | (1.815) | (1.884) | (1.844) | (1.882) |
| *OverFirm* | + | 3.230*** | 3.446*** | 3.963*** | 4.392*** |
| | | (3.157) | (3.192) | (2.719) | (4.252) |
| *logAsset* | - | -1.227*** | -1.194*** | -1.282*** | -1.258*** |
| | | (-7.309) | (-7.212) | (-7.682) | (-7.162) |
| *MB* | + | 2.364*** | 2.384*** | 2.317*** | 2.346*** |
| | | (12.576) | (12.593) | (12.358) | (12.369) |
| *σ(Sales)* | - | 1.734** | 1.746** | 1.659** | 1.775** |
| | | (2.238) | (2.243) | (2.127) | (2.250) |
| *σ(CFO)* | + | 15.814*** | 16.432*** | 15.571*** | 16.200*** |
| | | (3.078) | (3.224) | (2.906) | (3.121) |
| *σ(INV)* | + | 0.049*** | 0.050*** | 0.049*** | 0.050*** |
| | | (3.558) | (3.570) | (3.551) | (3.566) |
| *Z_Score* | - | -1.884*** | -1.912*** | -1.893*** | -1.907*** |
| | | (-5.832) | (-5.908) | (-5.833) | (-5.866) |
| *Tangibility* | + | 10.163*** | 10.043*** | 10.227*** | 10.178*** |
| | | (7.533) | (7.406) | (7.519) | (7.547) |
| *Ind_Kstruct* | - | -8.208*** | -8.448*** | -8.234*** | -8.272*** |
| | | (-3.800) | (-4.094) | (-3.917) | (-3.848) |
| *CFOsale* | - | -1.336*** | -1.347*** | -1.353*** | -1.343*** |
| | | (-2.754) | (-2.781) | (-2.779) | (-2.762) |
| *DIV* | - | -1.267*** | -1.278*** | -1.147*** | -1.283*** |
| | | (-4.177) | (-4.218) | (-3.788) | (-4.230) |
| *OCycle* | - | -1.173*** | -1.207*** | -1.164*** | -1.180*** |
| | | (-3.200) | (-3.331) | (-3.158) | (-3.249) |
| *Loss* | - | -3.571*** | -3.592*** | -3.612*** | -3.585*** |
| | | (-10.260) | (-10.614) | (-10.737) | (-10.544) |
| *AQ* | + | 1.928 | 4.849 | 5.463 | 5.000 |
| | | (0.205) | (0.514) | (0.587) | (0.527) |
| *AQ x OverFirm* | - | 2.488 | -3.674 | -4.325 | -3.683 |
| | | (0.159) | (-0.236) | (-0.277) | (-0.235) |
| *Constant* | | 20.619*** | 20.103*** | 20.749*** | 20.317*** |
| | | (6.775) | (6.600) | (6.968) | (6.583) |
| Industry FE | | Yes | Yes | Yes | Yes |
| Firm & Year clusters | | Yes | Yes | Yes | Yes |
| Adjusted R2 | | 0.216 | 0.215 | 0.215 | 0.215 |
| Sample size | | 21,852 | 21,852 | 21,852 | 21,852 |
| Chow Test: *F*-Statistic | | 2.88** | 3.51** | 3.17** | 4.01*** |

This table presents the regression analysis results for mature firms (non-financially constrained) where the firm age (*Firm_Age*) is greater than 13. *Firm_Age* is measured as the number of years since the firm first appears in Compustat with a stock price. The first row reports the coefficient estimate and the second row reports the two-way clustered t-statistic based on standard error clustered by firm and year (in parentheses). The last row reports the Chow test's *F*-Statistic for tests on homogeneity of coefficients on *LIQ* and *LIQxOverFirm* between two subsamples of young and mature firms reported in Table 15 and 16, respectively. Industry fixed effect based on Fama and French's classification scheme is included in all regressions but the coefficients are not reported. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively, based on one-tailed tests if the coefficient has a predicted sign, and two-tailed tests otherwise. See Appendix A for other variable definitions.

**TABLE 17**
**Univariate Analyses for High vs Low Business Risk Firms**

| | High Business Risk (*IncVol*>=0.016) n=20,574 | | | Low Business Risk (*IncVol*<0.016) n=20,581 | | | Test of Differences |
|---|---|---|---|---|---|---|---|
| **Variable** | **Mean** | **Median** | **Std. Dev.** | **Mean** | **Median** | **Std. Dev.** | **t-statistic** |
| *INV* | 17.759 | 11.922 | 18.610 | 11.826 | 8.148 | 12.999 | -37.490*** |
| *LIQFHT* | -0.944 | -0.438 | 1.237 | -0.475 | -0.162 | 0.784 | 45.885*** |
| *LIQZERO* | -0.080 | -0.047 | 0.087 | -0.062 | -0.024 | 0.080 | 22.440*** |
| *LIQTURN* | 0.869 | 0.787 | 0.527 | 0.767 | 0.716 | 0.438 | -21.238*** |
| *LIQindex* | -0.076 | 0.106 | 0.919 | 0.075 | 0.261 | 0.730 | 18.454*** |
| *OverFirm* | 0.521 | 0.556 | 0.230 | 0.497 | 0.500 | 0.217 | -10.684*** |
| *Total assets* | 1,300.019 | 151.336 | 7,107.682 | 4,791.544 | 869.290 | 14683.678 | 30.703*** |
| *logAsset* | 5.177 | 5.019 | 1.815 | 6.843 | 6.768 | 1.817 | 93.067*** |
| *MB* | 2.275 | 1.652 | 1.763 | 1.659 | 1.358 | 1.010 | -43.478*** |
| *σ(Sales)* | 0.336 | 0.246 | 0.296 | 0.234 | 0.160 | 0.238 | -38.407*** |
| *σ(CFO)* | 0.102 | 0.080 | 0.075 | 0.045 | 0.037 | 0.033 | -98.901*** |
| *σ(INV)* | 18.363 | 8.281 | 28.301 | 9.888 | 5.079 | 15.452 | -37.701*** |
| *Z_Score* | 1.040 | 1.218 | 1.590 | 1.491 | 1.425 | 0.974 | 34.757*** |
| *Tangibility* | 0.242 | 0.165 | 0.223 | 0.317 | 0.250 | 0.237 | 33.118*** |
| *Ind_Kstruct* | 0.138 | 0.093 | 0.105 | 0.199 | 0.180 | 0.124 | 53.544*** |
| *CFOsale* | -0.173 | 0.064 | 1.091 | 0.107 | 0.098 | 0.225 | 35.992*** |
| *Slack* | 4.810 | 1.023 | 10.067 | 1.444 | 0.212 | 4.656 | -43.530*** |
| *DIV* | 0.243 | | | 0.532 | | | |
| *Firm_Age* | 14.652 | 11.000 | 12.838 | 24.124 | 18.000 | 18.605 | 60.112*** |
| *OCycle* | 4.645 | 4.727 | 0.791 | 4.559 | 4.641 | 0.704 | -11.606*** |
| *Loss* | 0.395 | | | 0.153 | | | |
| *AQ* | -0.072 | -0.055 | 0.056 | -0.040 | -0.032 | 0.031 | 71.437*** |
| *IO* | 0.444 | 0.417 | 0.298 | 0.606 | 0.652 | 0.262 | 58.751*** |
| *Analyst* | 5.123 | 3.000 | 6.425 | 7.662 | 6.000 | 7.321 | 37.393*** |
| *G_Score* | -0.768 | 0.000 | 2.569 | -1.432 | 0.000 | 3.542 | -21.790*** |
| *G_Dummy* | 0.911 | | | 0.848 | | | |

This table presents the descriptive statistics of variables used in regression analyses for high business risk firms where income volatility (*IncVol*) is greater than or equal to 0.016, and for low business risk firms where *IncVol* is less than 0.016. *IncVol* is defined as the standard deviation of quarterly operating income before depreciation divided by quarterly book value of assets. It is measured over 20 quarters prior to the end of fiscal year *t* with a minimum of 8 quarterly observations. Unvariate analysis results for comparing the means of variables of these two subsamples are reported. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively. See Appendix A for other variable definitions.

**TABLE 18**

**Conditional Relation between Investment and Stock Liquidity: High Business Risk Firms (*IncVol >= 0.016*)**

| Variable | Pr. Sign | *LIQFHT (1)* | *LIQZERO (2)* | *LIQTURN (3)* | *LIQindex (4)* |
|---|---|---|---|---|---|
| *LIQ (1)* ***$H_{1a}$: under-invest*** | + | 1.346*** | 7.922* | 1.472* | 1.257*** |
| | | (5.102) | (1.564) | (1.301) | (2.403) |
| *LIQ x OverFirm (2)* | - | -3.589*** | -35.669*** | -2.175* | -3.498*** |
| | | (-6.037) | (-3.883) | (-1.347) | (-4.148) |
| *(1)+(2)* ***$H_{1b}$: over-invest*** | - | -2.243*** | -27.750*** | -0.703 | -2.241*** |
| | | (-5.109) | (-5.312) | (-0.836) | (-4.285) |
| *IO* | + | 3.879*** | 4.384*** | 3.260*** | 4.017*** |
| | | (4.391) | (5.223) | (3.521) | (4.931) |
| *Analyst* | + | 0.132*** | 0.119*** | 0.117*** | 0.141*** |
| | | (3.391) | (3.137) | (2.934) | (3.766) |
| *G_Score* | ? | -0.389*** | -0.386*** | -0.408*** | -0.380** |
| | | (-2.637) | (-2.617) | (-2.766) | (-2.575) |
| *G_Dummy* | ? | 3.781*** | 3.810*** | 4.014*** | 3.760*** |
| | | (2.844) | (2.864) | (3.014) | (2.825) |
| *OverFirm* | + | 0.999 | 1.037 | 5.638*** | 3.778*** |
| | | (0.793) | (0.792) | (2.982) | (3.114) |
| *logAsset* | - | -1.481*** | -1.363*** | -1.554*** | -1.490*** |
| | | (-6.422) | (-6.064) | (-7.165) | (-6.370) |
| *MB* | + | 2.384*** | 2.419*** | 2.343*** | 2.391*** |
| | | (13.672) | (13.864) | (14.168) | (13.725) |
| *σ(Sales)* | - | -0.279 | -0.254 | -0.286 | -0.163 |
| | | (-0.366) | (-0.338) | (-0.369) | (-0.211) |
| *σ(CFO)* | + | 12.175*** | 12.831*** | 12.100*** | 12.522*** |
| | | (4.080) | (4.411) | (3.919) | (4.192) |
| *σ(INV)* | + | 0.028*** | 0.028*** | 0.027*** | 0.028*** |
| | | (3.174) | (3.164) | (3.003) | (3.158) |
| *Z_Score* | - | -2.231*** | -2.281*** | -2.247*** | -2.250*** |
| | | (-8.303) | (-8.579) | (-8.246) | (-8.385) |
| *Tangibility* | + | 10.121*** | 9.860*** | 10.273*** | 10.175*** |
| | | (8.019) | (7.762) | (8.086) | (8.029) |
| *Ind_Kstruct* | - | -13.701*** | -14.387*** | -13.779*** | -13.986*** |
| | | (-5.006) | (-5.536) | (-4.972) | (-5.060) |
| *CFOsale* | - | -1.105*** | -1.129*** | -1.124*** | -1.122*** |
| | | (-4.277) | (-4.374) | (-4.360) | (-4.372) |
| *DIV* | - | -0.842* | -0.910** | -0.784* | -0.932** |
| | | (-1.569) | (-1.700) | (-1.471) | (-1.756) |
| *Firm_Age* | - | -0.050*** | -0.051*** | -0.051*** | -0.052*** |
| | | (-3.657) | (-3.662) | (-3.636) | (-3.742) |
| *OCycle* | - | -1.933*** | -1.964*** | -1.897*** | -1.919*** |
| | | (-6.604) | (-6.680) | (-6.439) | (-6.530) |
| *Loss* | - | -4.251*** | -4.282*** | -4.295*** | -4.279*** |
| | | (-10.346) | (-10.630) | (-10.643) | (-10.527) |
| *AQ* | + | 3.519 | 7.291 | 9.575 | 6.805 |
| | | (0.436) | (0.904) | (1.186) | (0.843) |
| *AQ x OverFirm* | - | 1.565 | -6.044 | -9.875 | -5.038 |
| | | (0.115) | (-0.443) | (-0.723) | (-0.368) |
| Constant | | 25.631*** | 24.677*** | 23.528*** | 24.516*** |
| | | (8.650) | (8.264) | (7.679) | (8.207) |
| Industry FE | | Yes | Yes | Yes | Yes |
| Firm & Year clusters | | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | | 0.295 | 0.294 | 0.292 | 0.294 |
| Sample size | | 20,574 | 20,574 | 20,574 | 20,574 |

This table presents the regression analysis results for high business risk firms where income volatility (*IncVol*) is greater than or equal to 0.016. *IncVol* is defined as the standard deviation of quarterly operating income before depreciation divided by quarterly book value of assets. It is measured over 20 quarters prior to the end of fiscal year *t* with a minimum of 8 quarterly observations. The first row reports the coefficient estimate and the second row reports the two-way clustered *t*-statistic based on standard error clustered by firm and year (in parentheses). Industry fixed effect based on Fama and French's classification scheme is included in all regressions but the coefficients are not reported. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively, based on one-tailed tests if the coefficient has a predicted sign, and two-tailed tests otherwise. See Appendix A for other variable definitions.

**TABLE 19**

**Conditional Relation between Investment and Stock Liquidity: Low Business Risk Firms (*IncVol* < *0.016*)**

| Variable | Pr. Sign | *LIQFHT (1)* | *LIQZERO (2)* | *LIQTURN (3)* | *LIQindex (4)* |
|---|---|---|---|---|---|
| *LIQ (1)* ***$H_{1a}$: under-invest*** | + | 0.761*** | -2.554 | 0.795 | 0.288 |
| | | (2.413) | (-0.506) | (0.780) | (0.498) |
| *LIQ x OverFirm (2)* | - | -1.851*** | -7.114 | -1.018 | -1.175* |
| | | (-2.766) | (-0.821) | (-0.763) | (-1.427) |
| *(1)+(2)* ***$H_{1b}$: over-invest*** | - | -1.090** | -9.667** | -0.223 | -0.886** |
| | | (-1.919) | (-1.989) | (-0.317) | (-1.877) |
| *IO* | + | 3.738*** | 4.547*** | 3.588*** | 4.158*** |
| | | (3.950) | (4.926) | (4.635) | (4.736) |
| *Analyst* | + | 0.135*** | 0.122*** | 0.130*** | 0.134*** |
| | | (5.792) | (5.168) | (5.564) | (5.841) |
| *G_Score* | ? | -0.268*** | -0.267*** | -0.271*** | -0.267*** |
| | | (-3.193) | (-3.180) | (-3.226) | (-3.187) |
| *G_Dummy* | ? | 2.229*** | 2.222*** | 2.243*** | 2.252*** |
| | | (2.738) | (2.726) | (2.749) | (2.762) |
| *OverFirm* | + | 2.871*** | 3.209*** | 4.533*** | 3.806*** |
| | | (2.874) | (3.038) | (3.328) | (3.891) |
| *logAsset* | - | -1.324*** | -1.229*** | -1.345*** | -1.305*** |
| | | (-9.410) | (-8.958) | (-9.884) | (-8.924) |
| *MB* | + | 2.090*** | 2.148*** | 2.065*** | 2.099*** |
| | | (10.635) | (10.818) | (10.609) | (10.664) |
| *σ(Sales)* | - | 2.428*** | 2.361*** | 2.359*** | 2.436*** |
| | | (3.609) | (3.512) | (3.541) | (3.575) |
| *σ(CFO)* | + | 5.943 | 6.573* | 5.718 | 6.512* |
| | | (1.215) | (1.344) | (1.155) | (1.323) |
| *σ(INV)* | + | 0.033*** | 0.033*** | 0.032*** | 0.033*** |
| | | (2.941) | (2.964) | (2.888) | (2.942) |
| *Z_Score* | - | -0.970*** | -0.989*** | -0.956*** | -0.992*** |
| | | (-4.310) | (-4.426) | (-4.360) | (-4.422) |
| *Tangibility* | + | 10.688*** | 10.542*** | 10.719*** | 10.642*** |
| | | (8.434) | (8.567) | (8.424) | (8.553) |
| *Ind_Kstruct* | - | -10.330*** | -10.705*** | -10.413*** | -10.485*** |
| | | (-5.536) | (-6.082) | (-5.750) | (-5.670) |
| *CFOsale* | - | 1.548*** | 1.549*** | 1.564*** | 1.574*** |
| | | (2.375) | (2.348) | (2.387) | (2.387) |
| *DIV* | - | -1.177*** | -1.184*** | -1.132*** | -1.195*** |
| | | (-3.834) | (-3.867) | (-3.736) | (-3.922) |
| *Firm_Age* | - | -0.017*** | -0.017*** | -0.018*** | -0.018*** |
| | | (-2.543) | (-2.508) | (-2.616) | (-2.631) |
| *OCycle* | - | -0.302 | -0.351 | -0.298 | -0.323 |
| | | (-0.882) | (-1.063) | (-0.861) | (-0.973) |
| *Loss* | - | -2.854*** | -2.905*** | -2.909*** | -2.889*** |
| | | (-10.284) | (-10.646) | (-10.648) | (-10.590) |
| *AQ* | + | 13.897** | 14.712** | 15.558** | 15.176** |
| | | (1.665) | (1.764) | (1.854) | (1.812) |
| *AQ x OverFirm* | - | -15.515 | -18.419 | -19.036 | -18.433 |
| | | (-0.836) | (-0.977) | (-1.005) | (-0.973) |
| Constant | | 16.691*** | 15.352*** | 15.963*** | 16.010*** |
| | | (6.346) | (5.556) | (6.217) | (5.838) |
| Industry FE | | Yes | Yes | Yes | Yes |
| Firm & Year clusters | | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | | 0.151 | 0.151 | 0.150 | 0.150 |
| Sample size | | 20,581 | 20,581 | 20,581 | 20,581 |
| Chow Test: *F*-Statistic | | 2.34* | 4.45*** | 0.79 | 3.12** |

This table presents the regression analysis results for low business risk firms where income volatility (*IncVol*) is less than 0.016. *IncVol* is defined as the standard deviation of quarterly operating income before depreciation divided by quarterly book value of assets. It is measured over 20 quarters prior to the end of fiscal year *t* with a minimum of 8 quarterly observations. The first row reports the coefficient estimate and the second row reports the two-way clustered *t*-statistic based on standard error clustered by firm and year (in parentheses). The last row reports the Chow test's *F*-Statistic for tests on homogeneity of coefficients on *LIQ* and *LIQxOverFirm* between two subsamples of high and low business risk firms reported in Tables 18 and 19, respectively. Industry fixed effect based on Fama and French's classification scheme is included in all regressions but the coefficients are not reported. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively, based on one-tailed tests if the coefficient has a predicted sign, and two-tailed tests otherwise. See Appendix A for other variable definitions.

**TABLE 20**
**Univariate Analyses for High vs Low Proportion of Monitoring Institutional Ownership**

| Variable | High Monitoring IO (*MonIO*>=10.7%) n=14,509 Mean | Median | Std. Dev. | Low Monitoring IO (*MonIO <10.7%*) n=14,511 Mean | Median | Std. Dev. | Test of Differences t-statistic |
|---|---|---|---|---|---|---|---|
| *INV* | 15.515 | 10.546 | 16.166 | 14.986 | 9.943 | 16.009 | -2.798*** |
| *LIQFHT* | -0.516 | -0.222 | 0.714 | -0.401 | -0.162 | 0.594 | 14.888*** |
| *LIQZERO* | -0.061 | -0.028 | 0.072 | -0.050 | -0.020 | 0.065 | 13.592*** |
| *LIQTURN* | 0.840 | 0.760 | 0.476 | 0.908 | 0.867 | 0.474 | 12.177*** |
| *LIQindex* | -0.079 | 0.125 | 0.868 | 0.079 | 0.276 | 0.777 | 16.402*** |
| *OverFirm* | 0.530 | 0.556 | 0.219 | 0.536 | 0.556 | 0.216 | 2.667*** |
| *Total assets* | 3594.924 | 580.887 | 11049.212 | 3924.075 | 576.568 | 14845.005 | 2.142** |
| *logAsset* | 6.446 | 6.365 | 1.885 | 6.503 | 6.357 | 1.772 | 2.640*** |
| *MB* | 1.992 | 1.518 | 1.426 | 2.045 | 1.527 | 1.492 | 3.081*** |
| *σ(Sales)* | 0.267 | 0.187 | 0.261 | 0.265 | 0.186 | 0.257 | -0.497 |
| *σ(CFO)* | 0.067 | 0.050 | 0.057 | 0.069 | 0.050 | 0.062 | 3.125*** |
| *σ(INV)* | 13.707 | 6.704 | 21.095 | 14.676 | 6.561 | 24.186 | 3.637*** |
| *Z_Score* | 1.210 | 1.253 | 1.207 | 1.230 | 1.262 | 1.228 | 1.362 |
| *Tangibility* | 0.285 | 0.207 | 0.237 | 0.289 | 0.210 | 0.242 | 1.338 |
| *Ind_Kstruct* | 0.172 | 0.143 | 0.120 | 0.176 | 0.142 | 0.125 | 2.755*** |
| *CFOsale* | -0.016 | 0.093 | 0.772 | -0.009 | 0.100 | 0.787 | 0.759 |
| *Slack* | 2.963 | 0.397 | 7.471 | 3.187 | 0.447 | 7.974 | 2.477** |
| *DIV* | 0.397 | | | 0.443 | | | |
| *Firm_Age* | 19.616 | 14.000 | 17.428 | 20.974 | 14.000 | 18.350 | 6.464*** |
| *OCycle* | 4.577 | 4.672 | 0.772 | 4.592 | 4.654 | 0.716 | 1.623 |
| *Loss* | 0.270 | | | 0.235 | | | |
| *AQ* | -0.051 | -0.039 | 0.042 | -0.050 | -0.038 | 0.043 | 2.291** |
| *MonIO* | 0.240 | 0.197 | 0.137 | 0.042 | 0.038 | 0.033 | -169.074*** |
| *Analyst* | 7.739 | 6.000 | 7.359 | 7.252 | 5.000 | 6.600 | -5.937*** |
| *G_Score* | -1.389 | 0.000 | 3.448 | -1.198 | 0.000 | 3.226 | 4.887*** |
| *G_Dummy* | 0.848 | | | 0.869 | | | |

This table presents the descriptive statistics of variables used in regression analyses for firms with high proportion of institutional ownership (*MonIO*) where *MonIO* is greater than or equal to 10.7%, and for firms with low proportion of institutional ownership where *MonIO* is less than 10.7%. *MonIO* is computed as the total number of monitoring IO divided by the sum of monitoring and non-monitoring IO. Monitoring institutions are defined in Bushee's (2001) as dedicated institutions that are also classified as independent by Brickley et al. (1988). Non-monitoring institutions are defined as either Transient institutions (Bushee 2001), Quasi-indexing institutions (Bushee 2001), or Bushee's (2001) dedicated institutions that are also classified as non-independent by Brickley et al. (1988). Unvariate analysis results for comparing the means of variables of these two subsamples are reported. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively. See Appendix A for other variable definitions.

**TABLE 21**

**Conditional Relation between Investment and Stock Liquidity: High Proportion of Monitoring Institutions (*MonIO* >= 10.7%)**

| Variable | Pr. Sign | *LIQFHT (1)* | *LIQZERO (2)* | *LIQTURN (3)* | *LIQindex (4)* |
|---|---|---|---|---|---|
| *LIQ (1)* ***$H_{1a}$: under-invest*** | + | 2.278*** | 9.406 | 2.489** | 1.431** |
| | | (3.812) | (1.278) | (2.192) | (2.296) |
| *LIQ x OverFirm (2)* | - | -5.676*** | -31.302** | -2.921* | -3.171*** |
| | | (-5.376) | (-2.386) | (-1.600) | (-3.212) |
| *(1)+(2)* ***$H_{1b}$: over-invest*** | - | -3.398*** | -21.900*** | -0.432 | -1.739*** |
| | | (-5.377) | (-3.135) | (-0.468) | (-3.542) |
| *Analyst* | + | 0.160*** | 0.152*** | 0.149*** | 0.165*** |
| | | (4.370) | (4.176) | (3.983) | (4.543) |
| *G_Score* | ? | -0.302*** | -0.306*** | -0.319*** | -0.303*** |
| | | (-2.782) | (-2.816) | (-2.933) | (-2.781) |
| *G_Dummy* | ? | 2.920*** | 2.970*** | 3.082*** | 2.952*** |
| | | (2.809) | (2.854) | (2.961) | (2.837) |
| *OverFirm* | + | 1.761* | 2.358** | 6.725*** | 4.103*** |
| | | (1.360) | (1.752) | (3.482) | (3.370) |
| *logAsset* | - | -1.608*** | -1.564*** | -1.834*** | -1.697*** |
| | | (-8.457) | (-8.051) | (-9.232) | (-8.724) |
| *MB* | + | 2.545*** | 2.560*** | 2.461*** | 2.532*** |
| | | (11.986) | (11.960) | (12.217) | (11.953) |
| *σ(Sales)* | - | -0.170 | -0.166 | -0.248 | -0.076 |
| | | (-0.212) | (-0.208) | (-0.301) | (-0.094) |
| *σ(CFO)* | + | 18.268*** | 18.901*** | 17.585*** | 18.543*** |
| | | (4.192) | (4.306) | (3.959) | (4.219) |
| *σ(INV)* | + | 0.027** | 0.027** | 0.027** | 0.027** |
| | | (2.121) | (2.126) | (2.111) | (2.149) |
| *Z_Score* | - | -1.961*** | -2.013*** | -1.973*** | -1.997*** |
| | | (-7.035) | (-7.329) | (-6.972) | (-7.186) |
| *Tangibility* | + | 10.888*** | 10.754*** | 11.161*** | 10.941*** |
| | | (7.704) | (7.647) | (7.404) | (7.660) |
| *Ind_Kstruct* | - | -11.786*** | -11.939*** | -11.507*** | -11.627*** |
| | | (-4.547) | (-4.842) | (-4.269) | (-4.421) |
| *CFOsale* | - | -1.170*** | -1.201*** | -1.209*** | -1.189*** |
| | | (-3.370) | (-3.416) | (-3.376) | (-3.383) |
| *DIV* | - | -1.452*** | -1.474*** | -1.213*** | -1.482*** |
| | | (-3.896) | (-3.925) | (-3.194) | (-3.922) |
| *Firm_Age* | - | -0.021*** | -0.022*** | -0.019** | -0.023*** |
| | | (-2.363) | (-2.559) | (-2.177) | (-2.569) |
| *OCycle* | - | -2.180*** | -2.210*** | -2.149*** | -2.175*** |
| | | (-6.709) | (-6.745) | (-6.527) | (-6.641) |
| *Loss* | - | -3.289*** | -3.312*** | -3.389*** | -3.304*** |
| | | (-8.845) | (-8.941) | (-9.114) | (-8.908) |
| *AQ* | + | 15.161* | 21.157** | 22.462** | 20.444** |
| | | (1.377) | (1.916) | (2.011) | (1.841) |
| *AQ x OverFirm* | - | -11.786 | -23.423 | -25.977* | -22.097 |
| | | (-0.632) | (-1.251) | (-1.372) | (-1.173) |
| Constant | | 31.613*** | 31.064*** | 29.822*** | 31.139*** |
| | | (10.687) | (10.265) | (9.401) | (10.431) |
| Industry FE | | Yes | Yes | Yes | Yes |
| Firm & Year clusters | | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | | 0.301 | 0.299 | 0.299 | 0.299 |
| Sample size | | 14,509 | 14,509 | 14,509 | 14,509 |

This table presents the regression analysis results for firms with high proportion of institutional ownership (*MonIO*) where *MonIO* is greater than or equal to 10.7%. *MonIO* is computed as the total number of monitoring IO divided by the sum of monitoring and non-monitoring IO. Monitoring institutions are defined in Bushee's (2001) as dedicated institutions that are also classified as independent by Brickley et al. (1988). Non-monitoring institutions are defined as either Transient institutions (Bushee 2001), Quasi-indexing institutions (Bushee 2001), or Bushee's (2001) dedicated institutions that are also classified as non-independent by Brickley et al. (1988). The first row reports the coefficient estimate and the second row reports the two-way clustered *t*-statistic based on standard error clustered by firm and year (in parentheses). Industry fixed effect based on Fama and French's classification scheme is included in all regressions but the coefficients are not reported. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively, based on one-tailed tests if the coefficient has a predicted sign, and two-tailed tests otherwise. See Appendix A for other variable definitions.

**TABLE 22**

**Conditional Relation between Investment and Stock Liquidity: Low Proportion of Monitoring Institutions (*MonIO < 10.7%*)**

| Variable | Pr. Sign | *LIQFHT (1)* | *LIQZERO (2)* | *LIQTURN (3)* | *LIQindex (4)* |
|---|---|---|---|---|---|
| *LIQ (1)* ***$H_{1a}$: under-invest*** | + | 1.012** | 5.302 | 2.033** | 0.806* |
| | | (1.815) | (0.910) | (1.651) | (1.475) |
| *LIQ x OverFirm (2)* | - | -2.746** | -19.711* | -2.604* | -1.810** |
| | | (-2.359) | (-1.666) | (-1.441) | (-1.834) |
| *(1)+(2)* ***$H_{1b}$: over-invest*** | - | -1.734** | -14.410** | -0.571 | -1.005* |
| | | (-1.786) | (-1.962) | (-0.561) | (-1.613) |
| *Analyst* | + | 0.156*** | 0.150*** | 0.153*** | 0.159*** |
| | | (4.594) | (4.301) | (4.479) | (4.608) |
| *G_Score* | ? | -0.336*** | -0.337*** | -0.345*** | -0.335*** |
| | | (-2.772) | (-2.778) | (-2.845) | (-2.762) |
| *G_Dummy* | ? | 3.098*** | 3.114*** | 3.136*** | 3.106*** |
| | | (2.684) | (2.698) | (2.717) | (2.691) |
| *OverFirm* | + | 1.976* | 1.908* | 5.162*** | 3.063*** |
| | | (1.547) | (1.444) | (3.097) | (2.481) |
| *logAsset* | - | -1.373*** | -1.333*** | -1.515*** | -1.418*** |
| | | (-7.767) | (-7.899) | (-9.007) | (-8.429) |
| *MB* | + | 2.173*** | 2.187*** | 2.136*** | 2.163*** |
| | | (12.384) | (12.375) | (12.741) | (12.326) |
| *σ(Sales)* | - | 0.969 | 0.987 | 0.969 | 1.078 |
| | | (1.067) | (1.064) | (1.042) | (1.156) |
| *σ(CFO)* | + | 14.160*** | 14.470*** | 13.703*** | 14.335*** |
| | | (3.068) | (3.159) | (2.872) | (3.081) |
| *σ(INV)* | + | 0.027*** | 0.027*** | 0.027*** | 0.027*** |
| | | (3.299) | (3.308) | (3.193) | (3.295) |
| *Z_Score* | - | -2.139*** | -2.156*** | -2.138*** | -2.160*** |
| | | (-7.587) | (-7.657) | (-7.459) | (-7.691) |
| *Tangibility* | + | 10.141*** | 10.053*** | 10.442*** | 10.224*** |
| | | (8.256) | (8.077) | (8.354) | (8.344) |
| *Ind_Kstruct* | - | -13.158*** | -13.289*** | -12.978*** | -13.083*** |
| | | (-6.538) | (-6.612) | (-6.411) | (-6.404) |
| *CFOsale* | - | -1.536*** | -1.542*** | -1.554*** | -1.537*** |
| | | (-4.911) | (-4.942) | (-4.999) | (-4.919) |
| *DIV* | - | -1.495*** | -1.544*** | -1.369*** | -1.516*** |
| | | (-3.779) | (-3.951) | (-3.401) | (-3.950) |
| *Firm_Age* | - | -0.020** | -0.021** | -0.019** | -0.021** |
| | | (-1.780) | (-1.843) | (-1.784) | (-1.870) |
| *OCycle* | - | -1.473*** | -1.480*** | -1.433*** | -1.457*** |
| | | (-3.805) | (-3.865) | (-3.701) | (-3.786) |
| *Loss* | - | -4.196*** | -4.185*** | -4.210*** | -4.186*** |
| | | (-8.863) | (-8.855) | (-9.056) | (-8.907) |
| *AQ* | + | 11.017 | 13.797 | 14.428 | 13.357 |
| | | (0.923) | (1.174) | (1.223) | (1.136) |
| *AQ x OverFirm* | - | -1.123 | -6.405 | -7.073 | -5.638 |
| | | (-0.058) | (-0.336) | (-0.371) | (-0.295) |
| Constant | | 26.072*** | 25.887*** | 24.698*** | 25.886*** |
| | | (7.703) | (7.556) | (7.428) | (7.567) |
| Industry FE | | Yes | Yes | Yes | Yes |
| Firm & Year clusters | | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | | 0.263 | 0.263 | 0.263 | 0.263 |
| Sample size | | 14,511 | 14,511 | 14,511 | 14,511 |
| Chow Test: *F*-Statistic | | 6.72*** | 3.48** | 4.77*** | 1.38 |

This table presents the regression analysis results for firms with low proportion of institutional ownership (*MonIO*) where *MonIO* is less than 10.7%. *MonIO* is computed as the total number of monitoring IO divided by the sum of monitoring and non-monitoring IO. Monitoring institutions are defined in Bushee's (2001) as dedicated institutions that are also classified as independent by Brickley et al. (1988). Non-monitoring institutions are defined as either Transient institutions (Bushee 2001), Quasi-indexing institutions (Bushee 2001), or Bushee's (2001) dedicated institutions that are also classified as non-independent by Brickley et al. (1988). The first row reports the coefficient estimate and the second row reports the two-way clustered *t*-statistic based on standard error clustered by firm and year (in parentheses). The last row reports the Chow test's *F*-Statistic for tests on homogeneity of coefficients on *LIQ* and *LIQxOverFirm* between two subsamples of firms with high and low proportion of monitoring institutions reported in Tables 21 and 22, respectively. Industry fixed effect based on Fama and French's classification scheme is included in all regressions but the coefficients are not reported. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively, based on one-tailed tests if the coefficient has a predicted sign, and two-tailed tests otherwise. See Appendix A for other variable definitions.

**TABLE 23**

**Conditional Relation between Investment and Stock Liquidity: Top Tertile of Monitoring Institutions (*MonIO* >= 16.3%)**

| Variable | Pr. Sign | *LIQFHT (1)* | *LIQZERO (2)* | *LIQTURN (3)* | *LIQindex (4)* |
|---|---|---|---|---|---|
| *LIQ (1)* ***$H_{1a}$: under-invest*** | + | 2.098*** | 6.829 | 1.774* | 1.174** |
| | | (3.139) | (0.849) | (1.417) | (1.737) |
| *LIQ x OverFirm (2)* | - | -5.789*** | -28.496** | -1.596 | -2.995*** |
| | | (-4.938) | (-2.026) | (-0.772) | (-2.753) |
| *(1)+(2)* ***$H_{1b}$: over-invest*** | - | -3.691*** | -21.670*** | 0.178 | -1.821*** |
| | | (-5.349) | (-3.066) | (0.167) | (-3.335) |
| *Analyst* | + | 0.164*** | 0.158*** | 0.148*** | 0.171*** |
| | | (3.825) | (3.672) | (3.356) | (4.036) |
| *G_Score* | ? | -0.285** | -0.288** | -0.306** | -0.284** |
| | | (-2.100) | (-2.118) | (-2.250) | (-2.088) |
| *G_Dummy* | ? | 3.038** | 3.085** | 3.275** | 3.056** |
| | | (2.335) | (2.368) | (2.511) | (2.345) |
| *OverFirm* | + | 1.549 | 2.516* | 5.807*** | 3.998*** |
| | | (0.992) | (1.538) | (2.963) | (2.748) |
| *logAsset* | - | -1.550*** | -1.533*** | -1.814*** | -1.645*** |
| | | (-6.949) | (-6.677) | (-7.502) | (-7.055) |
| *MB* | + | 2.786*** | 2.782*** | 2.662*** | 2.767*** |
| | | (12.579) | (12.415) | (12.361) | (12.327) |
| *σ(Sales)* | - | 0.093 | 0.091 | 0.039 | 0.199 |
| | | (0.099) | (0.096) | (0.041) | (0.207) |
| *σ(CFO)* | + | 19.271*** | 20.022*** | 18.631*** | 19.742*** |
| | | (3.699) | (3.772) | (3.414) | (3.694) |
| *σ(INV)* | + | 0.029** | 0.029** | 0.028** | 0.029** |
| | | (1.908) | (1.916) | (1.869) | (1.920) |
| *Z_Score* | - | -1.878*** | -1.942*** | -1.911*** | -1.923*** |
| | | (-5.801) | (-6.086) | (-5.890) | (-5.982) |
| *Tangibility* | + | 11.044*** | 10.878*** | 11.332*** | 11.085*** |
| | | (7.098) | (6.982) | (6.779) | (7.048) |
| *Ind_Kstruct* | - | -11.628*** | -11.710*** | -11.331*** | -11.466*** |
| | | (-3.334) | (-3.498) | (-3.161) | (-3.271) |
| *CFOsale* | - | -1.114*** | -1.149*** | -1.156*** | -1.135*** |
| | | (-2.856) | (-2.907) | (-2.886) | (-2.879) |
| *DIV* | - | -1.206*** | -1.230*** | -0.964** | -1.265*** |
| | | (-2.748) | (-2.723) | (-2.139) | (-2.834) |
| *Firm_Age* | - | -0.020** | -0.022** | -0.019** | -0.022** |
| | | (-1.907) | (-2.074) | (-1.766) | (-2.114) |
| *OCycle* | - | -2.302*** | -2.328*** | -2.275*** | -2.298*** |
| | | (-6.032) | (-6.039) | (-5.880) | (-5.960) |
| *Loss* | - | -2.790*** | -2.801*** | -2.888*** | -2.802*** |
| | | (-6.333) | (-6.380) | (-6.549) | (-6.376) |
| *AQ* | + | 19.766* | 26.187** | 27.142** | 25.669** |
| | | (1.622) | (2.130) | (2.181) | (2.082) |
| *AQ x OverFirm* | - | -16.617 | -29.590* | -31.325* | -28.343* |
| | | (-0.787) | (-1.390) | (-1.453) | (-1.328) |
| Constant | | 30.484*** | 29.918*** | 29.510*** | 30.071*** |
| | | (9.081) | (8.855) | (8.041) | (8.955) |
| Industry FE | | Yes | Yes | Yes | Yes |
| Firm & Year clusters | | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | | 0.314 | 0.312 | 0.311 | 0.312 |
| Sample size | | 9,674 | 9,674 | 9,674 | 9,674 |

This table presents the regression analysis results for firms with high proportion of institutional ownership (*MonIO*) where *MonIO* is greater than or equal to 16.3%. *MonIO* is computed as the total number of monitoring IO divided by the sum of monitoring and non-monitoring IO. Monitoring institutions are defined in Bushee's (2001) as dedicated institutions that are also classified as independent by Brickley et al. (1988). Non-monitoring institutions are defined as either Transient institutions (Bushee 2001), Quasi-indexing institutions (Bushee 2001), or Bushee's (2001) dedicated institutions that are also classified as non-independent by Brickley et al. (1988). The first row reports the coefficient estimate and the second row reports the two-way clustered *t*-statistic based on standard error clustered by firm and year (in parentheses). Industry fixed effect based on Fama and French's classification scheme is included in all regressions but the coefficients are not reported. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively, based on one-tailed tests if the coefficient has a predicted sign, and two-tailed tests otherwise. See Appendix A for other variable definitions.

**TABLE 24**

**Conditional Relation between Investment and Stock Liquidity: Bottom Tertile of Monitoring Institutions (*MonIO < 5.9%*)**

| Variable | Pr. Sign | *LIQFHT (1)* | *LIQZERO (2)* | *LIQTURN (3)* | *LIQindex (4)* |
|---|---|---|---|---|---|
| *LIQ (1)* ***$H_{1a}$: under-invest*** | + | 0.690 | 2.732 | 1.213 | 0.445 |
| | | (1.082) | (0.459) | (1.030) | (0.853) |
| *LIQ x OverFirm (2)* | - | -1.915* | -13.962 | -0.964 | -0.978 |
| | | (-1.451) | (-1.098) | (-0.541) | (-0.952) |
| *(1)+(2)* ***$H_{1b}$: over-invest*** | - | -1.224 | -11.230* | 0.249 | -0.533 |
| | | (-1.074) | (-1.418) | (0.229) | (-0.769) |
| *Analyst* | + | 0.181*** | 0.176*** | 0.172*** | 0.182*** |
| | | (4.439) | (4.136) | (4.179) | (4.429) |
| *G_Score* | ? | -0.176 | -0.176 | -0.184 | -0.176 |
| | | (-1.145) | (-1.146) | (-1.195) | (-1.148) |
| *G_Dummy* | ? | 1.239 | 1.247 | 1.255 | 1.252 |
| | | (0.810) | (0.814) | (0.822) | (0.818) |
| *OverFirm* | + | 1.767 | 1.717 | 3.255** | 2.504** |
| | | (1.141) | (1.061) | (1.672) | (1.673) |
| *logAsset* | - | -1.291*** | -1.240*** | -1.417*** | -1.329*** |
| | | (-6.921) | (-6.464) | (-7.688) | (-6.878) |
| *MB* | + | 2.287*** | 2.304*** | 2.247*** | 2.276*** |
| | | (11.459) | (11.439) | (11.258) | (11.297) |
| *σ(Sales)* | - | 1.129 | 1.126 | 1.064 | 1.206 |
| | | (1.193) | (1.154) | (1.041) | (1.222) |
| *σ(CFO)* | + | 13.040*** | 13.316*** | 12.376*** | 13.046*** |
| | | (2.730) | (2.809) | (2.536) | (2.709) |
| *σ(INV)* | + | 0.018** | 0.018** | 0.017** | 0.018** |
| | | (2.010) | (2.021) | (1.936) | (2.008) |
| *Z_Score* | - | -2.128*** | -2.140*** | -2.115*** | -2.141*** |
| | | (-7.068) | (-7.145) | (-6.939) | (-7.133) |
| *Tangibility* | + | 9.600*** | 9.497*** | 9.856*** | 9.687*** |
| | | (6.696) | (6.604) | (6.872) | (6.750) |
| *Ind_Kstruct* | - | -14.247*** | -14.421*** | -13.960*** | -14.191*** |
| | | (-5.724) | (-5.861) | (-5.503) | (-5.569) |
| *CFOsale* | - | -1.680*** | -1.686*** | -1.702*** | -1.689*** |
| | | (-5.043) | (-5.069) | (-5.119) | (-5.068) |
| *DIV* | - | -1.419*** | -1.471*** | -1.281*** | -1.428*** |
| | | (-2.604) | (-2.748) | (-2.412) | (-2.731) |
| *Firm_Age* | - | -0.028** | -0.028** | -0.027** | -0.028** |
| | | (-2.131) | (-2.169) | (-2.098) | (-2.154) |
| *OCycle* | - | -1.992*** | -2.003*** | -1.966*** | -1.976*** |
| | | (-3.850) | (-3.916) | (-3.790) | (-3.843) |
| *Loss* | - | -4.495*** | -4.490*** | -4.497*** | -4.487*** |
| | | (-9.773) | (-9.936) | (-10.118) | (-9.924) |
| *AQ* | + | 11.850 | 13.970 | 13.709 | 13.625 |
| | | (0.828) | (0.990) | (0.965) | (0.965) |
| *AQ x OverFirm* | - | 4.227 | 0.154 | 1.199 | 0.698 |
| | | (0.183) | (0.007) | (0.053) | (0.031) |
| Constant | | 30.163*** | 29.900*** | 29.520*** | 30.035*** |
| | | (7.110) | (6.982) | (7.224) | (6.994) |
| Industry FE | | Yes | Yes | Yes | Yes |
| Firm & Year clusters | | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | | 0.267 | 0.267 | 0.267 | 0.267 |
| Sample size | | 9,673 | 9,673 | 9,673 | 9,673 |
| Chow Test: *F*-Statistic | | 10.21*** | 4.86*** | 6.88*** | 2.50* |

This table presents the regression analysis results for firms with low proportion of institutional ownership (*MonIO*) where *MonIO* is less than 5.9%. *MonIO* is computed as the total number of monitoring IO divided by the sum of monitoring and non-monitoring IO. Monitoring institutions are defined in Bushee's (2001) as dedicated institutions that are also classified as independent by Brickley et al. (1988). Non-monitoring institutions are defined as either Transient institutions (Bushee 2001), Quasi-indexing institutions (Bushee 2001), or Bushee's (2001) dedicated institutions that are also classified as non-independent by Brickley et al. (1988). The first row reports the coefficient estimate and the second row reports the two-way clustered *t*-statistic based on standard error clustered by firm and year (in parentheses). The last row reports the Chow test's *F*-Statistic for tests on homogeneity of coefficients on *LIQ* and *LIQxOverFirm* between two subsamples of firms with top and bottom tertile of monitoring institutions reported in Tables 23 and 24, respectively. Industry fixed effect based on Fama and French's classification scheme is included in all regressions but the coefficients are not reported. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively, based on one-tailed tests if the coefficient has a predicted sign, and two-tailed tests otherwise. See Appendix A for other variable definitions.

**FIGURE 1**

**A Conceptual Framework on the Relationship between Stock Liquidity and Investment Efficiency.**

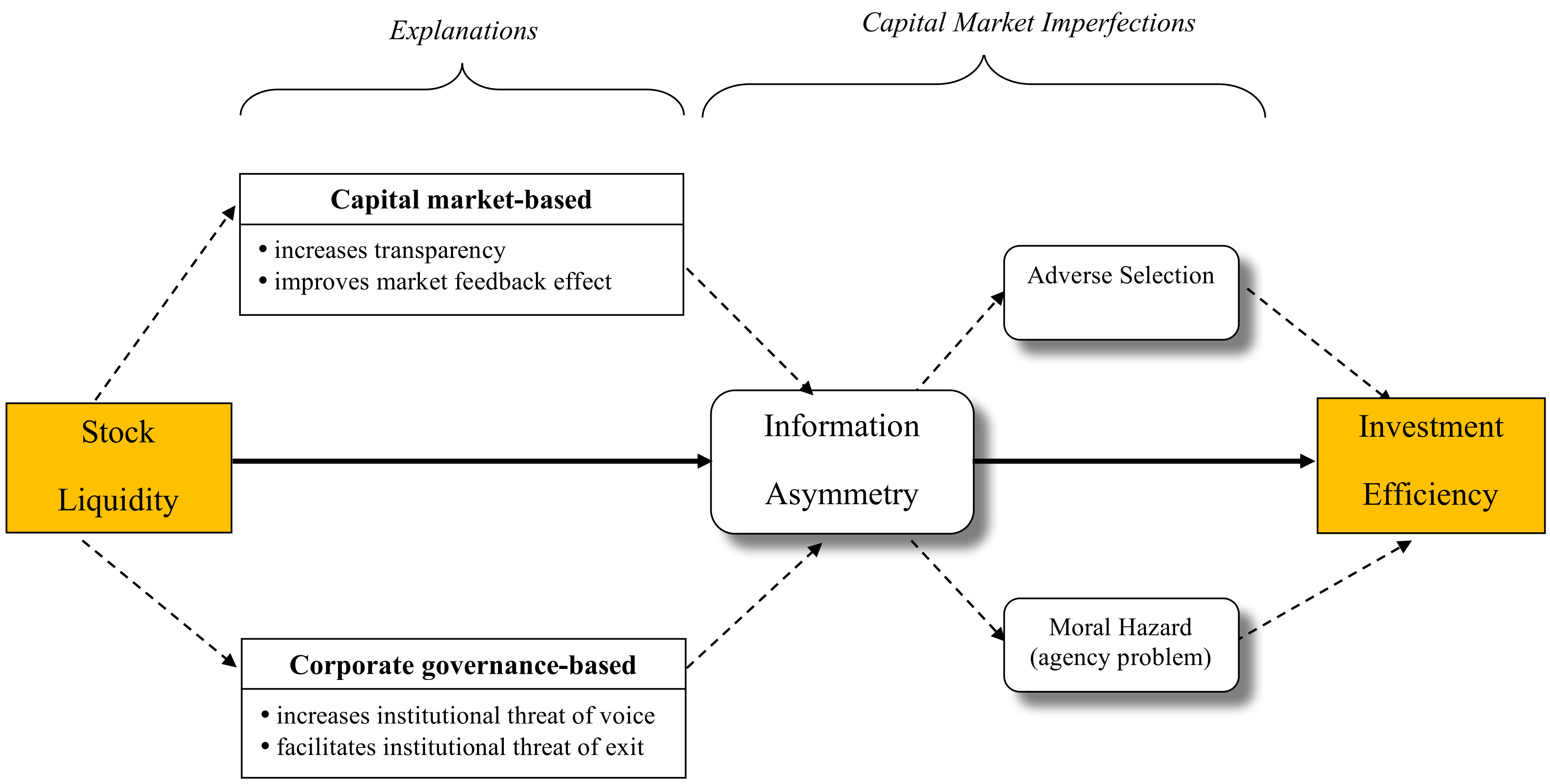
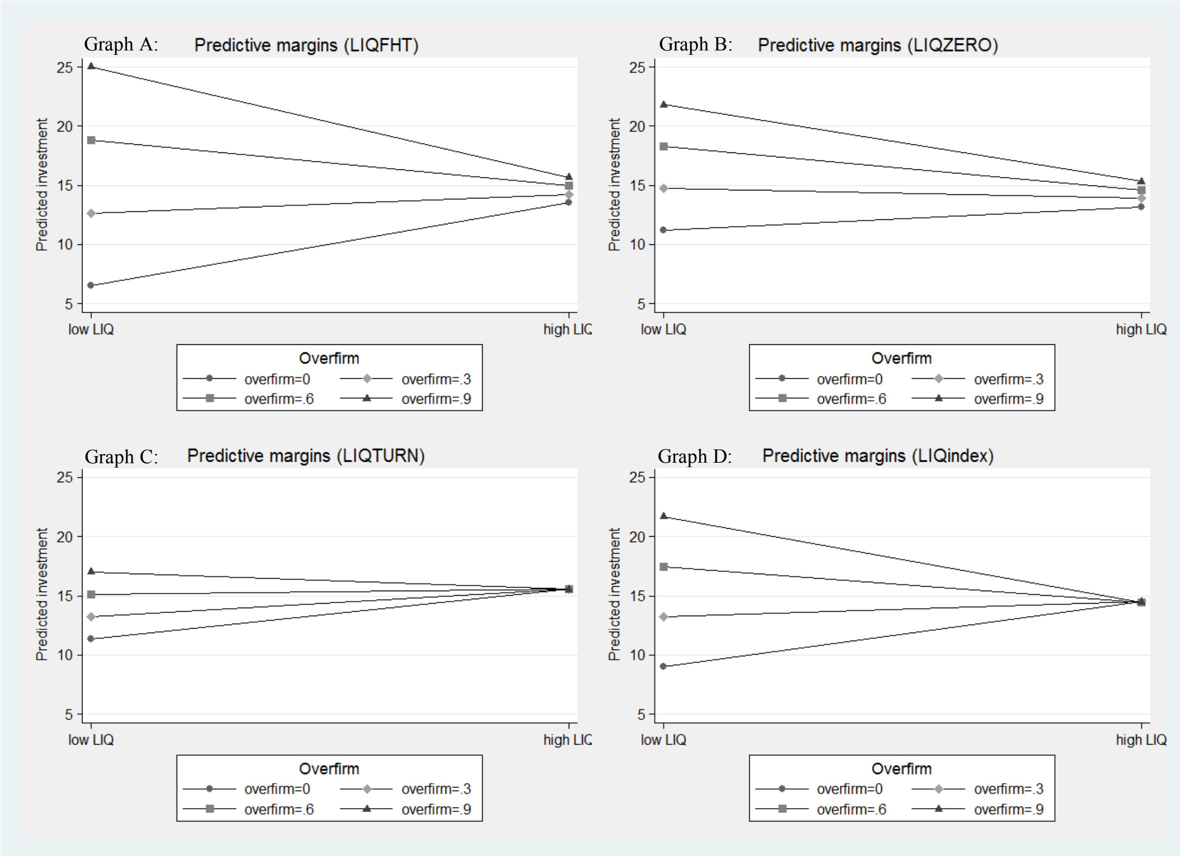


**FIGURE 2**
**The Marginal Effects of Stock Liquidity on Predicted Investment Levels across *OverFirm* Levels (Main Tests)**

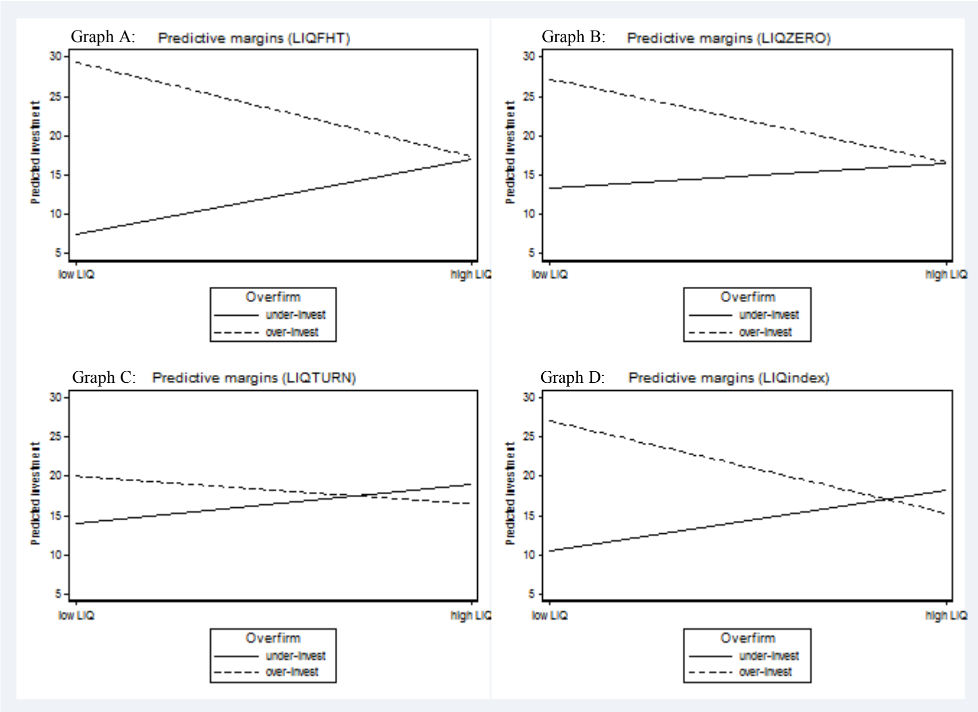



For each stock liquidity proxy (Graph A to D), the vertical axis plots predicted investment levels, while the horizontal axis plots the predictive margins of stock liquidity, and with separate lines for each level of *OverFirm* (the likelihood of overinvestment) ranging from 0 to 0.9 in 0.3 unit increments. This figure provides visual evidence in support of the main results reported in Table 4, depicting the degree to which investment efficiency is affected by stock liquidity. That is, it shows how stock liquidity slopes vary with increasing values of *OverFirm*.

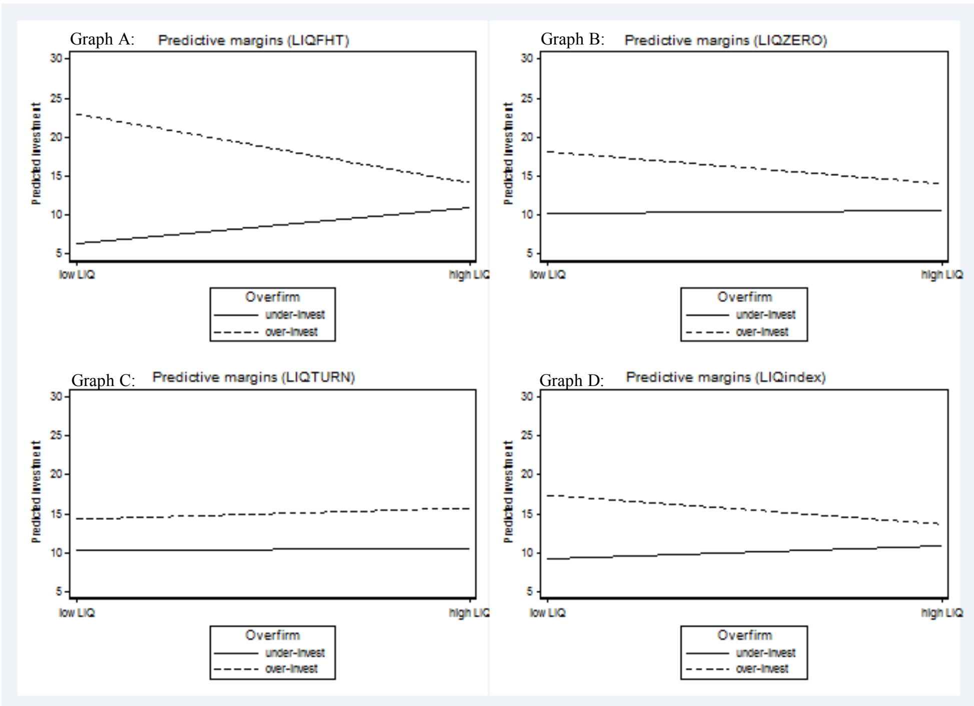
**FIGURE 3**

**The Marginal Effects of Stock Liquidity on Predicted Investment Levels across *OverFirm* Levels (Young vs Mature Firms)**

**Panel A: young firms (*Firm_Age* <= 13)**




**Panel B: mature firms (*Firm_Age* > 13)**

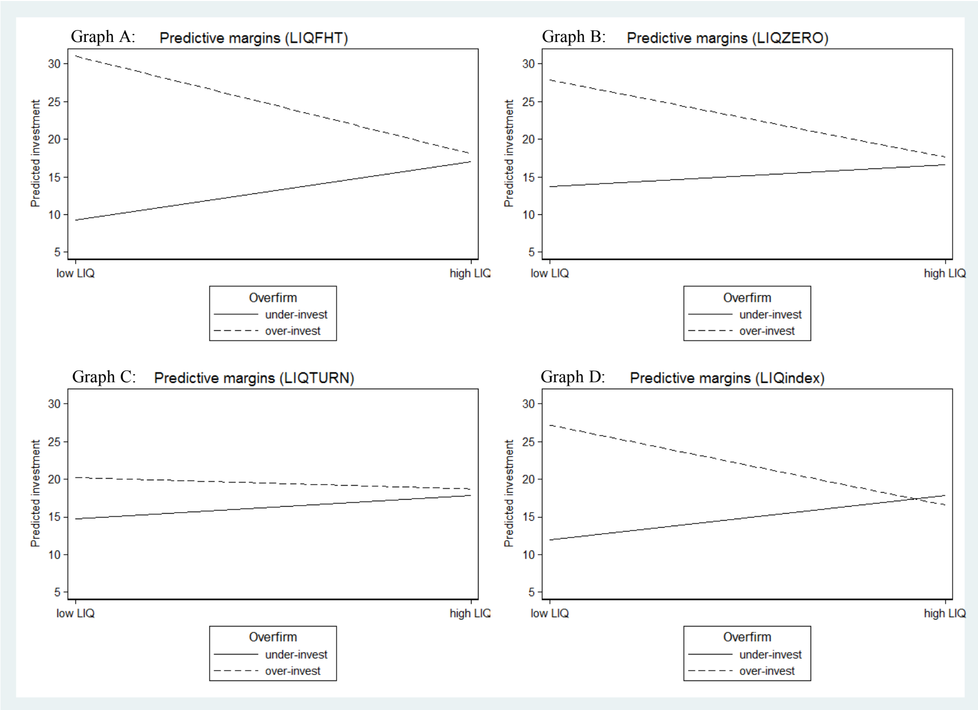



For each stock liquidity proxy, the vertical axis plots predicted investment levels, while the horizontal axis plots the predictive margins of stock liquidity, and with separate lines for low and high level of *OverFirm* (the likelihood of overinvestment). This figure provides graphical evidence in support of the results reported in Tables 15 and 16, depicting the degree to which investment efficiency is affected by stock liquidity in young firms characterised as financially constrained (Panel A) and in mature firms characterised as non-financially constrained (Panel B). That is, it shows how investment levels vary with stock liquidity across the individual sub-samples, when firm's *OverFirm* increases. The sample firms are split based on the median value of firm age (*Firm_Age*), where firms with *Firm_Age* <= 13 are categorised as financially constrained, while firms with *Firm_Age* > 13 as non-financially constrained.

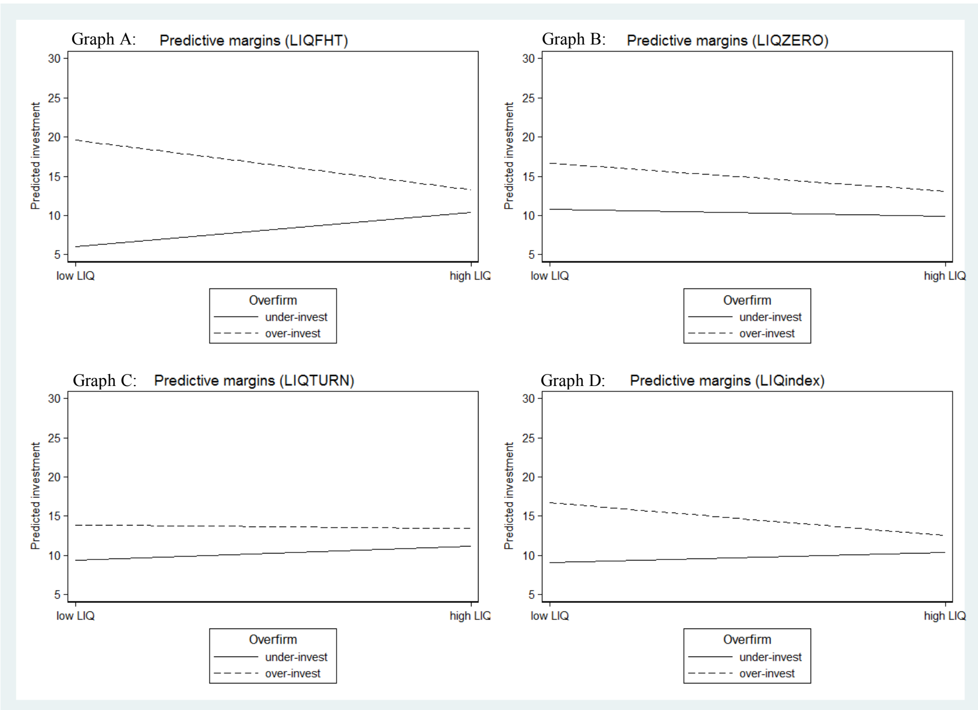
**FIGURE 4**

**The Marginal Effects of Stock Liquidity on Predicted Investment Levels across *OverFirm* Levels (High vs Low Business Risk Firms)**

**Panel A: firms with high business risk or uncertainty (*IncVol* >= 0.016)**




**Panel B: firms with low business risk or uncertainty (*IncVol* < 0.016)**



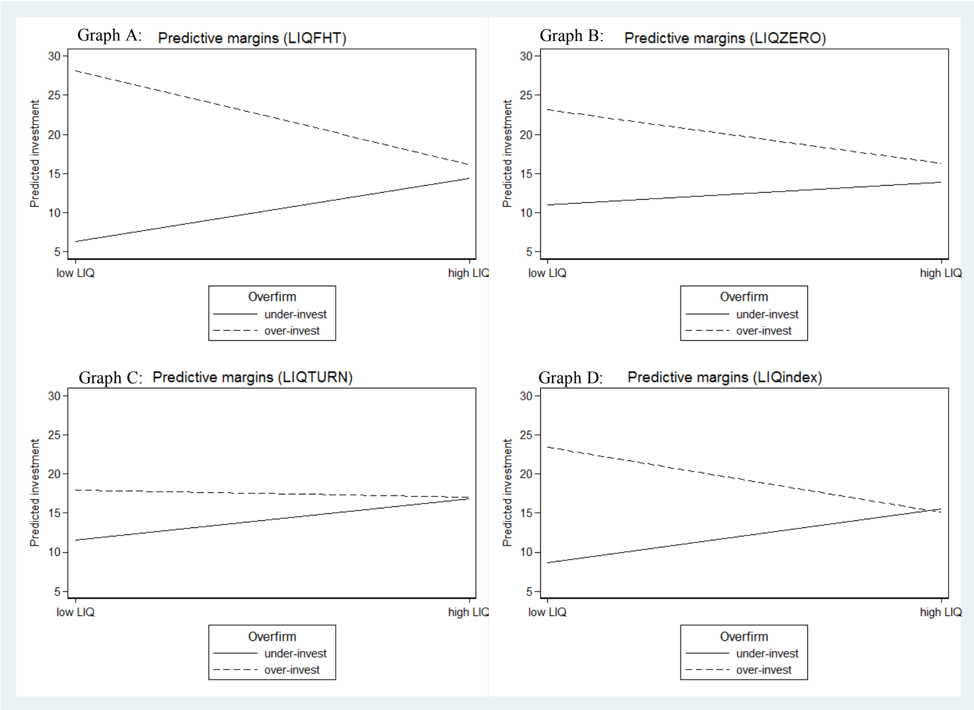

For each stock liquidity proxy, the vertical axis plots predicted investment levels, while the horizontal axis plots the predictive margins of stock liquidity, and with separate lines for low and high level of *OverFirm* (the likelihood of overinvestment). This figure provides graphical evidence in support of the results reported in Tables 18 and 19, depicting the degree to which investment efficiency is affected by stock liquidity in high business risk firms (Panel A) and in low business risk firms (Panel B). That is, it shows how investment levels vary with stock liquidity across the individual sub-samples, when firm's *OverFirm* increases. The sample firms are split based on the median value of operating income volatility (*IncVol*). High and low business risk refer to the right and left 50% of the distribution of *IncVol*, respectively (Fang et al. 2009).

**FIGURE 5**

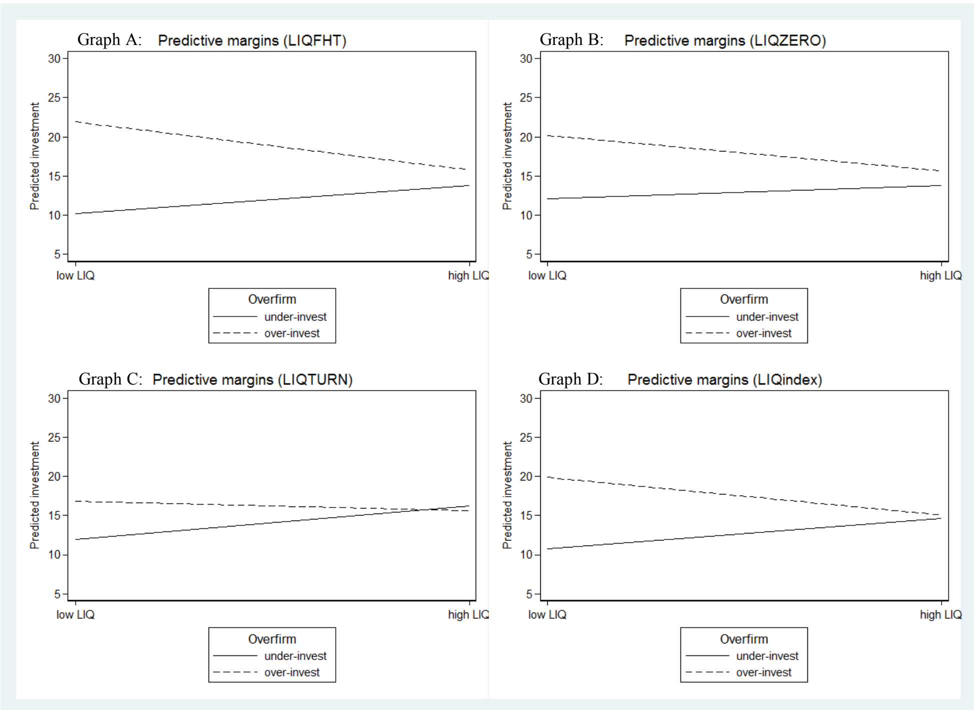
**The Marginal Effects of Stock Liquidity on Predicted Investment Levels across *OverFirm* Levels**

**(Firms with High vs Low Monitoring Institutional Ownership)**

**Panel A: firms with high monitoring institutional ownership (*MonIO* >= 10.7%)**



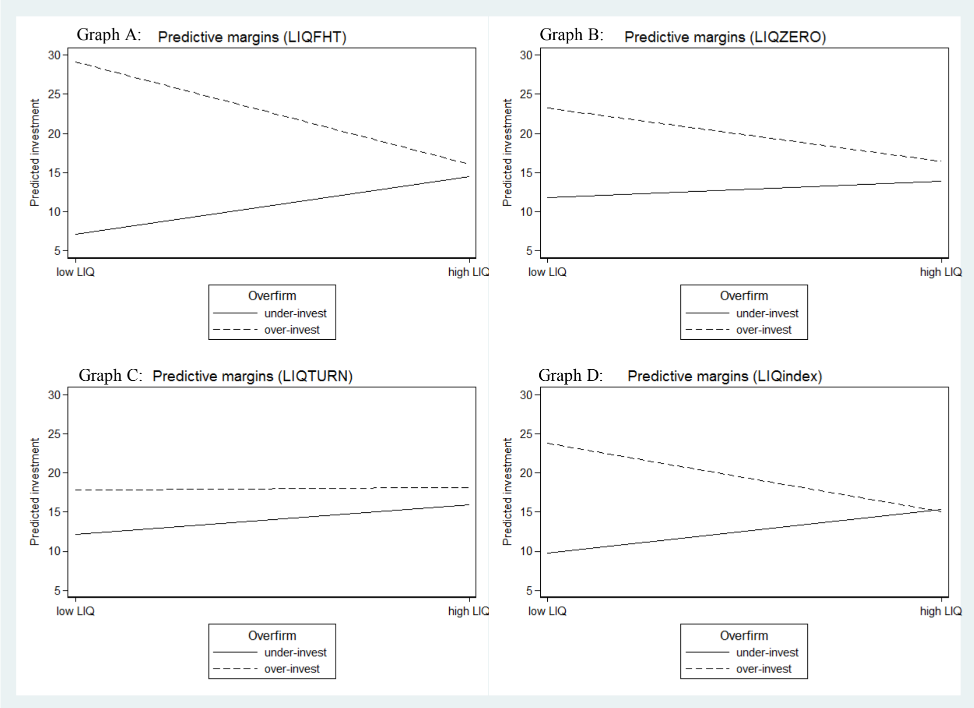

**Panel B: firms with low monitoring institutional ownership (*MonIO* < 10.7%)**



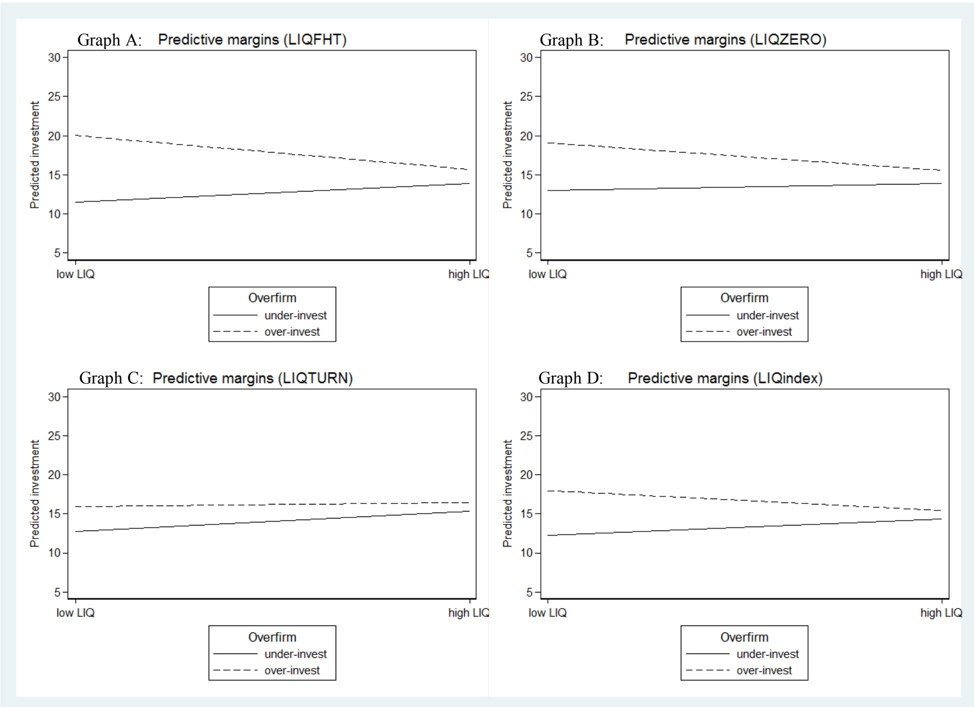

For each stock liquidity proxy, the vertical axis plots predicted investment levels, while the horizontal axis plots the predictive margins of stock liquidity, and with separate lines for low and high level of *OverFirm* (the likelihood of overinvestment). This figure provides graphical evidence in support of the results reported in Tables 21 and 22, depicting the degree to which investment efficiency is affected by stock liquidity in high monitoring institutions firms (Panel A) and in low monitoring institutions firms (Panel B). That is, it shows how investment levels vary with stock liquidity across the individual sub-samples, when firm's *OverFirm* increases. The sample firms are split based on the median proportion of monitoring institutions (*MonIO*). High and low monitoring institutions refer to the right and left 50% of the distribution of *MonIO*, respectively (Ramalingegowda and Yu 2012).

**FIGURE 6**
**The Marginal Effects of Stock Liquidity on Predicted Investment Levels across *OverFirm* Levels**
**(Firms with the Top Tertile vs the Bottom Tertile of Monitoring Institutional Ownership)**

**Panel A: firms with the top tertile of monitoring institutional ownership (*MonIO* >= 16.3%)**




**Panel B: firms with the bottom tertile of monitoring institutional ownership (*MonIO* < 5.9%)**




For each stock liquidity proxy, the vertical axis plots predicted investment levels, while the horizontal axis plots the predictive margins of stock liquidity, and with separate lines for low and high level of *OverFirm* (the likelihood of overinvestment). This figure provides graphical evidence in support of the results reported in Tables 23 and 24, depicting the degree to which investment efficiency is affected by stock liquidity in the top tertile of monitoring institutions firms (Panel A) and in the bottom tertile of monitoring institutions firms (Panel B). That is, it shows how investment levels vary with stock liquidity across the individual sub-samples, when firm's *OverFirm* increases. The sample firms are split into tertiles based on the proportion of monitoring institutions (*MonIO*). High and low monitoring institutions refer to the right and left 33.33% of the distribution of *MonIO*, respectively.

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