An Examination of Three Sources and Impact of Information Asymmetry in Financial Markets

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Certification

I certify that this thesis has not already been submitted for any degree and is not being submitted as part of candidature for any other degree.

I also certify that the thesis has been written by me and that any help that I have received in preparing this thesis, and all sources used, have been acknowledged in this thesis.

Signature of Candidate

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Synopsis

This dissertation presents three sets of empirical tests focused on sources of information asymmetry in financial markets. Specifically it determines the impact of CEO narcissism on earnings management, the factors which influence the release of privileged information by market intermediaries and asymmetrical information access related to technological enhancements. The results in this dissertation address a number of gaps in existing literature, which are of relevance to academics, and provide valuable insights for regulators and market participants.

The first set of empirical tests examines the impact of firm CEO's narcissism on earnings management. There is growing evidence to suggest that narcissistic leaders over-identify themselves with the organizations that they lead and expend considerable resources to achieve their goals, including engagements in unethical behaviour. Previous theoretical studies have conjectured the relation between leadership narcissism and accounting manipulation but lacking in empirical support. This dissertation examines this theoretical hypothesis adopting an unobtrusive yet psychologically supported proxy for narcissism based on the Narcissistic Personality Inventory (NPI) test. Results reported in this dissertation provides evidence that firms with more narcissistic CEOs are more likely to engage in such behaviour as evidence by the manipulation of accounts to present better earnings. The results highlight that information asymmetry caused by earnings management can be identified at an early stage by virtue of a CEO's personality. The implications of these results should be of particular interest to regulators and shareholders as management personality is potentially a prescription to corporate fraud.

The second set of empirical tests examines the extent of information leakage around analyst recommendations ('tipping'), the propensity to act on this privileged information received under different circumstances and its resulting profitability. While the earliest evidence of tipping was only documented for upgrade recommendations, there has been increasing evidence of this phenomenon for downgrade recommendations. Using a unique dataset from the ASX, which contains broker identifiers, this study extends the empirical literature on tipping by examining factors where this phenomenon is most prevalent, and the corresponding profit associated with the phenomenon. Results reported in this dissertation demonstrate that irrespective of market conditions, recipients react predominantly to tips on downgrade recommendations. Further analysis by cross-section of firms indicates that leaks on smaller and mid-capitalization stocks exhibit higher abnormal trading volume and affords greater profitability. When negative returns precede the public release of downgrade reports, results demonstrate that recipients are less likely to act. On investigation of short-selling around analyst recommendations, results document no signs of institutional exodus around analyst releases, suggesting that institutional investors do not react to short-term price fluctuations. The implications of this chapter enable a better understanding of supplementary factors that contribute to the phenomenon of tipping.

The final set of empirical tests investigates the impact of heightened levels of computerised trading on institutional execution costs. The advent of this new entrant into financial markets has attracted attention from regulators, exchanges, market participants and academics spurring empirical studies on the associated impacts on market quality. However, evidence on the impact to institutional investors has produced mixed results. This dissertation employs an exogenous event of co-location by 12 major exchanges worldwide to document the first empirical evidence on adverse effects to institutional trading costs as a result of intensified activity by computerised trading participants. Results of this dissertation provide that the reduction in exchange latency as a result of co-location attracts more activity by computerised traders and correspondingly, an increase in institutional execution costs.

Chapter 1: Introduction

1.1 Overview

The cost of adverse selection risks posed by asymmetric information on market participants is well-documented by theoretical and empirical studies. Seminal models developed by Kyle (1985) demonstrate that informed investors are able to maximise trading profits from their information, while Glosten and Milgrom (1985) show that asymmetric information causes liquidity providers to widen spreads to compensate for being adversely selected by better-informed traders. In impacting prices in financial markets, information asymmetry affects a firm's cost of capital (Diamond and Verrecchia, 1991). Lang and Lundholm (2000) provide empirical evidence that firms increase their information disclosures prior to security offerings and, in doing so, lower their cost of capital. In addition to widened spreads, volume and stock-return volatility are adversely affected as a result of heightened levels of information asymmetry (see Leuz and Verrecchia, 2000). The link between these three effects and the cost of capital is developed theoretically and empirically by several studies including Stoll (1978), Admati and Pfleiderer (1988), Amihud and Mendelssohn (1986) and Brennan and Subrahmanyam (1996). A firm's cost of capital plays a crucial role in the corporate decisions of firms, causing regulators and academics to continually explore initiatives to assist companies with lowering their cost of capital. As information asymmetry can impact a firm's cost of capital, this dissertation examines and identifies three causes of information asymmetry in financial markets – narcissism, tipping and computerised trading.

Extant literature either attempts to quantify the costs attributed to information asymmetry in markets or assumes markets are perfect and that no asymmetric information exists amongst its heterogeneous participants. Merton (1987) disentangles information asymmetry into two components: depth and breadth. Depth refers to the information asymmetry between investors and managers, and breadth, the information asymmetry amongst shareholders. While information disclosure and financial market intermediaries act to moderate the *depth* of information asymmetry, financial markets are continuously assumed to contain some extent of *breadth* in information asymmetry. The topics examined in this dissertation explore three key areas: (i) the presence of asymmetric information related to earnings management by narcissistic CEOs; (ii) privileged information release by market intermediaries; and (iii) technological enhancements related to direct market access. Specifically, the topics in relation to earnings management and information release of market intermediaries is in the realm of financial reporting and analyst recommendations. These mediums facilitate the information disclosure by firms to market participants relating to the *depth* in the context of reducing information asymmetry. Finally, analysis of tipping and institutional transaction costs following a new entrant to financial markets, as a result of advances in direct market access, speaks to the *breadth* in information asymmetry.

Financial reporting provides a regulated means of moderating information asymmetry in markets, by communicating accounting information to stakeholders in a standardised form. However, different accounting standards (either International Financial Reporting Standards (IFRS) or the Generally Accepted Accounting Principles (GAAP)), can result in different earnings figures. Likewise, the discretion afforded in the interpretation and adoption of the accounting standards facilitates an executive's ability to manage earnings or impact earnings quality. Extant literature on the phenomenon of earnings management provides evidence to question the credibility of information in financial reports. Kalchemeier (2010, page, Editorial) states, '[f]irms do not make decisions. Rather, people make decisions, and those decisions are shaped by the personalities of those involved.' Many papers have examined the determinants of accounting choices (reviewed by Fields, Lys and Vincent 2001; Dechow, Ge and Schrand, 2010) and report the impact of firm-level and market-level characteristics on earnings management. More recently, researchers are beginning to look at manager-specific factors and their influence on accounting policy. Tracking managers across firms-years, extant literature identifies the presence of strong managerial fixed effects on corporate decisions (Bertrand and Schoar, 2003); specifically a 'manager style' effect on: voluntary disclosures (Bamber, Jiang and Wang, 2010), accruals and accounting practices (Dejong and Ling 2013; Ge, Matsumoto and Zhang, 2011), and tax avoidance (Dyreng, Hanlon and Maydew, 2010). Such papers, however, have examined managerial effects in terms of corporate governance practice, financial incentives and institutional factors (Chava and Purnanandam 2010; Jia, Van Lent and Zeng, 2014). Research is now beginning to look at innate individual characteristics of CEOs that can affect financial policies and accounting numbers, such as: optimism and managerial risk-aversion (Graham, Harvey and Rajgopal, 2013), overconfidence (Schrand and

Zechman, 2012), gender (Srinidhi, Gul and Tsui, 2011; Huang and Kisgen 2013) and masculinity (Jia, Van Lent and Zeng, 2014). We extend this literature by examining the impact of another managerial specific variable, narcissism. In light of growing interests in management personality and earnings management, Chapter 3 of this dissertation examines the role of a firm's CEO's personality on the practice of earnings management.

Analyst research provides another medium in which information asymmetry can be mediated in financial markets. Information disseminated in analyst research is complementary to accounting standards, disclosure policies and the existence of market microstructure in minimising the cost of capital (Easley and O'Hara, 2004). Despite mixed empirical evidence on the value of analyst recommendations (see Womack, 1996; Barber, Lehavy, McNichols and Trueman, 2001; and Jegadeesh, Kim, Krische and Lee, 2004), several studies have demonstrated that analyst recommendations reduce information asymmetry. Asquith, Mikhail and Au (2005) and Lepone, Leung and Li (2012) document that analyst recommendations address information asymmetry in markets by disseminating privately held information and providing superior analysis of information released from companies. The value of such information, however, is time-sensitive, as potential profit opportunities can be realised if one has early access to this information (Green, 2006; Lepone, Leung and Li, 2013). Market participants with access to this information thus form a subset of informed market participants, increasing the *breadth* of information asymmetry. While early empirical evidence on tipping documented this phenomenon only around upgrade recommendations (see, for example, Irvine, Lipson and Puckett, 2007), research has increasingly provided stronger tipping evidence around downgrade recommendations (see Juergen and Lindsey, 2009; Busse, Green and Jegadeesh, 2012). The lacuna that exists in the literature is identification of firms and analyst recommendation factors which influence investors' propensity to act on the information leakage. Chapter 4 of this dissertation addresses this deficiency by identifying the circumstances in which investors demonstrate a higher propensity to respond to information leakage and quantifies any gains.

The received view in the academic literature is that large institutional fund managers are typically referred to as the subset of market participants who are informed (Chen, Jegadeesh and Werners, 2000; Mikhail, Walther, and Willis, 2004; Baker, Litov, Wachter and Wurgler, 2010). According to the Federal Reserve Board, this group of investors accounts for a total of 64 per cent of equity ownership in the US markets.[1] However, a recent entrant into financial markets, algorithmic or high frequency traders, has spurred significant debate amongst regulators, exchanges, traders and academics in relation to their impact on market quality. A stream of literature suggests an increase in high frequency trading has led to improvement in market quality, in particular, liquidity and informational efficiency.[2] However, some market participants and academics question the value of these benefits in light of the 'Flash Crash' on 6 May, 2009 (Kirilenko, Kyle, Samadi and Tuzun, 2011). The low latency attributed to computerised trading enables interaction at high speed with financial markets and

[1] Federal Reserve Board, 2011, 'Flow of funds account of the United States'. Available at http://www.federalreserve.gov/releases/z1/Current/. Accessed on 3 February 2015.

[2] See empirical works of Hendershott, Jones and Menkveld (2011), Hasbrouck and Saar (2011), Brogaard (2012) and Riordan and Storkenmaier (2011).

almost instantaneous access to the state of the limit order book.[3] The extensive infrastructure required to facilitate such access, however, is costly, creating a barrier to entry, which causes an information gap between market participants. In the context of *breadth* in information asymmetry, institutional investors may now be the *less* informed subset of market participants when trading against computerised traders who are experts in low-latency trading. This stems from the traditional view that institutional investors are predominantly slow traders (Barclay and Warner, 1993; Kyle, 1995). Empirical literature examining the impact of computerised trading on institutional investors is mixed and has thus far provided confounding results in different markets.[4] Consequently, Chapter 5 of this dissertation provides evidence on the effect of heightened levels of computerised trading on institutional execution costs across 12 markets. The remainder of this chapter delineates the objectives for each of the issues raised in this dissertation and concludes with an overview of the structure of this dissertation.

1.2 CEO Narcissism and Earnings Management

Amid a wide range of voluntary and involuntary corporate disclosures, periodic earnings announcements are the most anticipated form of information disseminated to investors and other market participants. The access to this regular, timely and comparable information allows investors to evaluate firm prospects, and make

[3] See theoretical discussions by Jovanovic and Menkveld (2011), Hoffman (2014) and Biais, Foucault and Moinas (2014), for example. In contrast to Kyle (1985), Jovanovic and Menkveld (2011) model HFTs as informed market makers (relative to their counterparts) due to their superior speed advantage. Hoffman (2014) observes that HFTs are able to revise their quotes quickly as news arrivals keep them informed relative to other market participants.

[4] See for example, Brogaard, Hagstromer, Norden and Riordan (2013), Boehmer, Fong and Wu (2014) and Brogaard, Hendershott, Hunt and Ysusi (2014).

informed investment decisions. Accounting figures provide a regulated means of communicating information on firm performance in hard counting of facts and figures to stakeholders. Yet, a wave of accounting scandals in the 2000s is a testament to the lack of reliability and accuracy of information from this highly anticipated disclosure (Ceresney, 2013). As earnings manipulation distorts information accessible to investors, it is imperative to understand determinants indicative of this practice.

A leading personality trait that has been of interest to leadership researchers is narcissism. A narcissist is described by various characteristics, including arrogance, self-absorption and hostility, but a lack of self-esteem (Rijsenbilt and Commandeur, 2013). According to the American Psychiatric Association, the grandiose belief in themselves, and demand for superiority from others, are simply defensive mechanisms for their lack of self-esteem and self-confidence. To reaffirm this belief, they constantly require admiration. The need for such external validation is found to result in narcissistic leaders expending considerable resources on enhancing their public image (Bass and Steidlmeier, 1999). Of greater concern are findings that narcissists tend to resort to unethical behaviour to obtain their goals (Duchon and Drake, 2009), as they continuously undertake actions that reinforce their self-image and maintain their ideal ego (Campbell and Foster, 2007). In organisations, narcissistic CEOs manifest this reinforcement by, for example, setting higher compensation packages for themselves (O'Reilly III, Doerr, Caldwell and Chatman, 2014). Over time, a narcissist's inflated sense of self-worth translates into a distorted view of their own abilities, and their inherent charisma, perceived or otherwise, enables them to manipulate and influence the perception of others (Chatterjee and Hambrick, 2011). While cash flows are easily reconciled, a change in reported earnings is less observable and, therefore, subject to greater discretion.

Chapter 2 indicates that the extant literature has found that personality traits play a role in accounting manipulation. In particular, overconfidence in executives has been found to be associated with incidences of accounting misstatements (Schrand and Zechman, 2012). Unlike earnings management, misstatements involve violation of accounting standards (Dechow, Ge, Larson and Sloan, 2010). Comparing the roles of Chief Financial Officer (CFO) and Chief Executive Officer (CEO) in the event of accounting fraud, Feng, Ge, Luo and Shevlin (2011) find that CFOs succumb to pressure from CEOs to manage earnings. Rijsenbilt and Commandeur (2013) further find a positive relationship between CEO narcissism and a propensity for corporate fraud, which includes intentional accounting misstatements. Theoretical studies by Duchon and Drake (2009) and Amernic and Craig (2010) have discussed the appealing aspects of financial reporting, in which narcissistic CEOs can communicate their 'desired goals'. This chapter extends the existing literature of management personality and earnings manipulation by examining the impact of another manager-specific variable – narcissism. Chapter 3 of this dissertation examines whether CEO narcissism has any influence on firm earnings management, a source of information asymmetry in financial markets. Emphasis is centred on manipulation within Generally Accepted Accounting Principles (GAAP), excluding an examination of fraud and intentional accounting misstatements.[5] This dissertation extends the work of Rijsenbilt and Commandeur (2013), who show that narcissistic CEOs have a higher inclination to

[5] The focus here is on the adoption and extent of earnings management by firms, measured by discretionary accruals.

engage in fraud. However, Rijsenbilt and Commandeur (2013) note that the narcissism proxies utilised in their study lacked psychological support based on the Narcissistic Personality Inventory (NPI) developed by Raskin and Terry (1988). Adopting Raskin and Shaw (1988)'s measure of narcissism[6], the narcissism score examined in this dissertation is computed from the responses in the question and answer sessions of analyst conferences held by companies. Specifically, the narcissism score for each sample CEO is the ratio of first person singular pronouns to total first person pronouns. This chapter provides the first empirical support for Amernic and Craig (2010), who propose that narcissistic CEOs use accounting choices to indulge their egos and inflate their perceived self-worth. The findings in this chapter contribute to the literature on management personality traits and accounting manipulation, providing stakeholders, in particular, investors and regulators, with a means of early prescription to potential corporate fraud.[7] While earnings management may not be illegal, it contributes to the extent of information asymmetry in markets.

1.3 Trading Behaviour around Information Leakage of Analyst Recommendations

Financial institutions spend significant resources collecting and analysing information to produce analyst research and recommendations. Reliant upon clients' trading volumes, brokerage houses produce these reports as evidence to persuade clients to

[6] This method is also consistent with prior empirical studies, including Chatterjee and Hambrick (2007) and Aktas, Bodt, Bollaert and Roll (2012).

[7] As noted in Rijsenbilt and Commandeur (2013), financial reporting fraud is intentional misreporting of financial statements, often initiated with minor earnings management.

trade. Studies examining the impact of analyst recommendations on prices suggest they have at least short-term investment value (see Stickel, 1995; Womack, 1996; Barber, Lehavy, McNichols, and Trueman, 2001; Jegadeesh, Kim, Krische, and Lee, 2004; Green, 2006). To ensure long-run viability of the equity research business amongst brokerage houses, the costly activity of producing analyst research must be recovered by profitable operations, which include trading profits and commissions from clients' trading volumes. Prior literature, including Agrawal and Chen (2008), Irvine (2004), and Jackson (2005), documents that increased issuance of stock recommendations enables brokerage firms to attract higher order flow, and therefore greater trading commissions.

The cost-benefit analysis of analyst research also applies to investors; the value of the bundled services must be greater than the premium paid for brokerage fees. The most direct method to recoup these costs is to make a financial gain from the information content of the analyst reports. Dimson and Marsh (1984) find that profitability occurs only in the period prior to public release. This provides brokers with an incentive to leak upcoming equity research to small groups of privileged clients, who in turn reward brokers with trading volume in subsequent trading rounds. Irvine, Lipson and Puckett (2007) first established empirical evidence of such behaviour, commonly referred to as the tipping phenomenon, when they found that institutions significantly net buy stocks prior to the public release of analysts' initial reports of positive recommendations. Using a proprietary dataset, Lepone, Leung and Li (2012) quantify the abnormal profit that can be captured through tipping and show that it amounts to approximately 0.5 per cent of upgrade and 1per cent for downgrade recommendations in Australia.

Chapter 4 of this dissertation contributes to the literature by examining how recipients of information leakage (henceforth 'recipients') react to these tips from their trading behaviour. The existing literature suggests that analyst research has a role in reducing information asymmetry between management and shareholders, by synthesising privately held information from management to financial markets.[8] Unequal access to these reports creates information asymmetry amongst shareholders, as the timeliness of this access creates an economic advantage for brokerage firms to engage in tipping.

The literature has thus far established the existence of tipping and provides substantial empirical evidence to support this hypothesis. Prior studies like Irvine, Lipson and Puckett (2007), Juergen and Lindsey (2009), Busse, Green and Jegadeesh (2012) and Lepone, Leung and Li (2012) document signs of abnormal net buying (selling) activity prior to positive (negative) analyst recommendations. Focusing only on analyst initiation coverage and positive research releases, Irvine, Lipson and Puckett (2007) first observe abnormal net buying prior to public release. On the contrary, Juergens and Lindsey (2009) find only abnormal trading activity prior to the public release of downgrade recommendations. Busse, Green and Jegadeesh (2012) provide further support for the findings on asymmetrical trading responses (between upgrade and downgrade recommendations) using institutional data from Plexus and Abel/Noser Solutions. Lepone, Leung and Li (2012) provide evidence consistent with the phenomenon of tipping in the Australian Equities Market.

[8] In a comparison of analyst reports with company annual reports, Rogers and Grant (1997) document that over half of the financial and operating data cited in analyst reports are not found in company reports. Evidence opposing the contention that analyst research contains private information also exists, albeit fewer in number. As an example, Easley, O'Hara and Paperman (1998) find no relation between the number of analyst coverage and the probability of private information events, concluding that analysts research do not contain and communicate private information.

Chapter 4 extends the literature on tipping by examining the extent of information leakage in analyst recommendations, and factors affecting recipients' propensity to act on tips. The different circumstances in which the analyst recommendations are being issued, which are examined in this chapter, include market conditions, level of recommendation changes and firm sizes. By examining profitability from trading on tips, Chapter 4 also establishes a relation between anticipated profitability and recipients' propensity to act. Since recipients are likely to compensate recommending brokers with trading volume only if they perceive the information received to be valuable, the recipients' propensity to act is dependent on the expectation of profit. Additionally, the chapter monitors events when stock prices move in the same direction as the recommendations and seek to identify a threshold level, which reduces the recipients' propensity to act on leaked information. With reference to abnormal volumes by broker-analysts, the study draws inferences on recipients' propensity to only reward full-service brokerage houses based on their anticipated profitability.

A key impediment to this area of research has been the lack of comprehensive data at the investment firm level. Unlike electronic trading systems in the US, the proprietary dataset employed Chapter 4 includes broker identities as disclosed by the ASX. Specifically, the data identify which brokerage houses are involved on both sides of each trade. The unique value of this dataset stems from the fact that data on broker identities on each trade are only available and released by the ASX. This enables a reliable mapping of trade to recommendation data, which allows an observation on how the broker-analysts traded around a period in which they have released a recommendation. Additionally, this provides an ability to accurately infer recipients' responses to information leakages.

1.4 The Impact of Co-Location on Institutional Trading Costs

In the last decade, financial markets worldwide have experienced a plethora of structural changes. The wave of technological advances continually demand faster trading speed as computerised traders with lower operating costs replace traditional human traders. While the hype was moving from milliseconds to microseconds when high frequency trading was first introduced to the market, *The Wall Street Journal* has reported that discussions around nanoseconds of latency are now the norm.[9] The very fact that market participants continually invest considerable resources in being fast, suggests there must be significant benefits to being faster than others (*Financial Times*, 2013).

Chapter 5 of this dissertation contributes to the discussion on information asymmetry by examining the effects of heightened activity in high frequency trading (HFT) across 12 major exchanges. Specifically, the dissertation focuses the analysis around the co-location of exchange servers at these 12 exchanges, and the effects on trading costs incurred by institutions. According to the Securities and Exchange Commission (SEC), one of the characteristics of HFTs includes the 'use of co-location services and individual data feeds offered by exchange and others to minimize network and other types of latencies' (SEC, 2010). Prior literature on algorithmic trading, and specifically HFT, has investigated the impact on traditional market quality indicators including bid-ask spreads, volatility and price discovery. However, there is little academic evidence examining the impact of this phenomenon on buy-side investors, the largest investor

[9] 'Wall Street's Need for Trading Speed: The Nanosecond Age', *The Wall Street Journal*, June 14, 2011.

group in financial markets, who are responsible for up to trillions of dollars in executions per year.[10]

Several studies have associated the growth in computerised trading with improved market quality, including increased liquidity, better price discovery and lower volatility (Hendershott, Jones and Menkveld, 2011; Hasbrouck and Saar, 2013; Brogaard, Hendershott and Riordan, 2013). Yet, due to their inherent speed, which creates a perceived informational advantage, they continue to attract considerable scepticism from other market participants over their ability to exasperate volatility (see for example, CESR 2010a, 2010b; Boehmer, Fong and Wu, 2014). In support of opposing views about HFT, we also observe that recent crashes in financial markets (for example, Flash Crash 2010 and Knight Capital market glitch 2013) have been largely attributed to heightened HFT activity. While the debate on whether HFT is beneficial or detrimental to markets remains ongoing, there has been evidence to show that the fraction of volume executed in equity markets by short-term traders (HFT and market makers) has increased[11], now accounting for approximately 70 per cent of trading in US Equities (Reuters Newswire, 2013). Correspondingly, there has been a reduction of volume executed by long-term fundamental and buy-to-hold investors. Emrich and Crow (2012) note that between 2001 and 2006, institutional trading accounts for 47 per cent of exchange traded volume, but has decreased to only 29 per cent since

[10] See, for example, the speech by Commissioner Luis A. Aguilar from the US Securities and Exchange Commission at George State University on "Institutional Investors: Power and Responsibility" on April 19, 2013.

[11] See 'High Frequency Trading – An Asset Manager's Perspective', *NBIM Discussion Note #1-2013*, 30/8/2013.

2008.[12] The question this chapter attempts to address is whether institutions, primarily the fundamental investors in financial markets, are adversely impacted by this wave of new traders.

In their interest to execute large blocks of orders, large institutional investors are typically liquidity demanders in financial markets, constantly attempting to minimise transaction costs. They face a constant trade-off between opportunity costs (trade urgency) and market impact, increasingly relying on computer-driven portfolio rebalancing and trading algorithms to optimise this trade-off. This reliance, however, creates a predictable trend in their order flows, which are potentially exploitable. As documented in Lillo and Farmer (2004), order splitting by large institutional trades creates strong identifiable autocorrelations of trade imbalances. HFTs' speed advantage enables them to receive information from the market, leading to a widespread belief that there are gaming opportunities available for HFTs to profit from other market participants.

In Chapter 5, this dissertation examines a proprietary database containing equity transaction records executed by institutional investors as compiled by Ancerno Ltd. The data contain trade records of 750 institutional investors, facilitated by 1,216 brokerage firms, amounting to approximately 48 million tickets over the period of 1999 to 2008. The distinctive feature of this Ancerno data, which has attracted

[12] The article documents that direct household ownership of US corporate equity has fallen since 2000, implying less retail flow. The authors also note that the reduction in natural liquidity in equity markets is caused by (i) exacerbation following the credit crisis in 2008; (ii) institutions which trade large sizes opting to route their orders in dark pools and other non-exchange venues. But the fact remains that the proportion of traded volume on exchanges by fundamental institutional investors is on a downward trend.

considerable attention in academic literature, is the inclusion of a complete history of trading activity by each institution.[13] More importantly, the dataset provides information on 'tickets' sent by a buy-side institution to a broker; each ticket normally resulting in more than one trade execution. These detailed data are particularly suited to examine the net impact on trading costs for institutions, the net benefit/effect from order splitting it accurately captured. This is of particular interest as extant literature establishes that transaction costs are a significant component of institutional trading profitability.[14]

1.5 Summary

The three studies in this dissertation examine issues in relation to the causes of information asymmetry in financial markets. This chapter outlines the questions surrounding these topics, and provides motivation for the analyses presented in the subsequent chapters.

The remainder of this dissertation is structured as follows. A review of the existing literature relevant to the issues raised in this dissertation is presented in the following chapter. Specifically, literature around earnings management, narcissism, equity analyst research, computerised trading and execution costs. Chapter 2 concludes with the development of hypotheses to be tested in the dissertation. Chapter 3 investigates

[13] See, for example, Goldstein, Irvine, Kandel and Weiner (2009), Goldstein, Irvine and Puckett (2011), Anand, Irvine, Puckett and Venkataraman (2013a, 2013b).

[14] In an examination of institutional trades in 37 countries, Chiyachantana, Jain, Jiang and Wood (2004) report average one-way trading costs in 1997to 1998 of 41 basis points, and in 2001, 31 basis points. A more recent study on fund performance by Anand, Irvine, Puckett and Venkataraman (2013a) documents that persistence of low transaction costs are a determinant of superior fund performance.

the relation between CEO narcissism and earnings management. Chapter 4 examines the information leakage around analyst recommendations and investors' propensity to act on this information under different circumstances. Chapter 5 investigates the impact of co-location on institutional execution costs.

Chapter 2: Literature Review

2.1 Introduction

This chapter provides an overview of the literature related to the three examinations presented in this dissertation in order to provide further motivation for the empirical analysis conducted.

Section 2.2 first outlines the identification and measurement of earnings management by synthesising existing models developed in the empirical literature. The section then discusses the factors and motivations for earnings management, and seeks to explain its prevalence. Specifically, providing reviews of the role that executives play, and in particular, the personalities associated with manipulating reported earnings described by the extant literature. Section 2.3 then discusses the literature around the publication of analyst reports; their value and impact on markets. Section 2.4 summarises the theoretical and empirical literature around a new breed of traders in financial markets today, algorithmic trading. In Section 2.5, an overview of execution costs is first provided, followed by a review of execution costs incurred by institutional investors.

Section 2.6 states the hypotheses tested in this dissertation and derived from the literature.

2.2 Earnings Management

Financial reporting is a key communicator of financial information to stakeholders in an audited and standardised format (Xiong, 2006). According to the Statement of Financial Accounting Concepts No. 1 (SFAC No. 1),

'Financial reporting should provide information about an enterprise's financial performance during a period.'

Agency theory brings into doubt the accuracy of financial reports by organisations, given the separation between ownership and management. This separation leads to possible misalignment of interests, as managers are likely to place their own interests above those of shareholders (and Meckling, 1976). Therefore, accounting standards, including the International Financial Reporting Standards (IFRS) and the US Generally Accepted Accounting Principles (GAAP), are responsible for regulating information in financial reports. However, in an attempt to accommodate various industries and business circumstances, managers are able to exercise discretion within the interpretation of mandated accounting standards. For a similar transaction or event, managers are offered a wide choice of alternative methods to reflect this in financial reports. A common example is the choice between LIFO (Last In First Out), FIFO (First In First Out) and weighted average methods for inventory costing, which is often strategically adopted to produce favourable earnings. In addition to accounting choices, previous studies have also suggested that earnings may be manipulated by discretionary accruals (see, for example, Healy, 1985; DeAngelo, 1986; Jones, 1991; Dechow, Sloan and Sweeney, 1995).

Accordingly, Healy and Wahlen (1999, p. 368) states that 'earnings management occurs when managers use judgement in financial reporting and in structuring transactions to alter financial reports to either mislead stakeholders about the underlying economic performance of the company or to influence contractual outcomes that depend on reported accounting numbers'. The National Commission on Fraudulent Financial Reporting[15] extends this view to include that earnings management practices are illegal (Merchant and Rockness, 1994). The widespread interest in earnings management has led researchers to develop reliable frameworks to detect earnings management.

2.2.1 Earnings Management Estimation

Several models have been put forward in the literature to estimate earnings management; these include: specific or single accruals (McNichols and Wilson, 1988; Petroni, 1992), aggregate accruals (Jones, 1991; Dechow, Sloan and Sweeney, 1995) and test on earnings distribution (Burgstahler and Dichev, 1997).

The specific or single accruals identify earnings management with the assumption that profit is the sum of cash flow and total accruals; a manipulation of one single accrual

[15] The Commission is a private-sector initiative, jointly sponsored and funded by the American Institute of Certified Public Accountants (AICPA), the American Accounting Association (AAA), the Financial Executives Institute (FEI), the Institute of Internal Auditors (IIA), and the National Association of Accountants (NAA).

(within a group of multiple classes of accruals) leads to profit manipulation. The single accrual selected must be sizeable and requires substantial judgement. Single accruals studies typically focus on one industry setting where the researchers' expectations of the selected accrual will likely reflect management's discretion. McNichols and Wilson (1988), for example, examine earnings management via provision in bad debts, while Petroni (1992) focuses on the estimation error in the claim loss reserve account. The aggregate accruals method decomposes total accruals into discretionary and nondiscretionary components. While nondiscretionary accruals reflect those that are economically determined and cannot be influenced by management, discretionary accruals are a measure of earnings management. The third method examines the statistical properties of earnings (Burgstahler and Dichev, 1997 and Degeorge, Patel and Zeckhauser, 1999). This approach studies the distribution of earnings around a benchmark, typically zero or last quarter's earnings, and infers discontinuity as a result of earnings management.

The aggregate accruals method is the most widely adopted approach employed by the accounting literature to measure earnings management (Dechow, Sloan and Sweeney, 1995). Table 2.1 summarises the extant models developed to estimate earnings management. In a first attempt to model manipulation, Healy (1985) argues that the adoption of earnings management by firms is systematic in every period. Therefore, he estimates earnings management by the mean of aggregate accruals (measured by lagged total assets) in the computing period. Aggregate accruals are computed as the difference between earnings before extraordinary items and cash flow from operations.

Table 2-1
Earnings Management Estimation Summary

Authors	Discretionary Accrual Proxy
Healy (1985)	Total Accruals
DeAngelo (1986)	Change in Total Accruals
Jones (1991)	Residual from regression of total accruals on change in sales and property, plant and equipment
Modified Jones from Dechow, Sloan and Sweeney (1995)	Residual from regression of total accruals on change in cash revenues and property, plant and equipment
DeChow (2002)	Residual from regression of total accruals on past, present and future cash flow of operations
McNichols (2002)	Residual from regression of total accruals on past, present and future cash flow of operations, similar to Dechow and Dichev (2002), but with the addition of change in sales and property, plant and equipment
Kothari, Leone and Wasley (2005)	In addition to explanatory variables in the Modified Jones Model, firm's Return on Asset is added to control for performance

Discretionary accruals are measured as follows:

$$\widehat{DA}_{i,t} = \frac{TA_{i,t}}{A_{i,t-1}} \tag{2.1}$$

where $\widehat{DA}_{i,t}$ is the estimated discretionary accruals, $TA_{i,t}$ is the aggregate accruals for firm i in year t, $A_{i,t-1}$ is the total assets at the beginning of year t. A major criticism of Healy (1985) is the assumption that total aggregate accruals, which may or may not be discretionary, amount to manipulated earnings.

Addressing the shortcomings of Healy (1985), DeAngelo (1986) estimates earnings management by the change in total accruals, the difference between total accruals in the current period and total accruals in the previous period. This model is presented as follows:

$$\widehat{DA}_{i,t} = \frac{(TA_{i,t} - TA_{i,t-1})}{A_{i,t-1}} \qquad (2.2)$$

where $\widehat{DA}_{i,t}$ is the estimated discretionary accruals, $TA_{i,t}$ is the aggregate accruals for firm *i* in year *t*, $TA_{i,t-1}$ is total accruals for the year *t-1* and A_{it-1} is the total assets for the year *t-1*. The largest criticism of this model is the assumption that total accruals in the previous period wholly reflect non-discretionary accruals. Additionally, non-discretionary accruals in the current period could also potentially be misclassified as discretionary.

A ubiquitous model of earnings management is first presented by Jones (1991), in which plant, property and equipment and sales growth are utilised to estimate nondiscretionary accruals. This model allows nondiscretionary accruals stemming from depreciation and ordinary changes in business activities of firms. Specifically, the Jones model is estimated as follows:

$$\frac{TA_{i,t}}{AvgA_{i,t}} = \propto_1 \frac{1}{AvgA_{i,t}} + \propto_2 \frac{\Delta R_{i,t}}{Avg\square_{i,t}} + \propto_3 \frac{PPE_{i,t}}{AvgA_{i,t}} + \varepsilon_{i,t} \qquad (2.3)$$

where $TA_{i,t}$ is the aggregate accruals for year *t*; $\Delta R_{i,t}$ is the change in revenues between year *t-1* and *t*; $PPE_{i,t}$ is the gross property, plant and equipment in year *t*; $AvgA_{i,t}$ is the average of total assets at the start and end of year *t*; $\propto_1, \propto_2, \propto_3$ are estimated parameters and $\varepsilon_{i,t}$ is the residual. Dechow, Richardson and Tuna (2003) confirm that the residuals to the Jones (1991) model are highly correlated (80 per cent) with total accruals. They report a positive association with earnings performance and a negative association with cash flow performance (Dechow, Sloan and Sweeney, 1995). As sales growth is considered a component of nondiscretionary accruals, Jones (1991) disregards the possibility of revenue manipulation. Dechow, Ge, Larson and Sloan (2011) subsequently confirm that residuals from the Jones model as a proxy for earnings management are subject to Type II error, in which accruals are incorrectly classified as nondiscretionary.

Dechow, Sloan and Sweeney (1995) in the Modified Jones model build on Jones (1991) and adjust sales growth for growth in credit sales. The Modified Jones model is presented below:

$$\frac{TA_{i,t}}{AvgA_{i,t}} = \beta_1 \frac{1}{AvgA_{i,t}} + \beta_2 \frac{\Delta R_{i,t} - \Delta AR_{i,t}}{AvgA_{i,t}} + \beta_3 \frac{PPE_{i,t}}{AvgA_{i,t}} + \varepsilon_{i,t} \tag{2.4}$$

where $TA_{i,t}$ is the aggregate accruals for year *t*; $\Delta R_{i,t}$ is the change in revenues between year *t-1* and *t*; $\Delta AR_{i,t}$ is the change in receivables between years *t-1* and *t*; $PPE_{i,t}$ is the gross property, plant and equipment in year *t*; $AvgA_{i,t}$ is the average of total assets at the start and end of year *t*; $\beta_1, \beta_2, \beta_3$ are estimated parameters and $\varepsilon_{i,t}$ is the residual.

Dechow and Dichev (2002) emphasise the importance of cash flows to short-term accruals. In contrast to Jones (1991), Dechow and Dichev (2002) intended to assess total accruals quality – they did not attempt to isolate management-driven effects from all other effects. Specifically, they model accruals as a function of past, present and future cash flows, since accruals anticipate the receipt/payment of future cash and must reverse if cash previously recognised in accruals is received/paid. In a review of the Dechow and Dichev (2002) model, McNichols (2002) suggests the consolidation of Dechow and Dichev (2002) variables with Jones (1991), where the variables sales growth and property, plant and equipment are added to the Dechow and Dichev (2002) cash flow variables.

$$\frac{TA_{i,t}}{AvgA_{i,t}} = \delta_1 \frac{1}{AvgA_{i,t}} + \delta_2 \frac{\Delta R_{i,t}}{AvgA_{i,t}} + \delta_3 \frac{PPE_{i,t}}{AvgA_{i,t}} + \delta_4 \frac{CFO_{i,t-1}}{AvgA_{i,t}} + \delta_5 \frac{CFO_{i,t}}{AvgA_{i,t}} + \delta_6 \frac{CFO_{i,t+1}}{AvgA_{i,t}} + \varepsilon_{i,t} \quad (2.5)$$

where $TA_{i,t}$ is the aggregate accruals for year t; $\Delta R_{i,t}$ is the change in revenues between year *t-1* and t; $CFO_{i,t}$ is the Cash Flow from Operations for firm i in year t; $PPE_{i,t}$ is the gross property, plant and equipment in year t; $AvgA_{i,t}$ is the average of total assets at the start and end of year t; $\delta_1, \delta_2, \delta_3, \delta_4, \delta_5, \delta_6$ are estimated parameters and $\varepsilon_{i,t}$ is the residual.

While Dechow and Dichev (2002) and McNichols (2002) address the potential correlation between total accruals and cash flow from operations, Kothari, Leone and Wasley (2005) addresses issues raised by the importance of the influence of firm performance in the computation of earnings management. According to Dechow, Sloan and Sweeney (1995) and Kasznik (1999), findings by the Jones (Jones, 1991) and Modified Jones (Dechow, Sloan and Sweeney, 1995) models imply a positive association between discretionary accruals and return on assets (ROA). Correspondingly, in the performance-matched discretionary accrual model by Kothari, Leone and Wasley (2005), discretionary accruals are measured by:

$$\frac{TA_{i,t}}{AvgA_{i,t}} = \theta_1 \frac{1}{AvgA_{i,t}} + \theta_2 \frac{\Delta R_{i,t} - \Delta AR_{i,t}}{AvgA_{i,t}} + \theta_3 \frac{PPE_{i,t}}{AvgA_{i,t}} + \theta_4 ROA_{i,t-1} + \varepsilon_{i,t} \quad (2.6)$$

where $TA_{i,t}$ is the aggregate accruals for year t; $\Delta R_{i,t}$ is the change in revenues between year *t-1* and t; $\Delta AR_{i,t}$ is the change in receivables between years *t-1* and t; $PPE_{i,t}$ is the gross property, plant and equipment in year t; $ROA_{i,t-1}$ is the return on asset for year *t-1*; $AvgA_{i,t}$ is the average of total assets at the start and end of year t; $\theta_1, \theta_2, \theta_3, \theta_4$ are estimated parameters and $\varepsilon_{i,t}$ is the residual. However, the performance matching as suggested by Kothari, Leone and Wasley (2005) acts to reduce the power of the Modified Jones test simply because a firm whose ROA is not caused by earnings management may potentially be matched to a firm whose ROA is boosted by discretionary accruals (see Dechow, Ge and Schrand, 2010; Stubben, 2010).[16] Therefore, the adoption of this performance-matching approach should only be applied when correlated performance is a concern within the sample firms.

Stubben (2010) develops an alternative proxy for earnings management, the discretionary revenue model. His model accurately addresses the findings of Dechow and Schrand (2004) and Turner, Dietrich, Anderson and Bailey (2001), noting that revenues are most commonly misstated, a common occurrence in SEC Accounting and Auditing Enforcement Releases cases. In the discretionary revenue model of Stubben (2010), he incorporates quarterly revenues to estimate discretion on an annual level, as follows:

$$\frac{\Delta AR_{i,t}}{AvgA_{i,t}} = \mu_1 \frac{1}{AvgA_{i,t}} + \mu_2 \frac{\Delta R1\_3_{i,t}}{AvgA_{i,t}} + \mu_3 \frac{\Delta R4_{i,t}}{AvgA_{i,t}} + \varepsilon_{i,t} \qquad (2.7)$$

[16] Take, for example, firms ABC and XYZ with ROA of 20 per cent each. Unlike firm ABC, firm XYZ's ROA is boosted by 2 per cent with the use of discretionary accruals. The ROAs of firm ABC and firm XYZ from non-discretionary accruals are 20 per cent and 18 per cent respectively. Matching firm XYZ to firm ABC implies that the non-discretionary accruals at firm XYZ should be the same as firm ABC, but this match is not accurate as firm XYZ should be matched to a firm with 18 per cent of ROA.

where $\Delta AR_{i,t}$ is the change in receivables between years *t-1*and *t*; $\Delta R1\_3_{i,t}$ is the change in revenues in the first three quarters between years *t-1* and *t*; $\Delta R4_{i,t}$ is the change in revenues in the fourth quarters between years *t-1* and *t*; $AvgA_{i,t}$ is the average of total assets at the start and end of year *t*; μ_1, μ_2, μ_3 are estimated parameters and $\varepsilon_{i,t}$ is the residual. Stubben (2010) expands his discretionary revenue model to control for firm characteristics related to performance and growth in his conditional revenue model. The conditional revenue model specifies the following:

$$\frac{\Delta AR_{i,t}}{AvgA_{i,t}} = \gamma_1 \frac{\Delta R_{i,t}}{AvgA_{i,t}} + \gamma_2 \frac{\Delta R_{i,t} \times SIZE_{i,t}}{AvgA_{i,t}} + \gamma_3 \frac{\Delta R_{i,t} \times AGE_{i,t}}{AvgA_{i,t}} + \gamma_4 \frac{\Delta R_{i,t} \times AGE_{SQ\,i,t}}{AvgA_{i,t}} +$$

$$\gamma_5 \frac{\Delta R_{i,t} \times GRR_{P\,i,t}}{AvgA_{i,t}} + \gamma_6 \frac{\Delta R_{i,t} \times GRR_{N\,i,t}}{AvgA_{i,t}} + \gamma_7 \frac{\Delta R_{i,t} \times GRM_{i,t}}{AvgA_{i,t}} + \gamma_8 \frac{\Delta R_{i,t} \times GRM_{SQ\,i,t}}{AvgA_{i,t}}$$

$$+\varepsilon_{i,t} \qquad (2.8)$$

where $\Delta AR_{i,t}$ is the change in receivables between years *t-1*and *t*; $\Delta R_{i,t}$ is the change in revenues between years *t-1* and *t*; $SIZE$ is the natural logarithm of total assets; AGE is the natural logarithm of the firm's age in years; AGE_SQ is the square of firm age to allow for nonlinear relation between age and credit policy (Petersen and Rajan, 1997); industry-median-adjusted growth in revenues (*GRR_P* if positive, *GRR_N* if negative), industry-median-adjusted gross margin (*GRM*) and its square (*GRM_SQ*) are proxies for operational performance of the firm relative to industry competitors; $AvgA_{i,t}$ is the average of total assets at the start and end of year *t*; $\gamma_1, \gamma_2, \gamma_3, \gamma_4, \gamma_5, \gamma_6, \gamma_7$ are estimated parameters and $\varepsilon_{i,t}$ is the residual.

Stubben (2010) compares and contrasts his discretionary revenue to accrual models, on the ability of predicting simulated and actual earnings management. Results provide that the revenue model is less biased and is better specified than accrual models. However, the disadvantage of the revenue model of Stubben (2010) is the inability to model the manipulation of expenses, the other half of a firm's profit figure.

2.2.2 Earnings Management Motivations

The established models developed to identify earnings management spurred research to understand motivations for firms to adopt this practice. Broadly, the literature canvases the motivations for earnings management into four broad categories: Capital Markets Hypothesis (2) Compliance (3) Financing and (4) Compensations. Firstly, the capital market expectations hypothesis, suggests managers manipulate earnings to meet investors' risk and return expectations (Graham, Harvey and Rajgopal, 2005; Daniel, Denis and Naveen, 2007; Athanasakou, Strong and Walker, 2009). The capital market expectations hypothesis proposes that earnings management is employed to meet expected earnings benchmarks and analyst expectations. Secondly, regulatory motivations describe the need for companies to comply with numerous regulations linked to accounting figures. This is particularly relevant for listed companies, creating pressure for managers to manipulate earnings to ensure compliance. For example, regulation around product pricing (Lim and Matolcsy, 1999) and compliance with industry standards (Christensen, Hoyt and Paterson, 1999) are among explanations for corporate executives to manage earnings.[17] The third motivation provided by the

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[17] Lim and Matolcsy (1999) examined listed Australian firms' earnings management in response to product price controls established by the government. The study finds that firms adopt income-reducing earnings management to be eligible for product price increases. In Christensen, Hoyt and Paterson (1999), the study examines firms in the property-liability insurance industry – a highly regulated

literature is related to debt financing, as creditors ordinarily impose covenants to ensure the viability of debt repayments. Kanagaretnam, Lobo and Mathieu (2003) and Perez and Hemmen (2010) find evidence that marginal increases in debt create incentives for managers to manipulate earnings. Further, managers exhibit an increased tendency to manage earnings to reduce the cost of further external financing (Dechow, Sloan and Sweeney, 1996). Lastly, although management compensation contracts are a corporate governance tool to address the agency theory hypothesis, they are often associated with firm performance reported in financial statements. This provides an incentive for managers to manage earnings (see, for example, Baker, Collins and Reitenga (2003) and Balachandran, Chalmers and Haman (2008)).

2.2.2.1 Executives and Earnings Management

Studies documenting the relation between the characteristics of executive compensation and earnings management are voluminous. Extant literature investigates this relation with two broad categories of executive compensation; (i) bonus plans and earnings-based compensation; and (ii) equity-based compensation including executive stocks options. Table 2-2 summarises the existing literature around executive compensation and earnings management.

Healy (1985) examines the parameters of typical bonus contracts for 94 firms, and reports that managers influence earnings in an attempt to maximise short-term bonuses. Additionally, Healy (1985) documents that managers participate in income-decreasing accruals when earnings are below the threshold stipulated for the eligibility

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environment. To meet high regulatory standards, the study finds that managers are more incentivised to manage earnings. This in turn causes earnings announcements to be less informative.

of bonus distribution. Healy's theory is largely referred to as the bonus-maximisation hypothesis. A large criticism of Healy (1985) is the way in which discretionary accruals are modelled, that is, the assumption of zero expected level of nondiscretionary accruals. Adopting the Modified Jones (Dechow, Sloan and Sweeney, 1995) model to estimate nondiscretionary accruals, Gaver, Gaver and Austin (1995) provide support for the findings of Healy (1985) and report evidence of income smoothing by managers. Managers appear to positively influence discretionary accruals when earnings fall below the lower bound. Contrary to Gaver, Gaver and Austin (1995)'s income-smoothing hypothesis, Holthausen, Larcker and Sloan (1995) find evidence of managers adopting income-decreasing discretionary accruals when compensation is already at its maximum. Guidry, Leone and Rock (1999) extend the analysis within business units of an organisation. The use of business units is of particular interest as centralised accounting policies preclude managers from adopting alternative accounting guidelines to manage earnings. Specifically, in the study, the parent organisation prescribes the GAAP applications, such as LIFO vs FIFO, resulting in discretionary accruals being a more critical component of earnings management for the business units. Given a setting where earnings management occurs within business units, the study also avoids potential loss of information at firm-level aggregation. Hence, this investigation increases the likelihood of earnings management behaviour being detected. Results lend support to findings that managers of business units also manipulate earnings to maximise their short-term bonus plans.

Central to the literature on corporate governance is the conflict of interest between shareholders and executives. As a mechanism to align these interests, contemporary executive compensation packages mainly include stock options and stock grants

(Murphy, 1999). As option-based compensation packages became more commonplace (see Murphy, 2003; Baker, 1999), research on the role of executive compensation in earnings management expanded to incorporate this growing trend, by focusing instead on equity-based compensation rather than total compensation. Evidence from these studies (Cheng and Warfield, 2005; Bergstresser and Philippon, 2006; Balachandran, Chalmers and Haman, 2008) adds support for the role of executive compensation in the adoption of earnings management, essentially, contradicting the design incentive effects of equity-based compensation.

Cheng and Warfield (2005) examined five components of the executive equity incentives: option grants, unexercisable options, exercisable options, restricted stock grants, and stock ownership. The study finds that earnings management increases by approximately 16.3 per cent for every one standard deviation increase in unexercisable options, using the probability of meeting or beating analysts' forecasts as a proxy for earnings management. In Bergstresser and Philippon (2006), the authors find that CEOs tend to exercise unusually large amounts of options and sell unusually large quantities of their firms' shares during years in which accruals make up a large component of a firm's reported earnings. The study suggests that equity-based compensation packages create strong incentives for CEOs to exercise upward earnings manipulation, rather than addressing issues related to corporate governance. Balachandran, Chalmers and Haman (2008) establish this relation in the Australian context. Examining 138 firms with on-market share buybacks, the study finds that in addition to discretionary accruals, Australian managers also engage in on-market share buybacks to drive up share prices. In particular, they find that the announcements of on-market share buybacks are enough to drive up share prices and these incidences are higher if the managers have option holdings in the firm.

Empirical research on management compensation and earnings management primarily examines remuneration of CEOs, CFOs or the entire executive management team. Jiang, Petroni and Wang (2010) examined the relative influence between CEOs and CFOs on the adoption of earnings management. The result found a stronger relation between a CFO's equity incentives and firm earnings management. This result is, however, challenged by Feng, Ge, Luo and Shevlin (2011), who examined 116 firm-years where Accounting and Auditing Enforcement Releases (AAERs) were issued by the US Securities and Exchange Commission (SEC). They find (i) no evidence of higher compensation packages for CFOs in manipulated firms; (ii) CEOs of manipulated firms have greater power within the organisation (proxied by the CEO also holding the position of Chairman of Board and co-/founder, when he is more likely to have a higher share of total compensation of top five executives); and (iii) a higher likelihood of CFOs leaving companies prior to the accounting manipulation period. The study concludes that CEOs of manipulating firms have substantial power in this process, including applying pressure on CFOs to undertake manipulation, to the extent that CFOs lose their jobs when they refuse to participate in accounting manipulation under CEO pressure. The distinction that Feng, Ge, Luo and Shevlin (2011) make between the relative effects of CFO versus CEO in a case of earnings management highlights the significance of individual personality in this area of research.

Table 2-2
Literature on Executive Compensation and Earnings Management

Authors	Sample	EM Model	Executive	Compensation Variable	Findings
Healy (1985)	94 Fortune US Industrial Firms (1930to1980)	Healy (1985)	Managers	Bonus plan grouped into lower, middle and upper bounds	Changes in accounting procedures are associated with adoption or modification of bonus plans
Gaver, Gaver and Austin (1995)	837 firm-years (1980to1990)	Healy (1985) & Modified Jones (Dechow, Sloan and Sweeney, 1995)	Managers	Bonus plan grouped into lower, middle and upper bounds	Income smoothing hypothesis (managers manipulate discretionary accruals upwards when earnings before discretionary accruals fall below the lower bound)
Holthausen, Larcker and Sloan (1995)	443 firm-years (1982 to 1984, 1987 to 1991)	Healy (1985) & Modified Jones (Dechow, Sloan and Sweeney, 1995)	Senior-Level Executives	Budget-based compensation scheme grouped into lower, middle and upper bounds	Managers manipulate earnings downwards if bonuses are already at their maximum
Guidry, Leone and Rock (1999)	117 business units (179 business-unit-years)(1994 to 1995)	Modified Jones (Dechow, Sloan and Sweeney, 1995)	Business-unit Managers	Compensation plans grouped into lower, middle and upper bounds	Managers of business units make discretionary accrual decisions based upon maximising short-term bonuses
Cheng and Warfield (2005)	9,472 firm-years (1993 to 2000)	Probability of EPS surprise being either negative, zero or one cent	CEO	Equity incentives - option grants, unexercisable options, ownership, exercisable options	CEOs with high equity incentives are more likely to meet or beat analysts' forecasts; and less likely to report large positive earnings surprises.

Bergstresser and Philippon (2006)	4,671 firm-years (1994 to 2000)	Modified Jones (Dechow, Sloan and Sweeney, 1995)	CEO	Equity incentives – measured as ratio of CEO's total compensation from a one percentage point increase in firm equity value	1. CEOs with overall compensation more dependent on value of stock and option holdings are associated with higher earnings management; 2. During high accrual periods, CEOs exercise unusually large number of options and also sell large number of shares.
Balachadran, Chalmers and Haman (2008)	138 on-market buyback firms (1996 to 2003)	Modified Jones (Dechow, Sloan and Sweeney, 1995)	Executives	On-market share buybacks, exercisable share options	Managers with option holdings use reported earnings (manage discretionary accruals) to influence share prices. Additionally, on-market buyback announcements are also used to drive up share prices.

2.2.3 Narcissism

Research in earnings management suggests that managers' characteristics play a vital role in affecting financial policies adopted by firms. Schrand and Zechman (2011) highlight the impact of selected personality tendencies on accounting-related behaviour and decisions. The study examines 49 misreporting firms subjected to SEC AAERs from the 1990s to 2000s and found an association between executive overconfidence and intentional misstatements in financial reports. This effect was not mitigated by higher internal/external monitoring through governance mechanisms, including block ownership, board size, board composition and measures of board member entrenchment. Consistent with theoretical predictions in de La Rosa (2008) and Gervais, Heaton and Odean (2010), Schrand and Zechman (2011)'s proxy of overconfidence is reflected in lower variable compensation of executives. Building upon the established relation between overconfidence and optimistic bias in prior literature,[18] Schrand and Zechman (2011) suggest that after an initial misstatement, overconfident executives are driven by their optimistic bias to continue down the slippery slope of subsequent misstatements. They continue to support their great optimism by hiring new employees, which often coincides with declining performance after an initial misstatement. This reflects the managers' optimism in both the firms' future performance and their ability to continue misreporting.

Amernic and Craig (2010) provide a theoretical framework proposing narcissism as a personality trait likely to lead to engaging in accounting manipulation. Narcissists are

[18] See, for example, Weinstein and Klein (1996). Overconfidence has also been associated with optimistic bias in executive decisions including investments and financing (see Malmendier and Tate, 2005; Ben-David, Graham and Harvey, 2007; Malmendier, Tate and Yan, 2011; Hirshleifer, Low and Teoh, 2012).

identified as individuals with grandiose belief in themselves and a need to continually reinforce this belief in others (Campbell and Foster, 2007). Narcissism has been the focus of a significant portion of research examining leadership (Chatterjee and Hambrick, 2007; Maccoby, 2007; Duchon and Drake, 2009; Chatterjee and Hambrick, 2011). To realise their grandiose beliefs, narcissists are focused on achieving their desired goals, often a mechanism they devise to provide self-affirmation (Duchon and Drake, 2009). The fear of falling short of these goals has been the leading subject of research documenting the tendency for narcissists to engage in unethical behaviour (Blickle, Schlegel, Fassbender and Klein, 2006; Brunell, Staats, Barden and Hupp, 2011). In an empirical study on corporate fraud, Rijsenbilt and Commandeur (2013) document a strong correlation between narcissistic CEOs and corporate fraud, one form of which includes intentional accounting misstatements as reported by the AAERs. The regularity, reliability and capacity of accounting to express results of complex activities in a single performance measure naturally facilitate a narcissist's requisite for frequent applause. Amernic and Craig (2010) theoretically posit that narcissistic CEOs over-identify themselves with the corporations they lead, assuming financial reports as their own 'personal report card'. With common traits such as dominance, self-confidence and grandiosity, there is growing evidence that narcissists often emerge as leaders (O'Reilly III, Doerr, Caldwell and Chatman, 2014).

2.2.3.1 Narcissism – Leaders

An individual is considered to suffer from narcissistic personality disorder if they display at least five of the nine items in the diagnostic criteria set out by the American Psychiatric Association. According to the diagnostic criteria, individuals are described as having an exaggerated sense of self-importance, causing them to overestimate their abilities and achievements. They have a tendency to undertake grandiose and highly visible actions, in order to seek the admiration they constantly seek from others. Narcissists are also characterised by an inflated sense of entitlement, and display arrogance or contempt towards others. In addition, they are interpersonally exploitative and unscrupulously use others for their own ends, as they have little capacity for empathy or understanding.

The literature on narcissistic leadership has provided confounding results on its impact on organisational performance. A narcissist's sense of entitlement and self-sufficiency are positively associated with charismatic leadership, often perceived to be more inspirational. In a study of the effectiveness of US presidents, Deluga (1997) finds that narcissistic presidents are perceived to be more charismatic, and it is this feature, which is positively associated with their leadership effectiveness. Often identified to favour grandiosity, narcissistic leaders frequently undertake bold and aggressive actions, drawing attention to their vision and leadership ability. This is especially evident in times of chaos and crisis where narcissistic leaders are able to assert more confidence to lead and rise to success, relative to their timid peers. Maccoby (2007) identifies that successful narcissists thrive under such conditions, for example, Churchill and Napoleon in wartime and Jobs, Elisson and McCaw during times of technological innovation. Another positive element of narcissists as leaders is that they are often a source of creativity and advocate innovative ideas (Goncalo, Flynn and Kim, 2010).

Amid the potential positive effects associated with narcissistic leadership is a wealth of evidence documenting its negative impact. Campbell and Foster (2007) affirm that narcissism is not only a cognitive diagnosis but frequently translates into behavioural tendencies. As narcissists commonly have an overinflated view of themselves, they perceive themselves to be superior to others. This also leads to poor interpersonal interactions, in particular, showing a lack of empathy (Judge, Piccolo and Kosalka, 2009), causing many authors to associate narcissism with destructive leadership (Padilla, Hogan and Kaiser, 2007). Their sense of entitlement also often leads to self-serving abuse of power (Maccoby, 2000), and in some cases, acting without integrity. In a study of various manager personality traits and white-collar crimes, Blickle, Schlegel, Fassbender and Klein (2006) find higher incidences of white-collar crimes in organisations with more narcissistic managers. The sample used in this German study includes white-collar crime offenders involved in bribery, counterfeiting, embezzlement, forgery, fraud, fraudulent bankruptcy, smuggling and tax evasion. Their excessive demand for admiration from others renders them highly sensitive to criticism (Maccoby, 2000), fostering an environment inhibiting information exchange within organisations (Nevicka, DeHoogh, Van Vianen, Beersma and McIlwain, 2011).

Literature focusing on the effects of narcissism as a CEO personality trait on company performance is scant. Chatterjee and Hambrick (2007) documents that narcissistic CEOs are more likely to undertake frequent and larger acquisitions, develop highly dynamic and grandiose strategic initiatives, but ultimately deliver for shareholders greater fluctuations in organisational performance. Chatterjee and Hambrick (2007)'s analysis of 111 CEOs in the computer hardware and software industry indicates that narcissistic CEOs take bold actions, which attract greater attention and, consequently, larger gains or losses. However, they do not find a significant performance differential between firms with narcissistic CEOs and non-narcissistic CEOs.[19] Further, Chatterjee and Hambrick (2011) report that in comparison to their less narcissistic peers, highly narcissistic CEOs are less responsive to recent objective performance. They are bolstered by social praise, supporting the view that narcissists have an enduring need for approval and admiration (Judge, Piccolo and Kosalka, 2009). Chatterjee and Hambrick (2011) also hypothesised the potential for narcissistic CEOs to be drawn to certain situations, allowing demonstration of narcissistic tendencies. However, in their test for endogeneity, the authors found that the narcissism measure adopted is not an endogenous proxy for other variables, one of which included was CEO board power.

Aktas, Bodt, Bollaert and Roll (2014) measured narcissism in CEOs who initiated mergers and acquisitions and examined their effect on the takeover process. Adopting the Raskin and Shaw (1988) methodology to estimate narcissism, the authors find that (i) narcissistic target CEOs achieve a higher bid premium; (ii) narcissistic acquiring CEOs have a higher likelihood of initiating deals and completing a faster negotiation process and; (iii) higher narcissism levels in target and acquirer firms decrease the probability of deal completion.

2.2.3.2 Narcissism – Measurement

Originally, narcissism was mostly viewed and characterised categorically; individuals were either classified as normal (absence of narcissism) or as abnormal (presence of

[19] Apart from corporate organisations, Resick, Whitman, Weingarden and Hiller (2009) find that CEO narcissism is negatively related to equitable rewards in their study of 75 CEOs in major league baseball organisations. The authors find that the authoritative component of narcissism and grandiosity positively impact organisational performance.

narcissism). Both clinicians and researchers adopted this view on narcissism until the mid-1980s. Researchers subsequently documented evidence that narcissism can be seen as a personality dimension whereby individuals can score on narcissism from low to high (see Raskin and Hall, 1979; Emmons, 1987; and Raskin and Terry, 1988).

The development of the Narcissistic Personality Inventory (NPI) first originated from the Diagnostic and Statistical Manual of Mental Disorders (DSM) II, which included 220 criteria. Raskin and Hall (1979) conducted several tests of internal consistency and item-total correlation within the 220 criteria to cull the criteria for NPI. These analyses produced a measure of narcissism with only 54 items with high internal consistency. The 54-item NPI was subsequently amended by Emmons (1984; 1987) using factor analysis, resulting in a conceptualisation of the narcissism concept into four major components: (i) authority/leadership; (2) superiority/arrogance; (3) self-admiration/self-absorption; (4) entitlement/exploitativeness. At present, the NPI is the primary survey adopted by most clinicians, and is a leading method adopted by researchers on narcissism (see Brunell, Staats, Barden and Hupp, 2011). The difficulty in implementing the NPI to measure narcissism lies in conducting the survey on a large scale. The requisite for individuals to participate in the NPI test impedes extensive empirical study on leadership narcissism, as top executives in organisations are reluctant to participate in survey research, and may also answer differently, knowing they are being evaluated (Cycyota and Harrison, 2006).

To address this, researchers adopt proxy measures for executive narcissism, which are deemed 'unobtrusive'. Chatterjee and Hambrick (2007; 2011) delineated this unobtrusive measure of narcissism with two criteria – indicators reflecting one or more aspects of the narcissistic personality (as per Emmons (1987)) and indicators reflecting a CEO's volition. The five-item narcissism index adopted by Chatterjee and Hambrick (2007; 2011) includes the prominence of a CEO's photograph in annual reports, CEO prominence in press releases, the use of the first person singular pronoun by the CEO in interviews, CEO's relative cash and non-cash compensation[20]. The authors conducted interviews with corporate communication and executive compensation consultants to confirm that the five-item narcissism index complies with the two criteria stipulated. Rijsenbilt and Commandeur (2013) extend this index to include 15 indicators, based on five major determinants of CEO behaviour, namely media exposure, compensation, power, growth and perquisites – (1) the *media* determinant, in particular, provides a platform for narcissistic CEOs to reinforce their intended perceived image; (2) as CEOs have considerable influence over their own compensation, CEO narcissism can also be inferred from the level of *compensation* received[21]; (3) the level of *power* the CEO possesses also communicates the need for grandiosity of a narcissistic CEO; (4) *growth* essentially describes the appetite for corporate acquisition by the firm, and, in particular, Rijsenbilt (2011) points out that a 'high growth target is a sign of hubris'[22]; (5) *perquisites* measures additional compensation taken by the CEO, not classified as salary or bonus. Rijsenbilt (2011) describes perquisites as a way in which CEOs legitimise their status. According to Rijsenbilt (2011), each of these determinants specifically corresponds to numerous NPI

[20] This is computed relative to the second-highest paid executive in the firm.

[21] In O'Reilly III, Doerr, Caldwell and Chatman (2014), the study documents that firms with more narcissistic CEOs have higher total direct compensation (this includes salary, bonus and stock options), have larger shareholdings, and greater discrepancies between CEO compensation and that of other members in the executive team.

[22] Studies including Aktas, Bodt, Bollaert and Roll (2014) have also documented that narcissists generally demonstrate a higher likelihood for corporate acquisitions, in particular, of larger target firms.

items. In recent studies on CEO narcissism and firm performance, a combination of selected proxies developed by Chatterjee and Hambrick (2007; 2011) and Rijsenbilt and Commandeur (2013) are adopted. Ham, Seybert and Wang (2014) adopted only the size of CEO signatures as measure of narcissism, validated by narcissism measured within a laboratory setting. Olsen, Dworkis and Young (2014) measured CEO narcissism as a composite of the relative size of compensation from the second highest paid executive and the size of CEO photographs in annual report. Buccholz, Lopatta and Maas (2014) adopted all 15 measures in Rijsenbilt and Commandeur (2013).

In a subsequent study, Aktas, Bodt, Bollaert and Roll (2014) comprehensively examined a total of 334 CEOs and the impact of CEO narcissism on the takeover process. The study adopted a method developed by Raskin and Shaw (1988), which established the prevalence of first person singular pronoun usage by narcissistic individuals. Specifically, Raskin and Shaw (1988) demonstrate a strong correlation between the proportion of first person singular pronouns to first person plural pronouns used in speech with the NPI scores. These results were documented to be robust to age, gender, content of speech analysed, and also persist after controlling for other personality traits – extroversion, neuroticism, psychoticism and loss of control, among others. When the correlation between NPI scores and second person and third person pronoun usage is tested, the relation is not found. Aktas, Bodt, Bollaert and Roll (2014) compute CEO narcissism scores from transcripts predominantly sourced from conference calls with analysts.[23] It is worth noting that in comparison to Rijsenbilt and

[23] Transcripts in this study include interviews with analysts or journalists available on the Lexis Nexis Academic and *The Wall Street* Transcript databases. Although Raskin and Shaw (1988) demonstrate that this narcissism indicator is independent of the topic of speech, Aktas, Bodt, Bollaert and Roll (2014) exclude interviews in relation to the attributed merger or acquisition, to avoid any possible influence of the deal on the measure of narcissism.

Commandeur (2013)'s list of measures for narcissism, the measure of narcissism as developed by Raskin and Shaw (1988) relies solely on a spontaneous speech as a result of a conversational transcript. This isolates potential external factors that could bias the measure, unlike measures as a result of pre-decided publications. The study finds that narcissism in CEOs of target and acquiring firms impacts takeover processes. Specifically, more narcissistic CEOs in target firms are associated with higher bid premiums but are less favoured amongst acquiring shareholders. For the acquiring firms, CEO narcissism results in deal initiations and swifter negotiations. The study, however, concludes that high narcissism in both takeover parties results in a lower probability of deal completion.

The adoption of CEO speech to infer company performance is also consistent with literature on measuring verbal and nonverbal vocal cues in detecting financial misreporting (see Hobson, Mayew and Venkatachalam, 2012; Larcker and Zakolyukina, 2012). In particular, the studies also adopt transcripts from analyst conference calls and earnings announcements. Hobson, Mayew and Venkatachalam (2012) examined a CEO's emotional profile (nonverbal vocal cues), measured by speech waveform, to detect financial misreporting, while in Larcker and Zakolyukina (2012), the investigation was conducted based on verbal cues of both CEOs and CFOs. The latter study documents differing cues in CEO and CFO speeches in the event of a financial misreporting. The implications of these studies provide evidence that the outcome of an earnings conference call goes beyond solely the announcement of earnings and company performance for the attributed period. Speeches by executives provide

Interviews related to litigation issues, transcripts from annual general meetings, and transcripts documenting CEO presentations are also removed.

additional information to assess the risk of misreporting (Hobson, Mayew and Venkatachalam, 2012). Earnings conferences also help shape analyst research reports.

2.3 Equity Analysts and Information Asymmetry

Analyst research is widely believed to increase the amount of information readily available to market participants (see Asquith, Mikhail and Au, 2005; Lepone, Leung and Li, 2012). Analyst research is the product of earnings announcements and analyst conference calls. Unlike voluntary disclosure by companies, analyst reports are also derived from 'private' information via relationships with management or by analysing publicly available information that is not easily interpreted by the public. Essentially, analyst research is expected to provide some form of informed opinion.

Within the investment community, institutions are segregated to either the buy-side or sell-side. Buy-side institutions typically comprise mutual funds, pension funds and insurance firms; institutions which invest in securities for the purposes of money management. Sell-side institutions, on the other hand, are involved in the creating, promoting, analysing and selling of securities in financial markets. Sell-side institutions are market intermediaries between issuers of the securities and the investing public. In the space of analyst research, buy-side research is restricted to the managers within the institution while sell-side recommendations are made available to buy-side investors. Extant literature on analyst research focuses on the dissemination of reports by the sell-side institutions (brokerage houses) to buy-side institutions (external).

Sell-side analyst research is thought to reduce information asymmetry in financial markets by disseminating private information or synthesised public information to all market participants. The reports generally attempt to forecast relative stock prices either by anticipating changes in firm fundamentals, or as a result of news or company announcements. As research departments at sell-side institutions do not generally generate direct income, their output indirectly complements other core lines which generate income, for example brokerage. Nevertheless, the value of information by sell-side analyst recommendations remains a contentious issue in the empirical literature.

2.3.1 Value of Analysts' Research

Empirical research assessing the value of analysts' research evaluates whether it has any impact on asset prices and resultant investment values at the time of its release. The earliest study on analyst recommendations by Givoly and Lakonishok (1979) investigates the effects of analyst earnings forecasts on stock prices using monthly NYSE data. The study finds abnormal returns of 2.7 per cent in a two-month holding period. Lys and Sohn (1990) confirm this finding, even when the measured forecasts are preceded by another forecasts, or by company earnings announcements. Similar results are reported for a sample of Canadian brokerage house stock recommendations. Controlling for non-synchronous prices, Bjerring, Lakonishok and Vermaelen (1983) find significant abnormal returns for investors in accordance with equity analyst recommendations.

Unlike earlier studies examining calendar-month returns, subsequent research on analyst reports has utilised more comprehensive data, which record the dates of recommendation changes and assesses price impact in higher granular time intervals. Stickel (1995) examines a comprehensive database, with over 17,000 recommendation changes extending over 1988 to1991 reported by Zack Investment Research. Stickel (1995) reports an average 1.15 per cent price increase over 11 business days centred on the release date of buy recommendations, and an average 1.28 per cent decline for sell recommendations. Womack (1996) further confirms these findings with data sourced from *First Call*, a real-time database reporting analysts' calls. The data examined by Womack (1996) are unique in that it includes analyst commentaries, earnings estimates and financial ratio analysis. Utilising these transcripts from the 14 most prominent US brokers in the database, Womack (1996) undertakes a key-word search to identify all recommendation changes. The study finds that recommendations contain valuable information, as price reactions to recommendation changes are found to be permanent, and not immediately mean-reverting. Adjusting for size, industry and the Fama-French three factor variables, Womack (1996) documents one-month excess return over 2 per cent, but with 8 per cent of standard deviation.

Focusing on an investor portfolio perspective, Barber, Lehavy, McNichols and Trueman (2001) assess the profitability of analyst recommendations using specific strategies, incorporating transaction costs in their analysis. While Stickel (1995) and Womack (1996) document evidence based on event-time returns, Barber, Lehavy, McNichols and Trueman (2001) apply a calendar-time performance evaluation. Using change in consensus ratings (across all analyst recommendations for a particular stock), the study finds that most highly recommended stocks earn a positive alpha of over 4 per cent per year and the least favourably recommended stocks earn a negative alpha of almost 5 per cent per year. The study, however, concludes that high-frequency portfolio rebalancing acts to erode these profits, consequently resulting in smaller realised returns from such strategies.[24]

In addition to apparent stock-picking abilities, Howe, Unlu and Yan (2009) also show that aggregate analyst recommendations are able to predict market excess returns, after controlling for other macroeconomic determinants. When examined by aggregate industry recommendations, analysts also demonstrate an ability to predict future industry performance.

2.3.2 Analyst Bias

In light of the well-documented evidence of the value of analyst research, there also exists evidence which highlights the presence of analyst bias. The most notable bias presented is a significantly lower number of sell and strong sell recommendations relative to buy and strong buy recommendations. This finding is supported in the US by Jegadeesh, Kim, Krische and Lee (2004) for a study over the period extending 1985 to 1999, where sell or strong sell recommendations made up less than 5 per cent of all recommendations. Womack (1996) finds that new buy recommendations occur seven times more often than sell recommendations in his dataset over the period of 1989 to 1991. Possible sources of the bias cited include the 'management relationships' and the 'selection bias' hypothesis.

[24] This conclusion is supported by Anand, Irvine, Puckett and Venkataraman (2013a), in establishing the importance of transaction costs in profitability. The main findings suggest that institutions persisting with low transaction costs consistently achieve superior fund performance.

Table 2-3
Analyst Bias Literature Summary

Author(s)	Market	Period	Database	Findings
Womack (1996)	US	1989-1991	First Call	New Buy recommendations occur seven times more often than sell recommendations.
Barber, Lehavy, McNichols and Trueman (2001)	US	1985-1996	Zacks Database	Only 3 per cent of recommendations are coded "sell"s.
Jegadeesh, Kim, Krische and Lee (2004)	US	1985-1998	Zacks Investment Research	Sell or strong sell recommendations made up less than 5 per cent of all recommendations.
Asquith, Mikhail and Au (2005)	US	1997-1999	Investext	The total issuance of upgrades is approximately twice the number of downgrades.

Francis and Philbrick (1993) discuss the management relationship hypothesis as they document that analyst over-optimism is associated with maintaining a favourable relationship with the management of the stocks they cover. As management compensation is related to stock prices, managers are in favour of optimistic analyst reports. An issue of negative research will likely reduce the analysts' level of access to valuable information, implying a trade-off decision faced by analysts between providing accurate forecasts and maintaining a working relationship with management. To ensure continual access to management information, analyst recommendations are associated with a positive bias in an attempt to please managers. Valuable management information, however, results in greater forecast accuracy. Modelling forecast bias and accuracy, Lim (2001) makes inferences on the utility of analysts, and finds consistency with results documented in Francis and Philbrick (1993). He finds that optimal analyst forecasts (with respect to accuracy) are often associated with bias, as he illustrates the trade-off analysts often encounter. A more recent study, Grant, Jarnecic and Su (2015) finds support for the phenomenon of analyst bias. The study documents asymmetric influence on a broker's market share when releasing relatively optimistic and relatively pessimistic analyst forecasts, with the release of relatively optimistic analyst forecasts generating larger influence on broker market share.

According to the 'selection bias' hypothesis, McNichols and O'Brien (1997) illustrate that analysts present a selection bias when initiating coverage on a new stock. Research analysts tend to initiate coverage on stocks they view favourably, and discontinue coverage in stocks in which they have unfavourable views. Such tendencies to cover favourable stocks create an apparent bias in consensus earnings estimates. Additional research suggests that analyst research coverage is associated with higher brokerage volume. Irvine (2001) finds an average brokerage market share of 3.8 per cent higher for covered stocks than uncovered stocks. Irvine (2004) further reports that 'buy' recommendations generate relatively more volume, both buying and selling, for an analyst's brokerage firm.

Another argument for analyst bias is in relation to costs of disseminating negative information. The consequence of making incorrect judgements with respect to negative information may be more severe for an analyst's reputation. Consistent with the cost argument for dissemination of information, the market reaction to analyst recommendations is also significantly asymmetric. Womack (1996), Boni and Womack (2006) and Asquith, Mikhail and Au (2005) find a larger market response to sell recommendations vis-à-vis buy recommendations. Boni and Womack (2006) also show that sell recommendations lead to larger market responses, approximately -4.69 per cent compared to 2.98 per cent for buy recommendations, in the three-day event period and in the post-recommendation period. To exceed the high costs of issuing negative research, disseminating negative information should generate higher value to investors. Hence, sell recommendations are perceived to have greater value.

In addition to recommendation bias by analysts, Brennan and Subrahmanyam (1995) propose the liquidity hypothesis as an alternative to explain the asymmetrical response to analyst recommendations. An increase in analyst coverage reduces bid-ask spreads in stocks and increases liquidity. Further, Irvine (2003) finds that the level of analyst coverage on its own is not sufficient to determine the increase in liquidity. He finds that initiation of analyst coverage is a stronger determinant of improvement in liquidity. While first-time negative recommendations do bring some liquidity to the stocks, the improvements are considerably less vis-à-vis positive recommendations.

2.3.3 Information Leakage around Analyst Recommendations

Given the perceived value inherent in analyst research, Green (2006) advances the literature by examining short-term profitability associated with early access to analyst recommendations. He finds that the value of analyst research is time-sensitive. Clients with early access (up to two hours) following analyst recommendations are able to capture, on average, two-day returns of 1.02 per cent by purchasing following upgrades and 1.50 per cent by selling (short) following downgrades. As the value of analyst research is time-sensitive, Irvine, Lipson and Puckett (2007) attempt to investigate abnormalities in the dissemination process. In this study, they examine the trading behaviour of institutions around the release of analyst recommendations. In particular, they focus only on 'Buy' and 'Strong Buy' analyst coverage initiations, where the issuance of recommendations is less likely to be clustered around confounding events. This study forms the first empirical evidence to document the existence of tipping, as they find a significant increase in institutional buying approximately five days prior to the public release of analysts' positive research.

Juergens and Lindsey (2009) provide further evidence of tipping. The authors examined market maker trading behaviour in Nasdaq PostData, for the period January 2002 to March 2005. Results provide evidence of information pre-release for downgrades, and elevated sell volume by market makers of the downgrading analysts' firms. However, in contrast to Irvine, Lipson and Puckett (2007), Juergens and Lindsey (2009) find no evidence in support of trading ahead of positive revisions. Comparing trading patterns preceding both positive and negative revisions, Juergens and Lindsey (2009) extend the literature by establishing larger responses to information on an upcoming downgrade recommendation. Specifically, due to the cost of disseminating negative information, studies have suggested that institutional investors exercise scepticism when receiving positive recommendation revisions (Iskoz, 2002; Malmendier and Shantikumar, 2014).

Busse, Green and Jegadeesh (2012) subsequently provide evidence in support of the asymmetric trading behaviour pre-release of analyst recommendations documented by Juergens and Lindsey (2009). Examining a longer sample period (1993to 2005), Busse, Green and Jegadeesh (2012) find that institutions are net sellers prior to the public release of downgrade recommendations, but not net buyers prior to upgrade recommendations. A key criticism of Juergens and Lindsey (2009) was the inability to clearly identify the direction of causality between the occurrence of analyst downgrade and abnormal selling activity by institutions; that is, if an upcoming analyst downgrade caused a surge in selling activity beforehand, or abnormal selling activity by institutions leads to the issue of a downgrade. To address this, Busse, Green and Jegadeesh (2012) directly investigate institutional order flow around recommendation revisions to establish that institutions incorporate analyst revisions into their trading decisions. Busse, Green and Jegadeesh (2012) find support for prior literature that sell-side analyst research is informative, and that buy-side institutions tend to trade in accordance with sell-side analyst recommendations. Further, the study finds that, contrary to Irvine, Lipson and Puckett (2007), institutions are not net buyers prior to upgrades but are significant net sellers over the five-day period prior to downgrades.[25]

Thus far, the literature has utilised aggregated market buy and sell volumes around analyst recommendations to present evidence in support of tipping. By definition, a stock's market buy volume must equal its market sell volume. Due to difficulties in attributing institutional abnormal trading activity to brokerage houses providing tips, the evidence presented only illustrates indirect evidence for tipping. Utilising a comprehensive dataset provided by the Australian Securities Exchange, including buying and selling broker identifiers, Lepone, Leung and Li (2013) map analyst recommendations to the order flow of their clients. They confirm empirical evidence of tipping in Australia, over the period January 1996 to June 2008. Accounting for 1 per cent (round trip) of transaction costs, the study finds that tipping provides abnormal profit opportunities of up to 0.4852 per cent for upgrades and 0.9642 per cent for downgrades.

[25] Irvine, Lipson and Puckett (2007) do not investigate the trading patterns prior to release of negative ratings, such as Sell or Strong Sell.

Extending the analysis on tipping, Christophe, Ferri and Hsieh (2010) employed a unique dataset of daily short sales between 2000 and 2001. The study finds that the average daily short-selling over days -3 to -1 from the downgrade date is approximately four times larger than on days not related to a downgrade recommendation. The study builds on theoretical predictions of Diamond and Verrechia (1987), suggesting that short-sellers are able to benefit from informational discrepancies by trading before negative information reaches the market.

Early access to information is economically beneficial (Grossman and Stiglitz, 1980). The literature above presents evidence on one form of early access to information, leakage of analyst recommendations, and the value associated with obtaining this advantage. As order flows in financial markets convey information on price movements[26], there must also be inherent value attributed to early access to information from the state of play in financial order books. Garvey and Wu (2010) and Biais, Foucault and Moinas (2014) have suggested that timely access to order books impacts execution costs for market participants[27]. The race for speed has caused a new breed of traders in financial markets today, computerised trading. Statistics have suggested that computerised trading now accounts for over 70 per cent of trading in US equities, 30-40 per cent of equities and futures trading volume in Europe and 5-10

[26] Brogaard, Hendershott and Riordan (2013) find that trading patterns by HFTs are correlated with limit order book imbalances, consistent with the ability to pre-empt price changes over short horizons measured in seconds. Carrion (2013) and Hirschey (2013) also find that HFTs can forecast short horizon price movements.

[27] Garvey and Wu (2010) examine geographically dispersed electronic traders in the United States and find a speed advantage to traders located geographically closer to the exchange. In addition to the ability to engage in trading strategies more conducive to speed, these traders also incur lower execution costs. In a theoretical study, Biais, Foucault and Moinas (2014) suggest that fast traders are able to obtain early information from fragmented markets, and consequently find attractive quotes. In addition to that, they also obtain advance information from their ability to access information from the market early, creating adverse selection costs for other market participants.

per cent of equity volume in Asia.[28] Yet, exchanges continue to encourage the growth of these traders by introducing new technology order types and information feeds, in support of innovation around them. With the ability to interact with financial markets in nanoseconds[29], the question remains as to the impact of these new traders or technology on financial markets, and, in particular, on institutional investors who are documented to account for the majority of equity ownership (Federal Reserve Board, 2011)[30].

2.4 Algorithmic trading

In light of a new entrant in financial markets, there has been growing research interest in the area of algorithmic trading. Financial economists, practitioners and regulators have been in regular debate over the pros and cons of this development. In an attempt to mediate these discussions, research in this area has sought to examine its consequences for financial markets and investors. The growing prevalence of algorithmic trading can be attributed to the increasing speed at which market participants can interact with exchanges. However, a subset of algorithmic trading, high frequency trading, has more recently been identified to be of greater concern, particularly since the May 6 2010 'flash crash'. Easley, Lopez de Prado and O'Hara

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[28] See 'High Frequency Trading – An Asset Manager's Perspective', *NBIM Discussion Note #1-2013*, 30/8/2013.

[29] Refer to *The Wall Street Journal* article. 'Wall Street's New for Trading Speed: The Nanosecond Age', *The Wall Street Journal*, June 14, 2011.

[30] Federal Reserve Board (2011), 'Flow of funds account of the United States', *Federal Reserve Statistical Release,* 11 June 2015.

(2011) present evidence that the sudden withdrawal of liquidity by HFTs amplified the volatility of the event.

While high frequency trading forms a subset of algorithmic trading, not all algorithmic trading can be associated with high frequency trading. Specifically, the SEC defines HFTs to be 'professional traders acting in a proprietary capacity that engage in strategies that generate a large number of trades on a daily basis' (SEC, 2010, pg. 45)[31]. Distinguished from algorithmic trading, high frequency trading is also characterised by very short investment horizons; frequent submission and cancellation of orders; and minimum end-of-day inventory positions (no significant unhedged positions overnight). These characteristics of high frequency trading are consistent with a range of active strategies employed by a diverse group of trading participants, ranging from proprietary market-making firms to quantitative hedge funds. Trading strategies employed by these predominantly proprietary traders include pseudo market-making and statistical arbitrage trading, and do not require human intervention. In contrast to high frequency trading, algorithmic trading is typically employed by agency traders. The objectives of the broad strategies employed by algorithmic traders are to achieve particular outcomes such as minimising implementation shortfall costs and minimising information leakage for block trades, or to stealthily capture liquidity.

2.4.1 Theoretical Literature

Cvitanic and Kirilenko (2010) are amongst the earliest theoretical works conducted on algorithmic and high frequency trading. In their model, the authors incorporate an

[31] Securities and Exchange Commission Concept Release on Equity Market Structure, 75 Fed Reg 3603, January 21, 2010.

electronic limit order book with participation by high (machine) and low frequency (human) traders. The authors argue that the introduction of automated high frequency trading reduces average trade value and volatility as market-making algorithms update their information in response to news announcements. Jovanovic and Menkveld (2011) develop a theoretical model where computerised traders act as informed market makers in an electronic limit order market, and assess the effects on investor welfare. The role of these market makers, they call middlemen, is to intermediate and reduce information friction between fast limit order and slow market order traders. They find that the participation of these middlemen lowers the effective bid-ask spreads, indicative of an improvement in liquidity. As high frequency traders are able to update their information faster than traditional market makers, they are able to reduce their exposure to adverse selection costs. In the event that markets are not faced with adverse selection problems to begin with, Jovanovic and Menkveld (2011) theorise that computerised traders may cause new adverse selection problems. Their ability to update their information set and react to a rapidly changing limit order book may reduce the willingness of slow (human) traders to trade with a better informed computerised trader. In such situations, spreads could widen, causing a reduction in market efficiency.

In contrast to Jovanovic and Menkveld (2011), Rosu (2014)'s theoretical study extends Kyle (1985) where HFTs are uninformed market makers. But Rosu (2014) introduces multiple informed traders and varies the fundamental value of an asset's price. In their model, the informed traders receive a 'signal', produced along with a gradual change in fundamental value of the asset. They find that information decays quickly, and this decay is faster with increased competition among informed traders, which 'generates the need for speed'. High rates of decay imply that information is quickly revealed in prices, making a market that is very efficient and liquid. The findings in Rosu (2014) multiple informed traders and varies the fundamental value of an asset's price. In their model, the informed traders receive a 'signal', produced along with a gradual change in fundamental value of the asset. They find that information decays quickly, and this decay is faster with increased competition among informed traders, which 'generates

Table 2-4
Algorithmic Trading (Theoretical) Literature Summary

Author(s)	Notes on Model	Impact of HFT
Jovanovic and Menkveld (2011)	Theoretical model developed with computerised traders as middlemen in financial markets	1. The results of the introduction of middlemen are mixed: the entry of high frequency trading tends to lowers spreads, but lower volume was noticed as well; 2. Fast traders are able to avoid adverse selection costs for themselves, subsequently imposing it on other market participants.
Cartea and Panelva (2012)	Markets consist of three groups of traders, retail, institutional and HFTs, with HFTs assumed to be unnecessary intermediaries	High frequency trading increases volatility in markets and causes larger price impacts; trading volume increases with the presence of HFTs.
Rosu (2014)	An extension of Kyle (1985) model, with the introduction of multiple informed traders	Indicates an improvement in liquidity and price discovery with the introduction of HFT.
Biais, Foucault and Moinas (2014)	Glosten and Milgrom (1985) framework	With speed advantage, HFTs generate adverse selection for other market participants.
Hoffman (2014)		Fast traders avoid adverse selection risk, imposing it on other market participants.

the need for speed'. High rates of decay imply that information is quickly revealed in prices, making a market that is very efficient and liquid. The findings in Rosu (2014) generally indicate improvements in liquidity but, more importantly, positive consequences on price discovery.

The positive effects aforementioned, however, come at the price of higher volatility in markets, according to Cartea and Penalva (2012). They developed a model with equity investors, professional traders and HFTs. Their model assumes that high frequency traders are a group of unnecessary intermediaries between equity investors and professional traders. On the basis of their speed advantage, high frequency traders are able to seize profit opportunities in their intermediary role.

On investigating high frequency trading effects on welfare implications, most theoretical models conclude negative consequences to other market participants, in particular, the increased adverse selection risk HFTs pose to other traders and increased volatility, leading to undesirable outcomes to liquidity traders., Foucault and Moinas (2014) find that investment in fast technology enables institutions to cope with market fragmentation. The ability to reap mutual gains from trade improves social welfare, and the advanced technology also provides faster access to value relevant information. This creates adverse selection, which reduces welfare. Using a Glosten and Milgrom (1985) framework, they find that HFTs overinvest in technology and exert negative externalities on other market participants. In a similar argument, Hoffman (2014) finds that fast traders are able to avoid being adversely selected, because their speed allows them to react to information first, reducing the risk of their limit orders being picked off after adverse price moves. Jovanovic and Menkveld (2011) earlier documented both the above findings on the ability of fast traders to avoid adverse selection costs for themselves, and impose it on other market participants.

2.4.2 Empirical Literature

The widespread interest in algorithmic and high frequency trading has also spurred the growth in empirical studies examining its consequences. Table 2-5 tabulates the existing literature that empirically examines this. The effects of algorithmic and high frequency trading have predominantly suggested positive implications for financial markets, but not all researchers are in agreement.

Hendershott, Jones and Menkveld (2011) show that computerised trading is associated with improved liquidity and better price discovery. The study uses the volume of message traffic, normalised by the number of trades, as a proxy for algorithmic trading. Their sample includes the introduction of autoquote on the NYSE in 2003 as an exogenous event to establish causality from algorithmic trading to market quality variations. The results of the study report that algorithmic trading, of which high frequency trading is a subset, significantly reduces both quoted and effective spreads. In the presence of algorithmic trading, the study also documents improved permanent price discovery as information is more efficiently being disseminated through quotes as opposed to trades.

Hasbrouck and Saar (2013) introduced a proxy for high frequency trading unique in the literature thus far, where trade and quote data in a millisecond environment is used to identify the strategic run of trades. The study finds that traders were interacting at as low as three milliseconds of latency. The study analyses trading activity on the NASDAQ for one chosen month in 2007 and 2008 each, allowing an analysis of high frequency trading in periods of high market stress. Hasbrouck and Saar (2013) further divide the trading days into 10-minute intervals and examine the impact of high frequency trading on volatility, depth and spreads. Allowing for a potential endogenous relation between high frequency trading and market quality, the study applies a two-stage simultaneous equation for each market quality metric and finds improvements to quoted depth, quoted bid-ask spreads and volatility, even during periods of market stress.

With a unique dataset provided by NASDAQ, Brogaard (2010) investigates the trading patterns of HFTs during times of heightened volatility. The dataset directly identifies 26 high frequency trading firms in the years 2008, 2009 and 2010. Dividing trading days into 15-minute intervals, he identifies periods of high volatility where prices fluctuate more than usual. During these times, he finds that HFTs supply more liquidity and demand less liquidity. Utilising the same dataset, Brogaard, Hendershott and Riordan (2013) document that HFTs play an important role in price discovery. HFTs are found to improve pricing efficiency by trading in the direction of permanent price changes and reversing transitory pricing errors, including in high volatility periods.

Opponents of algorithmic and high frequency trading, on the other hand, suggest that this subset of market participants has caused excess volatility in financial markets and question the traditional view of liquidity provision by limit orders to the market. Kirilenko, Kyle, Samadi and Tuzun (2014) show that high frequency trading exacerbated, but did not cause the May 6, 2010 "Flash Crash". The authors utilise audit trail data for the E-mini S&P 500 futures contracts on the day of the event to identify the specific algorithmic trading subset. The study finds that HFTs initially provided liquidity to fundamental sellers but subsequently contributed to the selling pressure that precipitated the incident.

Table 2-5
Algorithmic Trading (Empirical) Literature Summary

Study	Data Period	Market	HFT Proxy (Instrument)	Impact of HFT
Brogaard (2010)	Days in 2008to 2010	NASDAQ	26 Identified HFT Firms	HFT supplies more liquidity during high volatility periods. More often quotes at the BBO with lower depth and contributes significantly to price discovery.
Hendershott, Jones and Menkveld (2011)	2001to 2005	NYSE	Messages per $100 (quote automation)	HFT reduces spreads and adverse selection. Improves informativeness of quotes.
Hasbrouck and Saar (2011)	2007to 2008	NASDAQ	Strategic Runs (All Other Stock HFT-Participation)	HFT increases depth, reduces spreads and volatility.
Brogaard, Hendershott and Riordan (2013)	2008to 2009	NASDAQ & NYSE	Exchange Flagged	HFT improves price discovery
Hendershott, and Riordan (2013)	2008	Deutsche Borse	Exchange Flagged (via a pricing scheme, based on trading volume)	HFT contributes to efficient price discovery.
Brogaard, Hagstromer, Norden and Riordan (2013)	2012	NASDAQ OMX Derivatives Stockholm	Automated orders are flagged	HFT avoids adverse selection and imposes the costs on their counterparties.
Kirilenko, Kyle, Samadi and Tuzun (2014)	May 3-6, 2010	E-Mini	Audit trail data	HFT exacerbated volatility and the flash crash.
Chaboud, Chiquoine, Hjalmarsson and Vega (2014)	2003to 2007	Foreign Exchange	Exchange Flagged	HFT promotes informational efficiency improving price discovery, but increases adverse selection costs to slower traders.
Korakjczyk and Murphy (2014)	2012to 2013	Canadian equity Exchanges	Trader Characteristics	HFT provides more liquidity than Designed Market Makers. The costs to execute large trades are also significantly higher for more liquidity demanding trades than otherwise.
Boehmer, Fong and Wu (2014)	2001to 2011	42 Markets	Messages per $100	HFT promotes better market quality, but also higher volatility.
Brogaard, Hendershott, Hunt and Ysusi (2014)	2007to 2011	LSE	Exchange flagged (Firm-specific)	HFT is not associated with imposing higher execution shortfall costs to institutions.
Tong (2014)	2008to 2009	NASDAQ & NYSE	Exchange flagged	HFT is positively associated with stock liquidity but negatively associated with institutional trading costs.

While Hasbrouck and Saar (2013) find positive effects of high frequency activity based on certain measures of market quality, the authors document that many limit orders in electronic markets now have a ‘fleeting’ nature. This finding raises questions about the quality of high frequency trading-provided liquidity which is more often short-lived with validity periods measuring up to only milliseconds. Egginton, VanNess and VanNess (2011) lend support to this critique, showing a strong association between periods of extreme active quoting behaviour with degraded liquidity and elevated volatility. In their examination of algorithmic trading activity in the foreign exchange market, Chaboud, Chiquoine, Hjalmarsson and Vega (2014) find a stronger correlation among algorithmic ‘machine’ orders than the correlation among ‘human’ orders, bringing into question the contribution of algorithms to the transmission of systemic risk in financial markets.

While there has been growing interest in this subject, resources to accurately measure algorithmic and high frequency trading have been limited. Transaction and order level data that are available have lacked the ability to identify with precision orders and trade by a particular algorithmic or high frequency trading participant. To date, only Kirilenko, Kyle, Samadi and Tuzun (2014) have had access to this granular level of data, but are limited to the trading in index e-mini futures contracts around the flash crash of May 6, 2010. To address this, extant research has predominantly inferred the portion of computerised trading from intraday data to proxy for the intensity of algorithmic and high frequency trading. The advantage of this approach is the ability to construct a time-series of computerised trading activity, which permits sound inferences, as in Hendershott, Jones and Menkveld (2011). Several other studies, however, infer algorithmic and high frequency trading activity from periods of apparent high-frequency activity. Hasbrouck and Saar (2013) and Egginton, VanNess and VanNess (2011) identify episodes of market updates, which attract responses within milliseconds. The apparent downside to this method is the loss of breadth relative to the message-count sample, but it enables analysis with better certainty around a period with high frequency activity. With access to a proprietary dataset, Hendershott and Riordan (2013) and Brogaard, Hendershott and Riordan (2013) utilise a dataset that contains summary information about types of traders, in particular, high frequency trading or non-high frequency trading firms. The dataset provides, with accuracy, a summary of the aggregate order flow generated by 26 high frequency trading firms, over 2008-2009 at NASDAQ. The two datasets employed by empirical literature in this area of research have faced respective shortcomings – broader data enable stronger inferences, but makes a vague distinction between algorithmic trading, high frequency trading and slow trading; datasets that identify high frequency activity with certainty is limited to short time periods.

The lack of superior data has seen the emergence of research utilising trading system upgrades as proxies for increased high frequency trading activity. Brogaard, Hendershott, Hunt and Ysusi (2014) utilised the London Stock Exchange's implementation of technological upgrades over 2007 to 2011. Within this period, the authors identified five separate events, which ultimately reduced latency from 11 milliseconds to approximately 0.113 milliseconds for the fastest traders. In an examination of 42 exchanges worldwide, Boehmer, Fong and Wu (2014) take the implementation of co-location services as an instrument to algorithmic trading intensity. The study largely confirms prior studies on the positive effects of algorithmic traders to liquidity but in a broader context including 42 exchanges. Examining the

NASDAQ OMX Stockholm, Brogaard, Hagstromer, Norden and Riordan (2013) identified an initial date on which co-location services were offered and two subsequent upgrades to improve latency for market participants who opt to subscribe for the improved service. They are able to distinguish a spectrum of fast and slow traders by identifying participants who subscribed to which combination of upgrades offered by the exchange. Consistent with theoretical predictions, the study finds that co-located traders are able to reduce their adverse selection costs and non-co-located traders incur higher adverse selection costs on average.

Despite the lack of accurate measures to identify HFTs, empirical literature has thus far documented that HFTs are associated with positive effects on liquidity – measured by traditional bid-ask spreads and depth, but negative effects on volatility. There is an increasing focus on examining the effects of HFTs on large institutional trades, ultimately assessing the impact on the costs of these trades, which is arguably one aspect of market quality which can be assessed (Korajczyk and Murphy, 2014). Amongst the first empirical studies to publish the effects of high frequency trading on institutional execution costs is Brogaard, Hendershott, Hunt and Ysusi (2014). The study first establishes that LSE technological upgrades in 2007to 2011 resulted in higher high frequency trading activity and then extrapolated the effects of the LSE upgrade events to institutional execution costs. Results from the study failed to establish any relation between higher high frequency trading activity and institutional execution costs.

With the NASDAQ exchange-flagged HFTs, Tong (2014) also examines the effects of HFTs on execution price for large institutional trades. The data include trades in 120 stocks, which have been flagged by NASDAQ if a particular counterparty is HFT. Results of the study document a positive relation between HFT intensity and institutional trading costs, specifically a one standard deviation of increase in high frequency trading intensity resulting in institutional execution shortfall by over 30 per cent. The findings are robust to the Granger causality test, in which the study confirms that intensive HFT activity causes larger institutional trading costs, but not vice versa. However, the NASDAQ database, which identifies HFTs, has been criticised by some, as it may suffer a self-selection bias, because only HFTs that identified themselves as HFTs are in the data. Relying on the Securities and Exchange Commission's rule 15b9-1, HFTs have been able to conceal their trading identities.[32]

Korajcyzk and Murphy (2014) examine how HFTs and Designated Market Makers (DMM) interact with large institutional trades. The data employed by Korajcyzk and Murphy (2014) are an extensive set which includes all trade and order-level data for all Canadian equities markets over the period January 1, 2012 to June 30, 2013. Each record in the dataset contains a masked identification for the trader associated with the order, allowing the authors to infer the characteristics of each trader across time. Korajcyzk and Murphy (2014) first classify HFTs by four requirements: (i) highest quintile of number of trades as a percentage of all trades; (ii) net daily trading position as a percentage of volume of shares traded of 10 per cent or less; (iii) order-to-trade ratio that is greater than 1; and (iv) volume of shares actively traded as a percentage of all shares traded is less than 80 per cent. Traders satisfying the above requirements for

[32] See for example, public statement by Commissioner Luis A. Aguilar from the U. S. Securities and Exchange Commission on 'Enhancing Oversight of Our Equities and Options Markets' on March 25, 2015. Rule 15b9-1's exception for proprietary trading allowed certain HFTs to avoid the requirement of membership in a registered national securities association. The lack of membership meant that when trades are executed by HFTs, the source of trades is not being reported to the Financial Industry Regulatory Authority (FINRA).

at least 75 per cent of stock-days in which there is at least one trade and are active in at least 20 stock-days, are identified as HFTs. The study finds that HFTs and DMMs provide a significant amount of liquidity to large trades, by providing passive limit orders but, comparatively, results show that HFTs provide substantially more liquidity than DMMs. When the roles of these market participants are examined for very large trades, which accounts for a sizeable proportion of the stock's daily volume, HFTs are found to provide less liquidity than DMMs. The study concludes that trading costs are negatively related to HFTs and DMMs' liquidity provision, but when large institutional trades demand additional liquidity from these market participants, these trades ultimately incur higher implementation shortfall costs.

2.5 Execution Costs

The significance of execution costs is a central issue around assessing trading profitability by institutions. To understand the impact of computerised trading on financial markets today, the effects on institutional execution costs should be examined. This area in the empirical literature is still in its infancy. This section first outlines the components of execution costs associated with large trades. Section 2.5.1 subsequently discusses the existing literature around institutional execution costs.

The literature describes a perfect capital market as one in which all investors have equal access to complete information. The ability to possess all information available in the market ensures efficiency in markets, as asset prices reflect intrinsic value, or a general change in risk-return preferences of investors in the market. In efficient markets, prices reflect new information and the act of transacting should incur no additional impact, irrespective of trade sizes. Empirical literature, however, provides evidence of observed price effects associated with transactions (see for example, Kraus and Stoll, 1972; Holtausen, Leftwich and Mayers, 1987). The authors offer three potential explanations for the observations documented, in less than perfect capital markets: (i) liquidity costs; (ii) inelastic demand curves, and (iii) information effects.

Unlike in perfect capital markets, counterparties to trade large blocks of shares are not always readily available, and identification of such counterparties can be costly. Potential sellers of large blocks will have to provide a price concession to the purchaser who acts as an intermediary between the seller and the ultimate purchaser. A price reversion will then occur, to establish a new equilibrium unless the intermediary immediately sells the shares to reduce inventory (Holthausen, Leftswich and Mayers, 1987). Likewise, under such conditions, purchasers must pay a premium, owing to the cost of identifying potential sellers of smaller bundles of shares. Demsetz (1968) and Kraus and Stoll (1972) describe this temporary deviation of price as the liquidity cost.

In perfect capital markets, securities act as perfect substitutes for one another, leading to perfectly elastic demand curves for all securities. When there are insufficient perfect substitutes to a particular security, the excess demand curve facing sellers and excess supply curve facing buyers are not perfectly elastic. In such situations, buyers experience difficulty in purchasing securities at the prevailing price, and generally have to offer a premium to induce sellers to sell more shares (than the equilibrium number of shares). Equivalently, block sellers must offer a discount to induce buyers to hold the additional quantities for the sellers' disposal. Because a firm's prospect remains unchanged over this process, purchasers at the discounted price have higher expected returns in all future periods, and the equivalent argument applies for sellers at the premium price. Shleifer (1986), Goldstein and Kavajecz (2000), Biais, Hillion and Spatt (1995) and Levin and Wright (2002) document empirical evidence of the lack of elasticity in the demand and supply curves for securities in the US, France and the United Kingdom. The information hypothesis implies that imperfect substitution causes slower price reversals post-trade, especially in markets lacking resiliency.

Relaxing the assumption of equal access to full information by all investors yields a market with information asymmetry amongst investors. Informed traders respond to their private information by reacting to mispricing, caused by other investors who possess inferior information. Securities attain a new equilibrium price level only when transactions impounding new information occur. Equilibrium stock prices remain elevated after an informative buyer-initiated trade and depreciate after an informative seller-initiated trade. Until the arrival of new information, succeeding price changes are unwarranted. Easley and O'Hara (1987) document that adverse selection problems occur in the presence of block trades because uninformed traders do not exhibit a preference for executing trades in large blocks. As private information is often short-lived, the urgency to trade on information discrepancy results in large block trades by informed investors (Scholes, 1972). Thus, a positive relationship exists between trade size and private information. Contrary to this, Barclay and Warner (1993) show that informed investors act as stealth traders, splitting up large orders into medium-sized parcels[33], qualifying the relationship established between trade size and information content. In a later re-examination of the stealth-trading hypothesis by Barclay and Warner (1993), Chakravarty (2001) finds that a disproportionately large amount

[33] According to Barclay and Warner (1993), medium-sized parcels range between 500 and 9,999 shares in volume.

(approximately 79 per cent) of cumulative stock price changes are attributed to medium-sized trades initiated by institutional investors. The results of Chakravarty (2001)'s study confirm the stealth-trading hypothesis by Barclay and Warner (1993) but extend the findings to support the proposition that institutional trades are informative.

2.5.1 Institutional Execution Costs

A typical institutional order originates from a portfolio manager of a buy-side institution, who submits the order, inclusive of instructions, to the buy-side trading desk. To meet its best execution obligation, the buy-side trading desk decides on a number of factors, including whether to split the order and the trading horizon for the order. Additionally, the desk decides on the trading venue(s) and broker(s) to submit or split the orders amongst. The primary responsibilities of the trading desks are to ensure execution quality, monitor broker performance and select the strategy that best suits the portfolio manager's motive to trade. Regardless of strategy, a key factor in the execution quality of institutional trades is the execution costs incurred (Boehmer, 2005). Due to the proprietary nature of institutional trading data, early empirical research on the execution quality of institutional trades is scarce.

Chan and Lakonishok (1993) provide one of the earliest studies to examine execution costs for institutional trades. The study utilises a unique dataset, which includes all transactions (rather than exclusively block trades) executed by 37 large institutional money management firms. The sample employed in this study is comprehensive, extending to over one million transactions from July 1986 to December 1988, and provides more detail than that examined in previous literature. In addition to the price and time of each transaction, the data includes both the identity of the money manager submitting the trade and the direction of each trade. The availability of trade direction addresses the biases introduced by the tick test in previous studies on price effects. Chan and Lakonishok (1993) show that institutional purchases attract greater total and permanent price effects, but temporary effects are larger for institutional sales. The study confirms the presence of asymmetry in price effects between block purchases and sales, documented in Holthausen, Leftwich and Meyer (1987; 1991). Extending the information effects hypothesis, Chan and Lakonishok (1993) suggest that the differential information content of block purchases and sales provides an explanation for the asymmetry price response. 'Since an institutional investor typically does not hold the market portfolio, the choice of a particular issue to sell, out of the limited alternatives in a portfolio, does not necessarily convey negative information…[as] a result, there are many liquidity-motivated reasons to dispose of a stock. In contrast, the choice of one specific issue to buy, out of numerous possibilities on the market, is likely to convey favourable firm specific news' (Chan and Lakonishok, 1993, p. 185).

Research on institutional trading behaviour subsequently employed data provided by the Plexus Group, a consulting firm specialising in assisting institutional investors in monitoring and reducing equity trading costs. Keim and Madhavan (1995; 1997) employ this data to investigate the trading behaviour of institutional investors, and find support for the price impact asymmetry documented by Chan and Lakonishok (1993; 1995). Additionally, the authors document substantial variation across institutions in execution quality, and with the advantage of the Plexus data, which include the institutions' investing strategies; the authors attribute the differences to investment style and trade difficulty. Utilising the data from Plexus Group, Jones and Lipson (2001) examined the effect of decimalisation of prices and price increments on the NYSE, on institutional execution costs. With data records of date and time at which the order is released to a firm's trading desk, Jones and Lipson (2001) measure execution costs by identifying the prevailing midpoint prior to receipt of the order by the trading desk. Results show that institutions face higher execution costs after decimalisation, particularly for liquidity demanding orders. In an investigation of relationships in the brokerage industry, Conrad, Johnson and Wahal (2001) examined the execution costs of trades within the Plexus Group data. Specifically, the study investigates the execution costs of trades submitted to soft-dollar brokers versus others, and finds incrementally higher market impact costs for trades submitted to soft-dollar brokers.

Details of institutional trades from Plexus contain an anonymous identifier for institutions, which is periodically randomised. This restricts the ability to study institutional execution performance over time. Goldstein, Irvine, Kandel and Weiner (2009) employed data from a proprietary source consolidated by Ancerno Ltd to examine commissions paid by institutions to brokerage houses. The data contain trades of 750 institutional investors worldwide across 1,216 brokerage firms. Unlike Plexus, Ancerno Ltd contains the full trading history for each anonymised institution over time. The study finds that full-service brokers are able to extract more commissions from institutions. As institutions do not negotiate commissions frequently, the amounts of commissions paid do not differ with trade characteristics (in particular, execution costs). In their examination of institutional trading costs, Anand, Irvine, Puckett and Venkataraman (2013a; 2013b) examined the data from Ancerno Ltd. Anand, Irvine, Puckett and Venkataraman (2013a) examine the performance of institutional trading desks and conclude that execution costs vary as a result of differences in broker skills. The study documents that the performance of an institution's portfolio is largely driven by the execution quality of the broker. Anand, Irvine, Puckett and Venkataraman (2013b) investigate institutional trading costs in the US equity markets around events of liquidity crisis. Over the period of 2007-2009, the authors document increased execution costs incurred by institutions around key events of the Global Financial Crisis (GFC). The study also suggests that traditional liquidity measures, such as bid-ask spreads and depth in the limit order book, would not have portrayed the response of institutional investors to periods of market stress, such as that of the GFC.

2.6 Hypotheses Development

In this section, a set of testable hypotheses are developed in view of the extant research reviewed, and tests of these are reported in the succeeding chapters. The hypotheses developed in this section relate to two components of information asymmetry in financial markets identified by Merton (1987), which forms a theme to the dissertation.

2.6.1 CEO Narcissism and Earnings Management

Management personality traits have been the subject of understanding the incidences of earnings manipulation (see for example, Schrand and Zechman, 2012; Jiang, Petroni and Wang, 2010; Feng, Ge, Luo and Shevlin, 2011). Further research provides supporting evidence of a relation between financial reporting policy and innate characteristics of individual managers: overconfidence (Schrand and Zechman, 2012), gender (Srinidhi, Gul and Tsui, 2011) and masculinity (Jia, Van Lent and Zeng, 2014)

A common personality trait examined in the leadership literature is narcissism. Duchon and Drake (2009) suggest that organisations with narcissistic managers set unrealistically high goals, and resort to unethical behaviour to achieve these goals. A narcissist is described by various characteristics, including arrogance, self-absorption and hostility, but a lack of self-esteem (Rijsenbilt and Commandeur, 2013). To reaffirm this belief, they constantly require admiration. The need for such external validation is found to result in narcissistic leaders expending considerable resources on enhancing their public image (Bass and Steidlmeier, 1999). Over time, a narcissist's inflated sense of self-worth translates into a distorted view of their own abilities, and their inherent charisma, perceived or otherwise, enables them to manipulate and influence the perception of others (Chatterjee and Hambrick, 2011). Further theoretical predictions by Amernic and Craig (2010) suggest that narcissistic CEOs, in particular, are more likely to make earnings management decisions for their organisations as an effort to uphold their ego and preserve self-esteem. A narcissist's craving for applause must be obtained from external parties in the form of adulation and admiration (Wallace and Bausmeister, 2002). According to Amernic and Craig (2010), the investment community provides an appropriate crowd to provide this affirmation when CEOs announce their 'personal report card'. This dissertation forms the first hypothesis from theoretical developments from Amernic and Craig (2010).

> *$H_{3,1}$: CEO Narcissism is positively related to firm earnings management, ceteris paribus.*

2.6.2 Trading Behaviour around Information Leakage on Analyst Recommendations

Empirical evidence supports the view that analysts are reluctant to provide unfavourable recommendations and reports as they attract significant negative impacts (and high costs) on relationships with associated firms (Womack, 1996; Jegadeesh, Kim, Krische, and Lee, 2004). The nature of this reluctance results in a higher perception of value and superior credibility attributed to negative recommendation reports (Frankel, Kothari and Weber, 2006; Asquith, Mikhail and Au, 2006). This view is supported by Juergens and Lindsey (2009), who observed a disproportionate increase in trading volume around the release of downgrade recommendations compared to upgrade recommendations. The asymmetry of stronger price responses and profitability to downgrade recommendations compared to upgrade recommendations upon public release is also well documented (see Womack, 1996; Green, 2006; and Jegadeesh, Kim, Krische and Lee, 2004).

While some prior studies have examined the likelihood of the recipients' propensity to act on downgrade tips; no research has analysed how recipients behave in different market conditions (i.e. bull, bear and neutral). Chiyachantana, Jain, Jiang and Wood (2004) have documented that market conditions are a determinant of institutional trading costs, and hence performance. Specifically, purchases incur larger trading costs in bull markets, and sales incur larger trading costs in bear markets. Further, Moshirian, Ng and Wu (2009) find that analysts issue more positive research in bull markets, while in bear markets there is more issuance of negative research. The implication of Moshirian, Ng and Wu (2009) is that the market perceives the informativeness of upgrades and downgrades differently, dependent on the condition of the market, and responds accordingly. However, the sheer volume of positive stock recommendations issued by buy-side brokerage firms to entice trading volume and increase commission (Agrawal and Chen, 2008; Irvine, 2004; Jackson, 2005) suggests recipients may be inundated with numerous tips on upgrades. This in turn causes recipients to generally dismiss the issuance of positive research, as they remain sceptical about the relevance of upgrade recommendations (Iskoz, 2002; Malmendier and Shanthikumar, 2007). Following the above discussion, in an up-trending (bull) market, downgrades are likely to have a greater impact. However, in a down-trending (bear) market, upgrades do not necessarily yield any impact.

$H_{4,1}$: Market conditions and upgrade recommendation revisions are not associated with broker abnormal buy volume prior to the release day.

$H_{4,2}$: Market conditions and downgrade recommendation revisions are associated with broker abnormal sell volume prior to the release day.

Differences in the level of information asymmetry between market participants across stocks of varying size and liquidity can influence profit expectations. Bhushan (1989) observed that larger companies generally have better information disclosure, which leads to following and coverage by more analysts. Lang and Lundholm (1993) established that a bilateral positive relationship exists between a company's information environment and analyst coverage (see also Healy and Wahlen, 1999). This indicates that information asymmetry is likely to be most acute for mid- and small-sized companies where disclosure is sparse and analyst coverage limited.[34] Analyst reports in these firms are hence more likely to influence prices (Asquith, Mikhail and Au, 2005), as they reduce information asymmetry (Easley and O'Hara, 2004)[35] and tipping in these companies is potentially more profitable. In addition to firm size, Brav and Lehavy (2003) also document the role for 'degree of recommendation change' when assessing the value of analyst recommendations. They

[34] Earlier empirical work on firm size and information environments has established that smaller firms have less timely and efficient information dissemination processes in place (see, for example, Stickel, 1985). Further research then shows that a firm's information environment is positively related to the number of analyst following (Arya and Mittendorf, 2007).

[35] While it is debatable if analysts uncover new information or simply disseminate content that some market participants already know, there is evidence that analyst reports reduce information asymmetry.

suggest that a high level of recommendation revision implies a higher degree of uncertainty conveyed by analysts when assessing the firm's underlying prospects. As firm size and level of recommendation revisions create uncertainty among market participants, the next hypothesis tests whether firm size and recommendation level revision have an effect on abnormal trading volume.

> *$H_{4,3}$: Abnormal trading volumes prior to recommendation release day is negatively related to firm size and positively related to recommendation level revisions.*

Another aspect of profitability for recipients is the relative information value directly attributed to the analyst reports. Information shocks (for example, company announcements, media releases, unconfirmed rumours, social media tweets) may create stock price movements in the direction of the analyst reports prior to the official release by the analysts. Such incidences weaken the information value of the analyst reports, reduce potential profitability of the leaked information to recipients and lower their propensity to act. In the event where stock prices have moved in large amounts, impounding the information from an upcoming release, recipients are less likely to provide brokerage houses with the corresponding order flow. Conversely, if tipping is identified, analyst research recipients should achieve greater return in subsequent periods if they act on the valuable information.

> *$H_{4,4}$: Abnormal trading volume prior to recommendation release date is positively related to the abnormal returns.*

The ability of sophisticated investors to generate abnormal returns from informational advantage has generated a great deal of interest in empirical literature. Independently, research has found that different groups of sophisticated investors, institutional investors (see Grinblatt and Titman, 1993; Wermers, 2000; Ali, Durtschi, Lev and Trombley, 2004; Baker, Litov, Wachter and Wurgler, 2009) and short sellers (see Desai, Ramesh, Thiagarajan and Balachandran, 2002; Asquith, Pathak and Ritter, 2005; Boehmer, Jones and Zhang, 2008; Diether, Lee and Werner, 2009) are informed. In an examination around earnings announcements, Berkman and Mackenzie (2012) confirm the informational role of both institutional investors and short-sellers, but found that institutional investors take longer to respond. Theoretical discussions by Diamond and Verrechia (1987) suggest that short-sellers profit from trading on informational discrepancy before the market has impounded negative information. Adopting downgrade tips, Christophe, Ferri and Hsieh (2010) documents high short-selling activity prior to a downgrade recommendation. The informational event of downgrade recommendations is of particular interest in this regard, as recipients intending to act can execute by (i) selling a pre-owned stock or (ii) short-selling the attributed stock. The next hypothesis considers the types of recipients that are likely to act on “tips”.

> *$H_{4,5}$: Abnormal short-selling activity occurs prior to the release day of downgrade recommendation revisions.*

> *$H_{4,6}$: Abnormal institutional selling activity does not occur prior to the release day of downgrade recommendation revisions.*

2.6.3 The Impact of Co-Location on Institutional Execution Costs

Garvey and Wu (2009) and Brogaard, Hagstromer, Norden and Riordan (2013) highlight the importance of proximity in obtaining early access to market data. In light of rapid technological changes, exchanges worldwide have continually offered innovative solutions, in particular, the service to co-locate trading engines at the exchange server site. This technological improvement acts to reduce latency for market participants. Empirical evidence reports that latency reducing innovations introduced by exchanges have led to an increase in algorithmic and high frequency trading activity. Brogaard, Hendershott, Hunt and Ysusi (2014) document evidence for the London Stock Exchange while Frino, Mollica and Webb (2014) document this for futures trading on the Australian Securities Exchange.

> *$H_{5,1}$: Technological upgrades at exchanges lead to an increase in algorithmic and high frequency trading activity.*

The perceived advantage of algorithmic and high frequency trading with respect to speed and information has attracted the attention of regulators and market participants. Jovanovic and Menkveld (2011) theorise that high levels of algorithmic and high frequency trading are associated with lower trading turnover. The speed advantage of computerised traders reduces the likelihood of trading by slower traders, as they avoid being traded against informed fast traders. Additionally, other theoretical studies have suggested that computerised traders are associated with higher levels of adverse selection costs and excess volatility (see Foucault, 2012, Cartea and Penalva, 2012). In an empirical study, Boehmer, Fong and Wu (2014) confirm the positive relation between algorithmic trading intensity and volatility. Institutional investors are increasingly developing sophisticated trading algorithms in an attempt to hide and mask their order flows from computerised traders to avoid being picked off by high frequency traders (Jones, 2013; Macintosh, 2013). Additionally, Cartea and Penalva (2012) theoretically discuss the increased volatility caused by this subset of traders, translating to the incurrence of higher price impacts by other market participants:

> *$H_{5,2}$: The level of algorithmic and high frequency trading is positively related to the execution costs incurred by institutions.*

2.7 Summary

This chapter reviews the literature related to the issues examined in this dissertation and develops a number of hypotheses. Tests of these hypotheses are presented in the following chapters. The next chapter examines the relation between CEO narcissism and earnings management. The subsequent chapter examines the extent of information leakage on analyst recommendations and investor's propensity to act under different circumstances. The following chapter to this dissertation investigates the impact of co-location on institutional execution costs.

Chapter 3: CEO Personality and Earnings Management

3.1 Introduction

The first examination conducted in this dissertation relates to the first hypothesis on understanding how narcissistic personalities affect earnings management. As the literature review in Chapter 2 identifies, there is growing interest in understanding management personality traits around the incidence of earnings manipulation (see for example, Schrand and Zechman, 2012). Further research uncovers the relation between financial reporting policy and innate characteristics of individual managers: optimism and managerial risk-aversion (Graham, Harvey and Puri, 2013), gender (Huang and Kisgen, 2013; Srinidhi, Gul and Tsui, 2011), and masculinity (Jia, Van Lent and Zeng, 2014). The nature of earnings announcements – their periodicity and established financial reporting regulations – should create a reliable information source for investors. Yet, the practice of earnings manipulation essentially distorts the information accessible to investors. The literature identifies that CEOs in their leadership duties act on the discretion afforded to them in the adoption of accounting policy (Feng, Ge, Luo and Shevlin, 2011) and the leadership literature identifies that ‘[n]arcissism lies at the heart of leadership’ as Kets de Vries (2004, p. 188). Amernic and Craig (2010) posits in their theoretical discussion that narcissistic leaders over-identify with results as their ‘personal report card’ and are likely to lead to engaging in accounting manipulation. The first hypothesis tested in this dissertation ($H_{3,1}$) posits that CEO narcissism is positively related to firm earnings management, ceteris paribus.

The rest of this chapter is organised as follows. Sections 3.2 and 3.3 detail the data and research design used to test hypothesis $H_{3,1}$. Section 3.4 provides empirical results. Section 3.5 provides a summary of this chapter.

3.2 Data

3.2.1 Earnings Management

To test hypothesis $H_{3,1}$, financial accounting data for the period 2007 to 2013 are obtained from the Annual Compustat dataset, which includes all public files of exchange listed corporations. The sample of firms examined is limited to all NYSE listed securities with complete information on: Total Assets, Earnings Before Extraordinary Items, Change in Revenues, Property, Plant and Equipment, as required in the Jones model of earnings management (Jones, 1991); Change in Accounts Receivables, as required in the Modified Jones model of earnings management (Dechow, Sloan and Sweeney, 1995); and Cash Flow from Operations, as required in the Dechow-Dichev model (McNichols, 2002) of earnings management. Consistent with the empirical literature (see Burgstahler, Hail and Leuz, 2006; and Stubben, 2010), excluded from the sample are firms in the financial industry, as the relation between revenues and accruals can be distorted due to the regulatory compliance of such firms.

3.2.2 CEO Narcissism

Data on measures of narcissism are collected from transcripts of interviews held at analyst conferences, distributed via Bloomberg. Transcripts for analyst conferences of US-domiciled stocks listed on the NYSE over the fiscal years 2008 to 2012 are sampled.[36] Analyst conferences typically start with speeches by executives from the company and involve at least three participants from the firm: the CEO, CFO, and Head of Investor Relations; additional executive officers may be present in some instances. At annual analyst briefings, following the formal speeches in which executives disclose financial results, the conference opens up to a question and answer session. This component of the conference forms the area of interest to the analysis that follows, as it best captures and reflects the concept of narcissism in its spontaneity and unconsciousness (Aktas, Bodt, Bollaert and Roll, 2016).

3.3 Research Design

This section outlines the research design utilised in this chapter. Outlined are the methods implemented to: (1) estimate discretionary accruals and revenue; and (2) evaluate the relation between CEO narcissism and earnings management.

[36] The period of analysis is 2008-2012. However, as mentioned in the previous section, accounting data are obtained from Compustat including years 2007 and 2013 to construct lead and lag variables (in particular, cash flow from operations as per McNichols (2002)).

3.3.1 Earnings Management Models

To examine the relation between CEO narcissism and earnings management (*$H_{3,1}$*), four models of earnings management are estimated: the Jones model (Jones 1991; DeFond and Jiambalvo 1994), Modified Jones model (Dechow, Sloan and Sweeney 1995), Dechow-Dichev model (Dechow and Dichev 2002; McNichols 2002) and the discretionary revenue model of Stubben (2010). Consistent with Dechow, Sloan and Sweeney (1995), components of accruals that are 'nondiscretionary', or deemed beyond the control of the CEO, are removed.[37]

The first model employed by this chapter is the Jones model (Jones, 1991) to estimate nondiscretionary, or normal, accruals as a linear function of change in revenues and gross property, plant and equipment. Specifically, the following model is estimated for each industry- year.:

$$\frac{TA_{i,t}}{AvgA_{i,t}} = \propto_1 \frac{1}{AvgA_{i,t}} + \propto_2 \frac{\Delta R_{i,t}}{AvgA_{i,t}} + \propto_3 \frac{PPE_{i,t}}{AvgA_{i,t}} + \varepsilon_{i,t} \qquad (3.1)$$

where $TA_{i,t}$ is the Total Accruals for firm *i* in year *t*, measured as the difference between Earnings before Extraordinary Income and Operating Cash Flow from the Cash Flow statement. $\Delta R_{i,t}$ is the Change in Revenues between year *t-1* and *t*, $PPE_{i,t}$ is

[37] As defined in section 2.2.1, nondiscretionary accruals are accruals that are economically determined and cannot be influenced by management.

the gross value of Property, Plant and Equipment in year t, and $AvgA_{i,t}$ is the average Total Assets at the start of year t and at the end of year t.[38]

Regression (3.1) is estimated for all eligible observations from Compustat, which include 6,733 firm-years[39] for each industry-year. The resulting coefficients by industry and year are used to estimate a measure of nondiscretionary accruals for each firm as per equation (3.2) as follows:

$$\overbrace{NDA_{i,t}^{1}}^{est} = \overbrace{\propto_1}^{est} \frac{1}{AvgA_{i,t}} + \overbrace{\propto_2}^{est} \frac{\Delta R_{i,t}}{AvgA_{i,t}} + \overbrace{\propto_3}^{est} \frac{PPE_{i,t}}{AvgA_{i,t}} \qquad (3.2).$$

The difference between actual and predicted accruals is the computed nondiscretionary accruals:

$$\overbrace{DA_{i,t}^{1}}^{est} = \frac{TA_{i,t}}{AvgA_{i,t}} - \overbrace{NDA_{i,t}^{1}}^{est} \qquad (3.3)$$

[38] Earnings before Extraordinary Income is Compustat Data Item 18, Operating Cash Flow from the Cash Flow Statement is Compustat Data Item 308, Change in Revenues is Compustat Data Item 12, Gross Value of PPE is Compustat Data Item 7, Total Assets is Compustat Data Item 6.

[39] Over 2008-2012, there are a total of 7,692 firm-years available on Compustat. After the removal of financial firms and firm-year observations lacking input variables to estimate regression (3.2), the sample is left with 6,733 firm-years.

Equation (3.3) is estimated for 4,082 firm-year observations.[40] Discretionary accruals are expressed as a ratio of the firm's average total assets, as variables in equations (3.1) and (3.2) are scaled by average total assets.

The second model, the Modified Jones model (Dechow, Sloan and Sweeney, 1995) adjusts the Jones model (Jones, 1991) to exclude growth in credit revenues, as they find that potential discretion could be exercised for credit revenues. In the Modified Jones model, the change in revenues, $\Delta R_{i,t}$ in the Jones model, is substituted with change in revenues less change in receivables, $(\Delta R_{i,t} - \Delta AR_{i,t})$[41] providing an estimate of discretionary accruals as follows:

$$\overbrace{DA^2_{i,t}}^{est} = \frac{TA_{i,t}}{AvgA_{i,t}} - \beta_1 \frac{1}{AvgA_{i,t}} - \beta_2 \frac{\Delta R_{i,t} - \Delta AR_{i,t}}{AvgA_{i,t}} - \beta_3 \frac{PPE_{i,t}}{AvgA_{i,t}} \qquad (3.4).$$

Equation (3.4) is estimated for 4,069 firm-year observations.[42]

According to Dechow and Dichev (2002), discretionary accruals are the extent to which current accruals are not explained by cash flows from current, previous and subsequent years. Underlying this model is the assumption that current earnings

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[40] The difference between observations used in regression (3.1) and (3.3) relates to the availability of 4,082 transcripts to infer CEO narcissism matched, out of the 6,082 observations to estimate nondiscretionary accruals.

[41] Total Receivables is Compustat Data Item 2.

[42] Coefficients to estimate nondiscretionary accruals are first obtained from a sample of 6,708 firm-years and 274 industry-years. As in regression (3.3), the discrepancy is attributed to the availability of 4,069 transcripts to infer CEO narcissism matched, out of the 6,708 observations available to estimate nondiscretionary accruals, following the Jones (Dechow, Sloan and Sweeney, 1995) model.

represent current operating cash flows and accruals, which are estimates of future cash flow realisations. As mentioned in the literature review, the focus of Dechow and Dichev (2002) was to explain short-term working capital accruals (Dechow, Ge and Schrand, 2010). McNichols (2002) extends Dechow and Dichev (2002) to include change in revenue property, plant and equipment as additional control variables to estimate discretionary accruals, a proxy for earnings management. Specifically, these variables are found to be firm-specific characteristics related to nondiscretionary accruals, as developed in the Jones and Modified Jones models (Jones, 1991; Dechow, Sloan and Sweeney, 1995). In the Dechow-Dichev model, discretionary accruals for each firm are estimated by a cross-sectional regression as follows:

$$\overbrace{DA^{3}_{i,t}}^{est} = \frac{TA_{i,t}}{AvgA_{i,t}} - \delta_1 \frac{1}{AvgA_{i,t}} - \delta_2 \frac{\Delta R_{i,t}}{AvgA_{i,t}} - \delta_3 \frac{PPE_{i,t}}{AvgA_{i,t}} - \delta_4 \frac{CFO_{i,t-1}}{AvgA_{i,t}} - \delta_5 \frac{CFO_{i,t}}{AvgA_{i,t}} - \delta_6 \frac{CFO_{i,t+1}}{AvgA_{i,t}} \quad (3.5)$$

where $CFO_{i,t}$ is the Cash Flow from Operations for firm i in year t. Equation (3.5) is estimated for 4,021 firm-year observations.[43] The magnitude of discretionary accruals estimated here is consistent with Armstrong, Larcker, Ormazabal and Taylor (2013), who applied the above Dechow-Dichev (McNichols, 2002) model and examine the

[43] Coefficients to estimate nondiscretionary accruals are first obtained from a sample of 6,375 firm-years and 250 industry-years. As in regression (3.3) and (3.4), the discrepancy is attributed to the availability of 4,021 transcripts to infer CEO narcissism matched, out of the 6,375 observations available to estimate nondiscretionary accruals following the Dechow-Dichev (McNichols, 2002) model.

difference in actual and predicted accruals, not their variance.[44] The models outlined above are used to estimate discretionary earnings management.

Stubben's (2010) model estimates premature revenue recognition, as he argues that it is the most common form of revenue management. The discretionary revenue model he proposes controls for varying firm credit policies[45]. Specifically, the model estimates a firm's investment in receivables to be a function of its financial strength, operational performance relative to industry competitors, and stage in the business cycle. Regression (3.6) below implies discretionary revenue from the estimated nondiscretionary revenue by firm size, measured as the natural log of total assets ($SIZE$); firm age (AGE), measured as the natural log of the firm's age in years; AGE_SQ is the square of firm age to allow for nonlinear relation between age and credit policy (Petersen and Rajan, 1997); industry-median-adjusted growth in revenues (GRR_P if positive, GRR_N if negative), industry-median-adjusted gross margin (GRM) and its square (GRM_SQ) are proxies for the operational performance of the firm relative to industry competitors (all variables scaled by average total assets)[46]:

[44] The Dechow and Dichev (2002) and McNichols (2002) models take the standard deviation of residuals. However, the approach here follows that of Armstrong, Larcker, Ormazabal and Taylor (2013), as the availability of observations for each firm in the analysis here is limited to five years.

[45] Stubben (2010) points out that one of the limitations of accrual models is that a cross-sectional estimate implicitly assumes that firms within the same industry have a common accrual-generating process. Further, Dopuch, Seethamraju and Xu (2010) provided the relation between accruals and revenue changes, which was found to be dependent on firm-specific factors such as credit and inventory policies. The model of discretionary revenue thus incorporates the determinants of accounts receivable as described in Callen, Robbs and Segal (2008).

[46] Age is calculated as the number of years for which data for the attributed firm are available on Compustat. This method is consistent with prior literature (see for example, Bergstresser and Philippon (2006) and Bhattacharya, Desai and Venkataraman (2013).

$$\overbrace{DR^{4}_{i,t}}^{est} = \frac{\Delta AR_{i,t}}{AvgA_{i,t}} - \gamma_1 \frac{\Delta R_{i,t}}{AvgA_{i,t}} - \gamma_2 \frac{\Delta R_{i,t} \times SIZE_{i,t}}{AvgA_{i,t}} - \gamma_3 \frac{\Delta R_{i,t} \times AGE_{i,t}}{AvgA_{i,t}} - \gamma_4 \frac{\Delta R_{i,t} \times AGE_{SQ_{i,t}}}{AvgA_{i,t}}$$

$$-\gamma_5 \frac{\Delta R_{i,t} \times GRR\_P_{i,t}}{AvgA_{i,t}} - \gamma_6 \frac{\Delta R_{i,t} \times GRR\_N_{i,t}}{AvgA_{i,t}} - \gamma_7 \frac{\Delta R_{i,t} \times GRM_{i,t}}{AvgA_{i,t}} - \gamma_8 \frac{\Delta R_{i,t} \times GRM\_SQ_{i,t}}{AvgA_{i,t}} \qquad (3.6).$$

In this chapter, equation (3.6) is estimated for 4,060 firm-year observations.[47]

For ease of reference, the Jones model (Jones, 1991) is referred to as Model 1; Model 2 is the Modified Jones model by Dechow, Sloan and Sweeney (1995); Model 3 is the Dechow-Dichev model by McNichols (2002) and Stubben's (2010) discretionary revenue model is Model 4. All input variables for the four models are winsorised at 1 per cent by industry and year. In all models, the magnitude of discretion (earnings management) is scaled by average total assets of the firm in year *t* and *t-1*, consistent with the empirical literature[48]. *Positive* values of discretion suggest upward earnings manipulation while *negative* values of discretion suggest downward earnings manipulation. Yu (2008) finds that negative manipulation is utilised to manage expectations. In good years, negative earnings manipulation is used to hide some earnings for future reporting use. In bad years, firms could *take a bath* to make future earnings targets more feasible.

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[47] Coefficients to estimate nondiscretionary revenues are first obtained from a sample of 6,307 firm-years and 220 industry-years. As in regression (3.3), the discrepancy is attributed to the availability of 4,060 transcripts to infer CEO narcissism matched, out of the 6,307 observations available to estimate nondiscretionary revenues, following the model from Stubben (2010).

[48] See Srinidhi and Gul (2007) and Srinidhi, Gul and Tsui (2011).

Table 3-1
Summary Statistics

Panel A in this table represents the summary statistics of input variables from 6,733 firm-year observations to the models of earnings management, over the period 2008 to 2012. All variables are deflated by average total assets. All correlations in Panel B are significantly different from zero ($p < 0.01$). The variables are constructed as follows: *Accruals* = annual current accruals = earnings before extraordinary items less cash from operations; *AR* = Accounts Receivables; *R* = annual revenues; *PPE* = end of fiscal year gross property, plant and equipment; *CFO* = cash from operations; *Δ* = annual change.

Panel A: Descriptive Statistics

Variable	Mean	Std. Dev.	Median	Q1	Q3
Accrual	-0.0655	0.1024	-0.0523	-0.0912	-0.0236
ΔAR	0.0056	0.0563	0.0030	-0.0067	0.0178
ΔR	0.0560	0.2812	0.0387	-0.0239	0.1264
PPE	0.6527	0.4771	0.5815	0.2812	0.9618
CFO	0.1077	0.1314	0.0961	0.0587	0.1425

Panel B: Pearson (above), Spearman (below) Correlations

	Accruals	*ΔAR*	*ΔR*	*PPE*	*CFO*
Accruals		0.1989	0.1844	-0.2468	-0.3603
ΔAR	0.2700		0.3051	-0.0384	-0.0572
ΔR	0.2183	0.4819		-0.0429	0.1045
PPE	-0.2642	-0.0634	-0.0849		0.1654
CFO	-0.4648	-0.0319	0.1215	0.1278	

with the empirical literature[49]. *Positive* values of discretion suggest upward earnings manipulation while *negative* values of discretion suggest downward earnings manipulation. Yu (2008) finds that negative manipulation is utilised to manage expectations. In good years, negative earnings manipulation is used to hide some earnings for future reporting use. In bad years, firms could *take a bath* to make future earnings targets more feasible.

Table 3-1 reports descriptive statistics of the input variables and correlations between variables in estimating earnings management. Panel A illustrates that the mean (median) accruals are -6.6 (-5.2) per cent of average total assets. The average and

[49] See Srinidhi and Gul (2007) and Srinidhi, Gul and Tsui (2011).

median revenue change is approximately 5.6 and 3.9 per cent of average assets, respectively. Panel B of Table 3-1 presents the correlation coefficients of the input variables. Both Pearson and Spearman are reported for completeness. As results from both correlation measures provide qualitatively similar inferences, discussions are limited to the Pearson correlation tests. All the correlation coefficients reported are different from zero. The change in revenues is positively correlated with accruals (0.1844). Cash flow from operations is also positively correlated with change in revenues (0.1045), but less so than the correlation between accruals and change in revenues. This implies that change in revenues is driven more by accruals than by cash flows received by firms.

Table 3-2 presents coefficient estimates for each of the earnings management models. Results from Table 3-2 show that the accrual models provide a better fit for the sample data vis-à-vis the revenue model adopted. The Modified Jones model (Model 2) provides a lower Adjusted R-Square (0.5223) than that of the Jones model (Model 1) (0.5318). The coefficient on revenue change in the Jones model (Model 1) is 0.0190 and in Model 3 is 0.3859, and both are statistically significant at least at the 10 per cent level for approximately 32 per cent of the industry-year regressions. In the Dechow-Dichev model (3), coefficients of past and present cash flows (0.6772, -0.7775, respectively) are significantly related to firm accruals. The addition of cash flows into the accrual estimation also increases the Adjusted R-Square relative to the Modified Jones and Jones models, to 0.6625. The similarities of the estimators from Models 1, 2 and 3 are a result of variables shared across the three models. Unless the bias from incorrect omission of variables in the models is large, or the inefficiency from the

Table 3-2
Earnings Management Coefficient Estimates

This table summarises the coefficients of separate estimations of revenue and accrual models for industry-year regressions in the sample dataset, over the period of 2008 to 2012. The sample size consists of a total of 6,733 firm-year observations from 274 industry-years. '% Significant' is the proportion of coefficients that are statistically significant at the 10 per cent level, expressed in percentage. Variables are deflated by average total assets. Model 1 is the Jones model by Jones (1991); Model 2 is the Modified Jones Model by Dechow, Sloan and Sweeney (1995); Model 3 is the Dechow-Dichev model by McNichols (2002); and Model 4 is the Discretionary Revenue Model by Stubben (2010).

	Model1		**Model2**		**Model3**		**Model4**	
	Mean	**%**	**Mean**	**%**	**Mean**	**%**	**Mean**	**%**
ΔR x AGE							-0.0062	21.82
ΔR x AGE_SQ							0.0001	20.45
ΔR x GRM							-0.0466	21.36
ΔR x GRM_SQ							-6.7229	26.82
ΔR x GRR_N							-0.0008	25.00
ΔR x GRR_P							0.0001	23.18
ΔR x SIZE							-0.0184	24.09
ΔR	0.0190	33.94			0.3859	32.80	0.3276	28.18
PPE	-0.1044	79.93	-0.1019	79.20	-0.0454	39.20		
ΔR - ΔAR			0.0665	33.21				
$\boldsymbol{CFO_{t-1}}$					0.6772	30.80		
$\boldsymbol{CFO_{t}}$					-0.7775	61.20		
$\boldsymbol{CFO_{t+1}}$					-0.0242	27.60		
Firm-Year Observations	6,733		6,708		6,375		6,307	
Industry-Year Observations	274		274		250		220	
Adjusted R-Square	0.5318		0.5223		0.6625		0.4224	

*** denotes statistical significance at the 1 per cent level

** denotes statistical significance at the 5 per cent level

* denotes statistical significance at the 10 per cent level

Variable Definitions:

AR = end of fiscal year accounts receivable;

AC = annual current accruals = earnings before extraordinary items less cash from operations;

R = annual revenues;

PPE = end of fiscal year gross property, plant and equipment;

CFO = cash from operations;

SIZE = natural log of total assets at end of fiscal year;

AGE = age of firm (years);

GRR_P = industry-median-adjusted revenue growth (=0 if negative);

GRR_N = industry-median-adjusted revenue growth (=0 if positive);

GRM = industry-median-adjusted gross margin at end of fiscal year;

_SQ = square of variable; and

Δ = annual change.

incorrect inclusion of variables is large, the consistent results from the three models are expected. Table 3-4 also shows that out of the 220 industry-year coefficients, all variables in Stubben (2010)'s discretionary revenue model are statistically significant less than 30 per cent of the time, with the exception of variable Cash Flow from Operations (61.2 per cent). Stubben (2010)'s discretionary revenue model also shows the lowest Adjusted R-Square in comparison to the accrual models.

3.3.2 CEO Narcissism

Psychology literature has developed a number of tests or questionnaires to identify narcissistic individuals; the most accepted and cited method, however, remains the Narcissistic Personality Inventory (NPI) score (Rhodewalt and Morf, 1995). The NPI is a questionnaire, originally designed to diagnose narcissistic personality disorder, which enables the measurement of narcissism in large samples rather than individual cases (for examples of studies validating the NPI see Emmons, 1987; Raskin and Hall, 1979; Raskin and Hall, 1981). The development of the NPI questionnaire is an illustration of the general steps taken to develop an indicator of a psychological concept (Aktas, Bodt, Bollaert and Roll, 2016). The NPI measures narcissism in four dimensions: (i) exploitativeness/entitlement, (ii) leadership/authority, (iii) superiority/arrogance and (iv) self-absorption/self-admiration. Raskin and Shaw (1988) have shown that the proportion of first person singular pronouns to first person plural pronouns used by individuals in their speech is highly correlated with NPI scores and may in fact be a better indicator vis-à-vis tests which predispose individuals to a particular mindset. Raskin and Shaw (1988) find their results are robust to age, gender and the topic of speech analysed. The correlation also persists even after controlling for other personality traits (extraversion, neuroticism, psychoticism and locus of control).

The measure developed by Raskin and Shaw (1988) satisfies the four steps generally used in the development of an indirect indicator of a psychological concept: (i) identification of concept, (ii) refinement of criteria, (iii) testing of criteria and (iv) repeated tests. First, as a result of a long clinical practice, Freud (1914) established the existence of narcissism, as a way to describe a certain behavioural phenomenon that he had observed in patients. Then, medical practitioners refined the concept to assist with constructing criteria for clinical diagnosis. In the case of narcissism, the Diagnostic and Statistical Manual of Mental Disorders (American Psychiatric Association, 1994) demonstrates the culmination of this process. Third, questionnaires designed from the application of diagnostic criteria are administered in large samples. The direct measure of a psychological diagnosis is obtained from repeated comparisons of data from results of these questionnaires. These steps are reflected in the development of the NPI questionnaire. Raskin and Shaw (1988) provide empirical support for their method as evidenced by a positive correlation between an indirect indicator devised, and the questionnaire-based direct measure. As with the case in Aktas, Bodt, Bollaert and Roll (2014), the analysis presented in this chapter utilises the narcissism measure by Raskin and Shaw (1988), which can be traced back to its theoretical origins in Freud (1914).[50]

[50] An alternative measure used in empirical research is one adopted by Chatterjee and Hambrick (2007; 2011). In Chatterjee and Hambrick (2007), additional indirect indicators are used in conjunction with the usage of first person pronoun indicators to form an index. Subsequently, in Chatterjee and Hambrick (2011), this usage of first person

In the spirit of Raskin and Shaw (1988), the narcissism score is measured by obtaining the ratio of first person singular pronouns (*I, me, my, mine, myself*) to total first person pronouns (*I, me, my, mine, myself, we, us, our, ours, ourselves*) in CEO speech. Specifically we examine the question and answer sections of the transcripts at earnings conferences. The transcripts from these events are fed into a Natural Language Processing (NLP) algorithm to provide counts of the number of utterances of first person singular and number of utterances of first person plural pronouns for each CEO, at every conference. A random sample of 20 transcripts was reviewed manually to evaluate the accuracy of the Natural Language Processing algorithm. The manual review confirmed response of the NLP algorithm.

Formally, the variable *Narcissism Score* is calculated as follows:

$$Narcissism\ Score = \frac{\sum n_{(I,\ me,\ my,\ mine,\ myself)}}{\sum n_{(I, me,\ my, mine, myself,\ we,\ us,\ our,\ ours,\ ourselves)}} \qquad (3.7).$$

3.3.3 CEO Narcissism and Earnings Management

This section details the research design employed to test the first hypothesis $H_{3,1}$ for this dissertation. To assess the relation between CEO narcissism and earnings management in the firm, the following regression is estimated:

$$Discretion_{i,t} = \ \alpha_t + \gamma_k + \beta NScore_{i,t} + \theta_1 BM_{i,t} + \theta_2 AGE_{i,t} + \theta_3 SIZE_{i,t} +$$

pronoun was dropped from the index. Accordingly, the authors fear that in their sample of firms in the IT industry, the phenomenon of self-referencing by CEOs has tended to decline.

$$\theta_4 LEV_{i,t} + \theta_5 ROA_{i,t} + \varepsilon_{i,t} \quad (3.8)$$

where t indexes years, i indexes firms, k indexes industries, α_t are year fixed effects, γ_k are industry fixed effects, and $\varepsilon_{i,t}$ is an error term. $NScore_{i,t}$ is the CEO Narcissism Score measured for firm i, from the analyst conference transcript for fiscal year t. Consistent with the literature (see, for example, Healy and Wahlen, 1999; and Fields, Lys and Vincent, 2001) the model controls for past performance, firm age, size, and capital structure. According to Dechow and Dichev (2002), firms with extreme performance are likely to overestimate discretionary accruals. To reduce measurement errors, the adopted models control for past performance via Return on Assets. Consistent with Bergstresser and Philippon (2006), firm age is based on the number of years Compustat records are maintained for the firm. Book-to-Market Ratio controls for growth effects, and leverage measures the Debt-to-Equity ratio of the firm.

3.3.4 Sample Selection

Table 3-3 details the sample selection criteria for the analysis, which combine Compustat data on accounting and Bloomberg data on question and answer session transcripts from analyst conferences. To measure the variable of interest, CEO narcissism, all Bloomberg transcripts of analyst conferences were downloaded for US-domiciled stocks listed on the New York Stock Exchange over the fiscal years 2008-2012.[51] For each firm-year, transcripts for fourth quarter results were sampled. This

[51] The period of analysis is 2008-2012; however, as mentioned in the previous section, accounting data are obtained from Compustat including years 2007 and 2013 to construct lead and lag variables (in particular, cash flow from operations as per McNichols (2002)).

Table 3-3
Selection Criteria

This table presents the sample selection criteria for sample data over 2007 to 2013 for Compustat data and 2008 to 2012 for Bloomberg data.

	No. of Firms	No. of Observations	No. of Firms	No. of Observations
Bloomberg download	1192	5467		
(less) Transcripts without Q&A, CEO participation in Q&A	(29)	(371)		
With data to compute Narcissism Score	1163	5096		
(less) Firm-Years with only one transcript to infer CEO Narcissism Score	(56)	(285)		
For each CEO, minimum of 2 Bloomberg transcripts	1107	4811		
Observations with Compustat download (Available Data within 2007-2013)	1082	4723		
(less) Firms and Observations in the Financial Industry	(138)	(583)		
	944	4140		
(less) Observations with missing control variables	(5)	(43)		
	939	4097		
(less) Observations with missing variables including Average Total Assets, Earnings Before Extraordinary Items, Change in Revenues, Property Plant and Equipment in Jones (1991)'s Discretionary Accruals Model	(3)	(15)		
	936	4082		
(less) Observations with additional missing variables (Change in Accounts Receivables) in Modified Jones (Dechow, Sloan and Sweeney, 1995)'s Discretionary Accruals Model			(3)	(13)
			933	4069
(less) Observations with additional missing variables in Stubben (2010)'s Discretionary Revenue Model			(2)	(9)
			931	4060
(less) Observations with additional missing variables including Cash Flow from Operations, Lag(Cash Flow from Operations) and Lead(Cash Flow from Operations) in Dechow-Dichev (McNichols, 2002) Discretionary Accruals Model	0	(61)		
	936	4021		

provides a total of 5,467 transcripts, which are parsed through a NLP algorithm, resulting in a total of 5,096 transcripts with measurable CEO narcissism scores. Where a transcript is available, but the NLP algorithm did not provide a response, each instance was investigated and one of three reasons for the zero response was identified: (i) the question and answer session was not held; (ii) CEO was absent; or (iii) CEO was present but did not participate in the question and answer session.

Following Chatterjee and Hambrick (2007; 2011), this chapter requires that the CEO speaks at a minimum of two conferences to infer a narcissism score. The score is computed by aggregating the sum of first person singular pronouns and sum of total first person pronouns uttered by the CEO in all transcripts available over the period to compute a narcissism score for each CEO. This removes any biases associated with the measurement of narcissism from only one transcript. The measure of CEO narcissism score in this chapter is, therefore, time invariant, consistently reflecting prevailing views that narcissism is a stable disposition (Livesley, Lang, Jackson and Vernon, 1993). After applying this filter, a sample of 4,811 transcripts are identified (1,107 firms), where a given CEO takes part in the question and answer session of the conference. Matching Bloomberg observations to Compustat data provides a total of 4,723 firm-year observations (1,082 firms). Removal of 138 firms in the financial industry reduces the sample to 583 firm-year observations. Additionally, 43 firm-year observations lacking control variables (Leverage, Book-to-Market Ratio, Age, Market Capitalisation and Return on Asset) are also removed. Within these 43 firm-year observations, three firms are completely removed from the sample dataset, as they lack control variables for the whole period of 2008-2012. The rest of Table 3-3 reconciles the number of observations lacking input variables that are removed, corresponding to the earnings management estimation models described in Section 3.3.1.

3.4 Results

3.4.1 Descriptive Statistics

Table 3-4 presents summary statistics for the 936 firms examined. The average firm in the sample has a market value of approximately $7.7 billion, a leverage ratio of 0.69, a book-to-market ratio of 0.58 and return on assets of 4 per cent. The mean narcissism score as reported in Table 3-4 is 0.26, with a median of 0.25. This is similar to Aktas, Bodt, Bollaert and Roll (2014), who report a mean narcissism score of 0.215 and median of 0.204. Results in Table 3-4 suggest that CEOs display variation in their narcissism score, with a standard deviation of 0.08.

In Panel A of Table 3-5, descriptive statistics are presented around the estimated signed discretionary value of all four models. Table 3-5 reports that the average for variable *discretion* adopted is negative. While most empirical studies only report the mean and median values of unsigned (absolute) discretionary accruals, similar to results reported in this chapter, Hibrar and Nichols (2007) document negative mean and median values for signed discretionary accruals.[52] By nature of construct, the expected mean of discretionary accruals should amount to zero. But the reported means here are not precisely zero, as coefficients reported in Table 3-5 are estimated first before limiting the sample to firm-years with available CEO

[52] The authors estimate discretionary accruals using Modified Jones model.

Table 3-4
Firm Descriptives

This table presents the summary statistics for 936 firms listed on the NYSE, for 2008-2012. *Narcissism Score* is the ratio of first person singular pronouns to total first person pronouns in the questions and answer session of analyst conferences, transcripts obtained from Bloomberg. *Leverage* is calculated as the Debt-to-Equity ratio; *ROA* is the Return on Assets computed by the ratio of earnings before extraordinary items on total assets; *Book-to-Market Ratio* is measured by the difference between total assets and total liabilities, divided by the stock market capitalisation of the firm; *Age* is the number of years beginning from the first year Compustat data are available for the firm; *Size* is the firm size calculated as the natural log of stock market capitalisation.

Variable	Mean	Std	Median	Q1	Q3
Narcissism Score	0.26	0.08	0.25	0.20	0.31
Market Capitalisation ($'m)	7,693.21	19,113.60	2,073.39	731.55	5,859.87
Leverage	0.69	1.67	0.32	0.13	0.72
ROA	0.04	0.11	0.04	0.01	0.08
Book-to-Market Ratio	0.58	0.79	0.52	0.32	0.77
Age	31.36	19.45	26.00	14.00	50.00
Size	21.81	1.49	21.72	20.76	22.75

narcissism score and control variables.[53] The largest estimate of accruals management is provided by Models 1 and 2 at approximately -0.8 per cent of average total assets. These two models also provide the largest deviation in estimate of discretionary earnings. While the mean values of all models indicate that firms on average negatively manipulate their earnings, the median values of Models 3 and 4 are 0.001 and 0, respectively. The median of Models 1 and 2 remains negative at approximately -0.3 per cent of average total assets. Panel B of Table 3-5 presents the descriptive statistics of unsigned and absolute discretionary values for all four models. The mean and median values estimated from all three accrual models are consistently larger than the revenue model.

[53] Hibrar and Nichols (2007) also attribute the negative mean discretionary accruals to a discrepancy between the number of observations to estimate nondiscretionary earnings and the number of observations to estimate discretionary earnings. This approach ensures a more detailed set of observations to estimate the coefficients for the first-stage estimation, consistent with Hibrar and Nichols (2007).

Panel C of Table 3-5 presents correlation coefficients of discretion as estimated from Models 1-4 and control variables of earnings management. All figures presented in Panel B of Table 3-5 are statistically significant at the 10 per cent level. As with discussions in Panel B of Table 3-5, discussions are focused on the Pearson correlation. The *discretion* variables obtained from all four models are positively correlated with one another, with higher correlation coefficients amongst the three accrual models, ranging from 0.80-0.99. The correlation coefficients reported between variable *discretion* of Model 4 and the three accrual models are consistently lower than 0.10. The variable *discretion* is also positively correlated with the variable *Narcissism Score*, with stronger correlations illustrated by the three accrual models. The correlation coefficient of *discretion* from Model 4 and *Narcissism Score* are insignificantly positive.

Table 3-5
Earnings Management and Correlation with Control Variables

Table 3-5 presents summary statistics of variables over the sample period of 2008 to 2012. Panel A of this table presents summary statistics of the signed values of discretionary accruals and revenues obtained from the four models. Panel B presents summary statistics of the absolute values of discretionary accruals and revenues obtained from the four models. Panel C presents the correlation matrix of key variables in the analysis. Model 1 is the Jones (1991) model. Model 2 is Modified Jones (Dechow, Sloan and Sweeney, 1995) model, Model 3 is the Dechow-Dichev (McNichols, 2002) model and Model 4 is Stubben (2010)'s discretionary revenue model. *Narcissism Score* is the ratio of first person singular pronouns to total first person pronouns in the question and answer session of analyst conferences, transcripts obtained from Bloomberg. *Book-to-Market Ratio* is measured by the difference between total assets and total liabilities, divided by the stock market capitalisation of the firm; Size is the firm size calculated as the natural log of stock market capitalisation; *Age* is the number of years beginning from the first year Compustat data are available for the firm; *Leverage* is calculated as the Debt-to-Equity ratio; *ROA* is the Return on Assets computed by the ratio of earnings before extraordinary items on total assets.

Panel A: Variable Discretion					
Model	**Mean**	**Std. Dev.**	**Median**	**Q1**	**Q3**
1	-0.0082	0.0733	-0.0033	-0.0319	0.0222
2	-0.0081	0.0736	-0.0033	-0.0318	0.0222
3	-0.0042	0.0603	0.0001	-0.0207	0.0198
4	0.0002	0.0334	0.0000	-0.0084	0.0074
Panel B: Variable Discretion (Absolute)					
1	0.0441	0.0592	0.0273	0.0115	0.0544
2	0.0443	0.0594	0.0274	0.0115	0.0549
3	0.0343	0.0498	0.0203	0.0081	0.0411
4	0.1530	0.0297	0.0079	0.0025	0.0184

Panel C: Pearson (above diagonal), Spearman (below diagonal) Correlation with Control Variables

	Discretion (Model 1)	Discretion (Model 2)	Discretion (Model 3)	Discretion (Model 4)	Narcissism Score	BM Ratio	Log (Market Capitalization)	Age	Leverage	Return on Assets
Discretion (Model 1)	1.0000	0.9933	0.8316	0.0721	0.0335	0.0786	0.0429	0.0926	-0.1149	0.5744
Discretion (Model 2)	0.9882	1.0000	0.8254	0.0900	0.0352	0.0745	0.0525	0.0927	-0.1153	0.5866
Discretion (Model 3)	0.6856	0.6749	1.0000	0.0214	0.0430	0.0268	0.1216	0.0899	-0.1543	0.6483
Discretion (Model 4)	0.1121	0.1202	0.0399	1.0000	0.0042	-0.0236	0.0321	-0.0273	-0.0164	0.0049
Narcissism Score	0.0381	0.0387	0.0400	0.0143	1.0000	-0.0131	0.0838	0.0669	0.0155	0.0290
BM Ratio	0.0660	0.0615	-0.0576	-0.0663	0.0113	1.0000	-0.1880	-0.0009	-0.0337	-0.0933
Size	-0.0040	0.0066	0.0998	0.0677	0.0726	-0.3313	1.0000	0.3259	-0.2417	0.3068
Age	0.1040	0.1034	0.1081	-0.0074	0.0756	0.0305	0.3142	1.0000	-0.0488	0.0501
Leverage	-0.0530	-0.0511	-0.1497	-0.0070	0.0040	0.3005	-0.1422	0.0561	1.0000	-0.2987
Return on Assets	0.2384	0.2467	0.4119	-0.0073	0.0263	-0.4476	0.3486	0.0435	-0.5178	1.0000

3.4.2 CEO Narcissism and Earnings Management

Table 3-6 presents results of test of hypothesis $H_{3,1}$, examining the relation between CEO Narcissism and earnings management. The dependent variable in the estimated regressions in Table 3-6 is the value of discretionary revenue or accruals in the respective Models 1 to 4. All three accrual models suggest CEO narcissism is positively related with higher accruals management. Specifically, according to Model 1, for every 0.01 increase in narcissism score for a CEO, discretionary accruals are reported approximately 2.095 basis points higher (as a percentage of total assets). Results for Model 2 show an increment of 2.236 basis points of reported discretionary accruals for every 0.01 increase in CEO narcissism score, and for Model 3 it is 2.218 basis points. Results from all three accrual models are statistically significant. In Model 4, the coefficient on CEO narcissism indicates a positive but insignificant relationship. Adjusted R-Square reported for Model 4 (0.01451) also shows the model provides the poorest fit.

Coefficients on firm size in the three accrual models are significantly negative, suggesting that larger companies exhibit lower levels of positive earnings management. Consistent with the empirical literature (see, for example, Kim, Park and Wier, 2012), the three models of discretionary accruals show a positive relation between earnings management and leverage and book-to- market ratio. In contrast to findings in the empirical literature (see Bergstresser and Phillipon, 2006; Armstrong, Larcker, Ormazabal and Taylor, 2013), the coefficients for firm age and return on assets are both significantly positive in the accrual models. This implies that in the sample data, more profitable firms and more established firms have a higher tendency to positively manipulate their accounting figures. Alternatively, this could be viewed as firms being found to be more profitable because they have positively manipulated their earnings. On the other hand, the revenue model exhibits a contrasting relation between revenue manipulation and size, and age. The coefficients for size and age in the revenue model show that larger and younger firms engage in higher positive revenue manipulation.

Table 3-6

Impact of CEO Narcissism on Earnings Management

This table reports coefficient estimates of industry-year-fixed effects regression of CEO Narcissism and earnings management, as estimated by the four models of discretionary revenue and accruals. The sample consists of a total of 936 firms listed on the NYSE over the period 2008 to 2012. The following equation being estimated is of the form:

$$Discretion_{i,t} = \alpha_t + \gamma_k + \beta NScore_{i,t} + \theta_1 BM_{i,t} + \theta_2 AGE_{i,t} + \theta_3 SIZE_{i,t} + \theta_4 LEV_{i,t} + \theta_5 ROA_{i,t} + \varepsilon_{i,t}.$$

Narcissism Score is measured by the ratio of first person singular pronouns to total first person pronouns in the question and answer Session of Analyst Conferences, transcripts obtained from Bloomberg. *Book-to-Market Ratio* is measured by the difference between total assets and total liabilities, divided by the stock market capitalisation of the firm; *Size* is the firm size calculated as the natural log of stock market capitalisation; *Age* is the number of years beginning from the first year Compustat data are available for the firm; *Leverage* is calculated as the debt-to-equity ratio; *Return on Asset* is computed by the ratio of earnings before extraordinary items on total assets. T-statistics are in parentheses.

	Model1		**Model2**		**Model3**		**Model4**	
	Coefficient	**T-stat**	**Coefficient**	**T-stat**	**Coefficient**	**T-stat**	**Coefficient**	**T-stat**
Narcissism Score	0.02095	(2.02)**	0.02236	(2.16)**	0.02218	(2.74)***	0.00143	(0.26)
Book-to-Market Ratio	0.00917	(4.73)***	0.00916	(4.71)***	0.00487	(3.10)***	-0.00036	(-0.53)
Size	-0.00801	(-8.85)***	-0.00761	(-8.44)***	-0.00349	(-5.06)***	0.00109	(2.89)***
Age	0.00033	(6.35)***	0.00032	(6.09)***	0.00022	(5.33)***	-0.00007	(-2.32)***
Leverage	0.00182	(2.06)**	0.00182	(2.00)**	0.00131	(1.67)*	-0.0002	(-0.59)
Return on Asset	0.46206	(19.05)***	0.4714	(19.17)***	0.41075	(14.03)***	-0.00635	(-1.29)
Year Fixed Effects	Yes		Yes		Yes		Yes	
Industry Fixed Effects	Yes		Yes		Yes		Yes	
Number of Observations	4,082		4,069		4,021		4,060	
Adjusted R-Square	0.39827		0.41109		0.46283		0.01451	

*** indicates statistical significance at the 0.01 level
** indicates statistical significance at the 0.05 level
* indicates statistical significance at the 0.10 level

3.5 Robustness Tests

Chatterjee and Hambrick (2011) suggest that narcissistic individuals are drawn to certain situations, and may have a tendency to speak or act in a certain way, given a particular scenario, such as an examination or speech. As extant literature documents, narcissistic CEOs demand applause, have very inflated self-views but also require these views to be continuously reinforced (Chatterjee and Hambrick, 2007). Privy to knowledge of underlying firm performance and earnings management prior to announcement, CEOs may demonstrate more or less narcissistic tendencies in their responses at the analyst conferences, to create a better perception amongst the investment community. As such, results need to be assessed in view of an endogeneity issue; perhaps the good results (managed earnings) cause CEOs to display narcissistic tendencies in their speech. Additionally, the research design requires that CEOs speak during the question and answer sessions to provide the ability to assess narcissism for CEOs. Therefore, sampled observations may suffer from a sample selection bias. To address these issues, two robustness tests are performed to evaluate the relation of CEO narcissism and earnings management.

3.5.1 Test of Endogeneity

The direction of causality between CEO narcissism and earnings management may be that earnings management behaviour influences how a CEO responds at earnings conferences. This potential endogeneity suggests that the error term in equation (3.8), $\varepsilon_{i,t}$ could be correlated with $NScore_{i,t}$in the same equation, causing the coefficient to be biased and inconsistent. To address this potential endogeneity, the measure of narcissism is modified by excluding the contemporaneous year in which earnings management is estimated. This has the effect of ensuring that the measure of CEO narcissism is unrelated to the period in which earnings management or performance is discussed or measured, meeting the criteria of an instrumental variable exogenous to the event.[54]

Specifically, the following regression is estimated:

$$Discretion_{i,t} = \alpha_t + \gamma_k + \beta Instr(Narcissism\ Score)_{i,t} + \theta_1 BM_{i,t} + \theta_2 AGE_{i,t}$$

$$+\theta_3 SIZE_{i,t} + \theta_4 LEV_{i,t} + \theta_5 ROA_{i,t} + \varepsilon_{1i,t} \qquad (3.9)$$

where *Instr(Narcissism Score)* for firm *i* in year *t* is measured from transcripts from years *t-1* to *t-n*, where *n* takes a minimum value of 2 and a maximum value of 4.[55] For example, if earnings management estimated for the dependent variable is for fiscal year 2012, *Instr(Narcissism Score)* is computed from transcripts in years 2008-2011; if earnings management estimated for the dependent variable is for fiscal year 2011, *Instr(Narcissism Score)* is computed from transcripts in years 2008-2010. The question and answer sessions used to compute *Instr(Narcissism Score)* in subsequent years are verified to accord with the same CEO in office, in year *t*.

[54] See, for example, Greene (2003) and Wintoki, Linck and Netter (2012). In Wintoki, Linck and Netter (2012), they provide a detailed description of the use of lagged variables as an instrument for otherwise endogenous relations between two variables. The study also documents the various research areas in finance and economics in which this method has been adopted to address this issue.

[55] See section 3.3.4; the minimum value of two is consistent with the main sample selection following Chatterjee and Hambrick (2007; 2011). The maximum value of four is limited to the availability of several years' worth of transcript and the requirement of a lag to perform this robustness test.

Table 3-7 presents the results of this robustness test. Results are largely consistent with results reported in Table 3-6, in support of hypothesis $H_{3,1}$. The coefficient on *Instr(Narcissism Score)* is positive and significant for all discretionary accrual models. The parameter coefficient on *Instr(Narcissism Score)* is positive, albeit insignificant, in Model 4, which models discretionary revenues. The three discretionary accrual models, again, provided higher Adjusted R-Square (ranging from 0.28 to 0.35), implying a better fit for the models. Results from Table 3-7 provide evidence that the relation between CEO narcissism and earnings management is caused by CEO narcissism.

Table 3-7

Causal Relation: CEO Narcissism and Earnings Management

This table reports coefficient estimates of industry-year fixed effects regression of instrumented CEO Narcissism Score on earnings management, as estimated by the four models of discretionary revenue and accrual models. The sample consists of firms listed on the NYSE and over the period of 2008 to 2012. The following equation being estimated is of the form:

$$Discretion_{,t} = \alpha_t + \gamma_k + \beta Instr(Narcissism\ Score)_{i,t} + \theta_1 BM_{i,t} + \theta_2 AGE_{i,t} + \theta_3 SIZE_{i,t} + \theta_4 LEV_{i,t} + \theta_5 ROA_{i,t} + \varepsilon_{i,t}$$

Instr(Narcissism Score) for year *t* is computed for the same CEO, but based on transcripts in years *t-1* to *t-n*, where n = 2, 3 or 4. *Book-to-Market Ratio* is measured by the difference between total assets and total liabilities, divided by the stock market capitalisation of the firm; *Size* is the firm size calculated as the natural logarithm of stock market capitalisation; *Age* is the number of years beginning from the first year Compustat data are available for the firm; *Leverage* is calculated as the debt-to-equity ratio; *Return on Assets* is computed by the ratio of earnings before extraordinary items on total assets. T-statistics are in parentheses.

	Model1		**Model2**		**Model3**		**Model4**	
	Coefficient	**T-stat**	**Coefficient**	**T-stat**	**Coefficient**	**T-stat**	**Coefficient**	**T-stat**
Instr(Narcissism Score)	0.01718	(2.57)***	0.01628	(2.44)***	0.00966	(1.84)*	-0.00086	(-0.2)
Book-to-Market Ratio	0.02311	(3.54)***	0.02395	(3.59)***	0.01568	(2.67)***	-0.00052	(-0.43)
Size	-0.00546	(-4.62)***	-0.00524	(-4.43)***	-0.00221	(-1.9)*	0.00099	(2.05)**
Age	0.00035	(4.78)***	0.00034	(4.7)***	0.00027	(4.85)***	-0.00005	(-1.41)
Leverage	0.00405	(2.29)**	0.00346	(2)**	0.00265	(1.46)	0.00034	(0.75)
Return on Asset	0.39636	(8.99)***	0.39609	(8.89)***	0.37195	(5.97)***	0.00202	(0.3)
Year Fixed Effects	Yes		Yes		Yes		Yes	
Industry Fixed Effects	Yes		Yes		Yes		Yes	
Number of Observations	1,964		1,960		1,915		1,956	
Adjusted R-Square	0.28489		0.28863		0.35002		0.01969	

*** indicates statistical significance at the 0.01 level
** indicates statistical significance at the 0.05 level
* indicates statistical significance at the 0.10 level

3.5.2 Self-Selection Bias

By construction, a lack of participation in the question and answer session by a CEO prevents measurement of narcissism. Removing firm-years in which the CEOs are present, but did not participate in the question and answer session, may introduce a self-selection bias into the dataset for this chapter. Therefore, the variability of CEO narcissism score available in this dissertation is limited to CEOs in which transcripts and responses are available for inference. However, the lack of data for measurement is not diagnostic of a CEO who necessarily scores low on narcissism. This section investigates if CEO verbosity at analyst conferences has any effect on the reported relation between earnings management and CEO narcissism, scored from CEO responses at analyst conferences. Narcissistic individuals' craving for applause from external parties must be reaffirmed in the form of adulation and admiration (Wallace and Bausmeister, 2002). The analyst conference is one setting in which a narcissist can have this superiority reaffirmed. In announcing their 'personal report card' (Amernic and Craig, 2010), they prompt the informed investment community to provide this affirmation. Further, Ashforth and Anand (2003) document a stronger role by the CEO in the propensity for fraud when the CEO is charismatic.

The robustness test in this section addresses whether a CEO's verbosity at an analyst conference is indicative of his narcissistic trait. This is conducted by adding an interaction variable between CEO Narcissism Score and a dummy variable that reflects how much a CEO participated in the question and answer session. First, a measure of the proportion of words spoken by CEOs in their responses relative to words by other executives is computed. Then, the median of this ratio acts as a benchmark for the dummy variable. Equation (3.8) is extended as follows:

$$Discretion_{i,t} = \alpha_t + \gamma_k + \beta NScore_{i,t} + \delta NScore * Dummy_{i,t} + \theta_1 BM_{i,t} + \theta_2 AGE_{i,t} +$$

$$\theta_3 SIZE_{i,t} + \theta_4 LEV_{i,t} + \theta_5 ROA_{i,t} + \varepsilon_{2i,t} \qquad (3.10)$$

where *Dummy* is a dummy variable that takes the value of 1 if the response by the CEO for firm i in year t in the question and answer session is more or equivalent to the median CEO in year t. The dummy variable takes the value of 0 if their responses were less than the median CEO in the same year. *Dummy* is an indicator of how much a CEO participated in the question and answer session and the inference from this test shows if CEO verbosity has any influence on the employed measure of CEO narcissism. If verbosity is irrelevant and the data do not suffer from a self-selection bias, it is expected that the interaction variable should result in an insignificant coefficient.

Results for the robustness, in view of a possible self-selection bias, are reported in Table 3-8. The positive coefficient on Narcissism Score is consistent with hypothesis $H_{3,1}$. Further, results in Table 3-8 suggest that the association between CEO Narcissism Score and earnings management is not conditional on the verbosity of the CEO's speech in question and answer sessions. This is highlighted by the statistically insignificant coefficient of the interaction variable of Narcissism Score and the dummy variable (for CEO's participation in the question and answer session). The results imply that CEO verbosity does not have an impact on the measured narcissism. Taken together, Table

3-7 and Table 3-8 indicate a lack of support for the possibility that a CEO could ‘game’ his participation in the question and answer session of analyst conferences.

Table 3-8
Volume of Speech: CEO Narcissism and Earnings Management

This table reports coefficient estimates of industry-year fixed effects regression of earnings management, estimated by the four models of discretionary accruals and revenue. The following equation being estimated is of the form:

$$Discretion_{i,t} = \alpha_t + \gamma_k + \beta NScore_{i,t} + \delta NScore * Dummy_{i,t} + \theta_1 BM_{i,t} + \theta_2 AGE_{i,t} + \theta_3 SIZE_{i,t} + \theta_4 LEV_{i,t} + \theta_5 ROA_{i,t} + \varepsilon_{i,t}$$

An interaction variable, $NScore * Dummy$ of CEO Narcissism and a dummy for the volume of speech is included in this regression. *Narcissism Score* is the ratio of first person singular pronouns to total first person pronouns in the question and answer" session of analyst conferences, transcripts obtained from Bloomberg. *Book-to-Market Ratio* is measured by the difference between total assets and total liabilities, divided by the stock market capitalisation of the firm; *Size* is the firm size calculated as the natural log of stock market capitalisation; *Age* is the number of years beginning from the first year Compustat data are available for the firm; *Leverage* is calculated as the debt-to-equity ratio; *Return on Asset* is computed by the ratio of earnings before extraordinary items on total assets. T-statistics are in parentheses.

	Model1	Model2	Model3	Model4
	Coefficient T-stat	Coefficient T-Stat	Coefficient T-Stat	Coefficient T-stat
Narcissism Score*Dummy (Volume of Speech)	-0.0005 (-0.07)	-0.0008 (-0.12)	0.0025 (0.46)	-0.0023 (-0.56)
Narcissism Score	0.0213 (1.83)*	0.0229 (1.99)**	0.0205 (2.27)**	0.0030 (0.49)
Book-to-Market Ratio	0.0092 (4.73)***	0.0092 (4.71)***	0.0049 (3.10)***	-0.0004 (-0.52)
Size	-0.0080 (-8.76)***	-0.0076 (-8.35)***	-0.0035 (-4.98)***	0.0011 (2.83)***
Age	0.0003 (6.37)***	0.0003 (6.10)***	0.0002 (5.38)***	-0.0001 (-2.34)***
Leverage	0.0018 (2.06)**	0.0018 (2.00)**	0.0013 (1.67)*	-0.0002 (-0.60)
Return on Asset	0.4621 (19.03)***	0.4714 (19.14)***	0.4106 (14.00)***	-0.0063 (-1.26)
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Number of Observations	4,082	4,069	4,021	4,060
Adjusted R-Square	0.39813	0.41095	0.46272	0.01458

*** indicates statistical significance at the 0.01 level
** indicates statistical significance at the 0.05 level
* indicates statistical significance at the 0.10 level

3.5 Summary

This chapter explores the role of management personality in corporate governance within the context of accounting discretion. In particular, this chapter conducts an examination of the relation between the narcissism of a firm's CEO and the extent of earnings management the firm is engaged in. The existing literature suggests that CEOs are the driving force behind a firm's engagement in accounting manipulation (Feng, Ge, Luo and Shevlin, 2011). Additionally, the literature establishes that firms involved in earnings management are driven by management with large financial incentives (Bergstresser and Phillipon, 2006; Jiang, Petroni and Wang, 2010). This chapter documents the unreliability of financial reporting as an effective tool to reduce information asymmetry in financial markets, as CEO narcissism increases the likelihood of distortion in financial reports by virtue of earnings manipulation.

Results in this chapter provide evidence in support of higher earnings inflation by firms with more narcissistic CEOs, as a result of earnings management. These findings are robust to the potential endogeneity that may exist between a CEO's speech during the analyst conference in which he/she announces the earnings that are estimated to potentially be a result of accounting manipulation. Additionally, further results demonstrate that the positive relation between CEO narcissism and earnings management is not conditional on a CEO's verbosity. This dismisses potential claims for a measurement error within the data.

Chapter 4 : Trading Behaviour around Information Leakage of Analyst Recommendations

4.1 Introduction

The literature review in Section 2.3.3 of Chapter 2 establishes the existence of information leakage, or tipping, by analysts. This chapter extends the literature by presenting the evidence around tipping and the different conditions in which investors exhibit a greater propensity to act on received tips, using a proprietary dataset containing broker IDs. Specifically, results are supported by the profitability realised when investors act on analyst tips under these conditions.

Several hypotheses developed in Chapter 2 are tested in this chapter. The chapter first tests hypotheses $H_{4,1}$ –– Market conditions and upgrade recommendation revisions *are not* associated with broker abnormal buy volume prior to the release day; and $H_{4,2}$ – Market conditions and downgrade recommendation revisions *are* associated with broker abnormal sell volume prior to the release day. Taken together, the asymmetry in abnormal trading volume around upgrades and downgrades shows that tipping exists around downgrade recommendations. As suggested by section 2.3.2 of Chapter

2, the prevalence of analyst bias and perceived informativeness of upgrades and downgrades in different market conditions warrant diverse responses by recipients. This chapter explores investors' propensity to act on tips across firm size, and the level of change in analyst recommendations ($H_{4,3}$). Hypothesis $H_{4,4}$ tests whether abnormal trading volume prior to recommendation release date is positively related to the abnormal returns. Utilising data on institutional short interest, the chapter tests hypotheses $H_{4,5}$ – A downgrade recommendation revision is related to abnormal short-selling activity prior to release day; and $H_{4,6}$ – A downgrade recommendation revision is not related to abnormal institutional selling activity prior to release day.

The remainder of this chapter is structured as follows. The next section describes the data, section 4.3 outlines the research design employed to test hypotheses $H_{4,1}$, $H_{4,2}$, $H_{4,3}$, $H_{4,4}$. Results are reported in section 4.4 and section 4.5 provides a summary of the chapter.

4.2 Data

Three sets of data are used in this chapter: ASX proprietary trade data, I/B/E/S recommendations and Data Explorers. Three distinct periods are sampled: (i) 29 November, 2004 to 29 November, 2006; (ii) 1 September, 2009 to 28 February, 2011 and (iii) 1 April, 2011 to 30 September, 2012, corresponding to Bull, Neutral and Bear markets respectively.

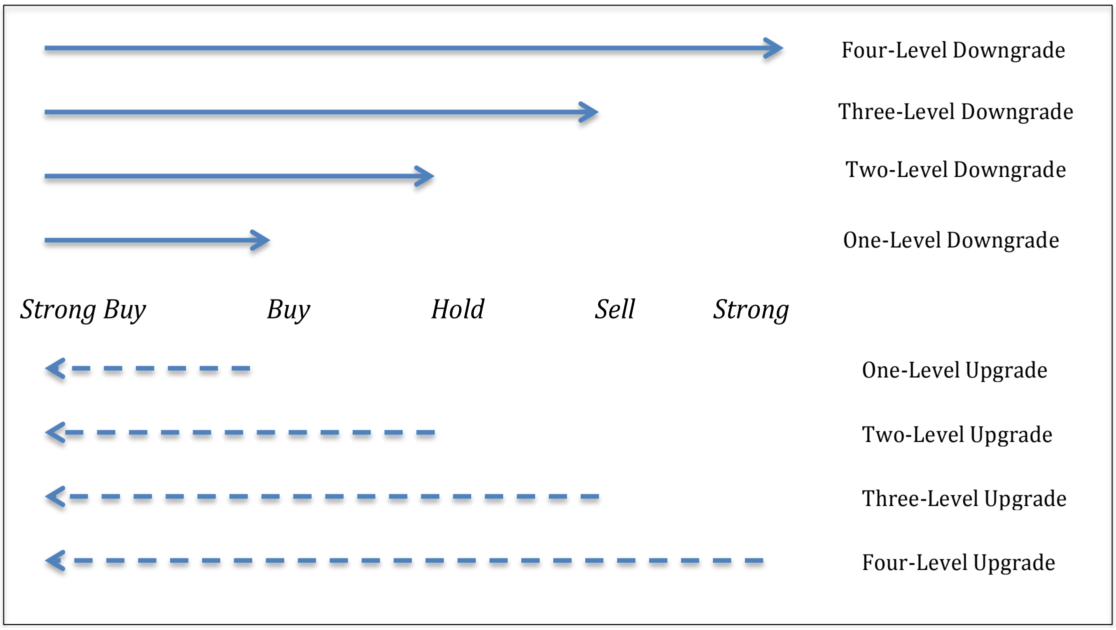
Proprietary trade data sourced from the ASX provide information for all trades and quotes. Each trade record details security name, stock code, date, time, volume, traded price, trade initiation, the buying and selling broker IDs. The data also contain the institution trading behind the masked broker IDs in the trade dataset for identification.[56]

Analyst recommendations are sourced from the I/B/E/S recommendations database via the Wharton Research Data Services (WRDS), and include the following fields: stock code, analyst firm, recommendation date, recommendation release time and the stock recommendation issued. Recommendations within the database are standardised to five levels: (1) strong buy (2) buy, (3) hold (4) sell and (5) strong sell. Chapter 2 identifies literature that finds analyst recommendations to be biased. Consistent with the approach of Jegadeesh, Kim, Krische and Lee (2004), this chapter infers upgrades and downgrades from *revisions* in analyst recommendations;[57] Figure 4-1 illustrates how upgrades and downgrades are classified. Positive revisions of recommendations – strong sell to sell, sell to hold, hold to buy and buy to strong buy – amount to upgrades. First-time buy and strong buy recommendations are also classified as upgrades. Similarly, negative revisions of recommendations – strong buy to buy, buy to hold, hold to sell and sell to strong sell – amount to downgrades. First-time sell and strong sell recommendations are also classified as downgrades. While the majority of recommendation revisions are one-level revisions; upgrade or downgrade to the immediate next recommendation level, on occasion a previous strong sell recommendation may be revised to a buy recommendation, bypassing sell and hold

[56] Equity trading on the ASX is conducted via a continuous order driven market, but opens and closes with a call auction. Trades that occur during the opening and closing call auctions are excluded from the sample.

[57] Jegadeesh, Kim, Krische and Lee (2004) found that revisions in analyst recommendations are stronger predictors of returns than the *level* of recommendations.

Figure 4-1
Levels in Recommendation Revisions
Figure 4-1 presents the method to account for the variety of levels in recommendation revisions in this chapter.



recommendations. Therefore recommendation revisions take four different levels, one-level (to the immediate next recommendation), two-level (bypassing one step of recommendation), three-level (bypassing two steps of recommendation), and four-level revisions (bypassing three steps of recommendation). First-time hold recommendations and recommendations with no change relative to prior release are excluded from the analysis.

To investigate short-selling activity around the downgrade recommendations within the sample dataset (Hypothesis $H_{4,5}$), data on stock lending are sourced from Data Explorers. Data Explorers cover 70 per cent (own estimate) of worldwide stock borrowing from its clients, which include trading desks, hedge funds and industry participants, allowing the database to include aggregated inventory information for over 22,000 funds, which lend through over 100 wholesale stock lending market participants across 33 countries.[58] Data Explorers do not report the level of short interest but provide a variable representing the level of stock lending. According to sources from Data Explorers, the correlation between the publicly reported level of short interest and the level of stock lending is approximately 90 per cent, supporting the use of stock lending as a reasonable proxy for short-selling.[59]

4.3 Research Design

This section outlines univariate and multivariate analysis employed to investigate the six hypotheses tested in this chapter. The methods implemented define and measure: (i) the three market settings; (ii) abnormal trade volume imbalance amongst broker-analysts; (iii) daily abnormal returns of stocks; and (iv) abnormal short-selling activity and institutional ownership around analyst recommendation releases.

4.3.1 Market Conditions

In order to understand investor behaviour in response to broker-analysts' tips, in view of market conditions ($H_{4,1}$), bull, neutral and bear periods in the Australian Equities Markets need to be identified. Practitioners, including financial analysts and financial market commentators, frequently make reference to bull and bear markets, often defining bear markets as occurring in a market decline of a (large) fixed per cent, of

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[58] See www.dataexplorers.co.uk. An extended discussion of details around the database can be found in Saffi and Sigurdsson (2010).

[59] Berkman and Mackenzie (2012) report a correlation of 0.92.

Figure 4-2
ASX200 Index

This chart illustrates the ASX200 Index and six-month Moving Average Return over October 2003 to October 2012.

market commentators, frequently make reference to bull and bear markets, often defining bear markets as occurring in a market decline of a (large) fixed per cent, of approximately 20 per cent. A bull market on the other hand, is referred to when a market experiences upswings of a (large) fixed per cent, of approximately 20 per cent.[60] In the academic literature, however, no such generally accepted definition exists. Researchers have provided definitions to fit the common understanding that bull markets consist of periods with substantial and sustained increase in stock prices and bear markets, periods with substantial and sustained decline in stock prices.[61]

[60] See for example, Chambers (2014).

[61] Chauvet and Potter (2000) and Pagan and Sossounov (2003).

In this chapter, the selection of sample periods adopts both academic and practitioner definitions of market cycles. Specifically, the definition of bull and bear markets will follow the approach in Pagan and Sossounov (2003), where bull and bear markets are identified according to peaks and troughs. Since a peak will always follow a trough and vice versa, the event space is divided into bull and bear periods respectively.[62] Figure 4-2 depicts the ASX200 Index level and six-month moving average index returns. The upward trend over 2003 to the first peak in July 2007 indicates a clear bull market. Immediately following, the market was in a bear market, with the trough in July 2009. The market cycle was trending upward again, until September 2009, after which it traded relatively sideways until another downward trend starting in April 2011. Over this period, a practitioner's definition provides two bear market periods: firstly, the distinctive August 2007 to July 2009 and secondly, from April 2011 onwards. The latter is selected as bear market for this chapter, where the cumulative returns approximated -20 per cent, and over this period the market failed to recover to its pre-bear levels.

4.3.2 Abnormal Trade Volume Imbalance

To analyse the extent of information leakage around the public release of analyst reports, the trading volumes of recommending brokers over a nine-day event period (four days pre-release and four days post-release) are examined, following Kadan, Michaely and Moulton (2014)). A limitation of the data provided is the inability to distinguish between trades undertaken by brokers on principal or agency basis. In this chapter, the recommending broker (broker *i*)'s buying (selling) volume is computed as

[62] This approach is also commonly adopted by literature requiring market cycle definitions, for example, Jansen and Tsai (2010).

a percentage of broker *i*'s total traded volume, consistent with Lepone, Leung and Li (2012). The trade volume imbalance (TVI) for recommendation *upgrades* in stock *i*, for broker *j*, on trading day *t*, is defined as,

$$UTVI_{(i,j,t)} = \frac{Buy\ Volume\ Traded_{(i,j,t)}}{Total\ Volume\ Traded_{(i,j,t)}} * 100 \qquad (4.1)$$

TVI for *downgrade recommendations* in stock *i*, for broker *j*, on trading day *t*, are defined as,

$$DTVI_{(i,j,t)} = \frac{Sell\ Volume\ Traded_{(i,j,t)}}{Total\ Volume\ Traded_{(i,j,t)}} *100 \qquad (4.2)$$

Abnormal trade volume imbalance is measured as the difference between actual and benchmark traded volume for the nine-day event period. Benchmark traded volume is the broker's average daily TVI over the 50-trading-day period ending 10 days prior to the analyst's recommendation release date.[63]

The abnormal trade volume imbalance (ATVI) for recommendation *upgrades* and *downgrades* is calculated as follows, respectively:

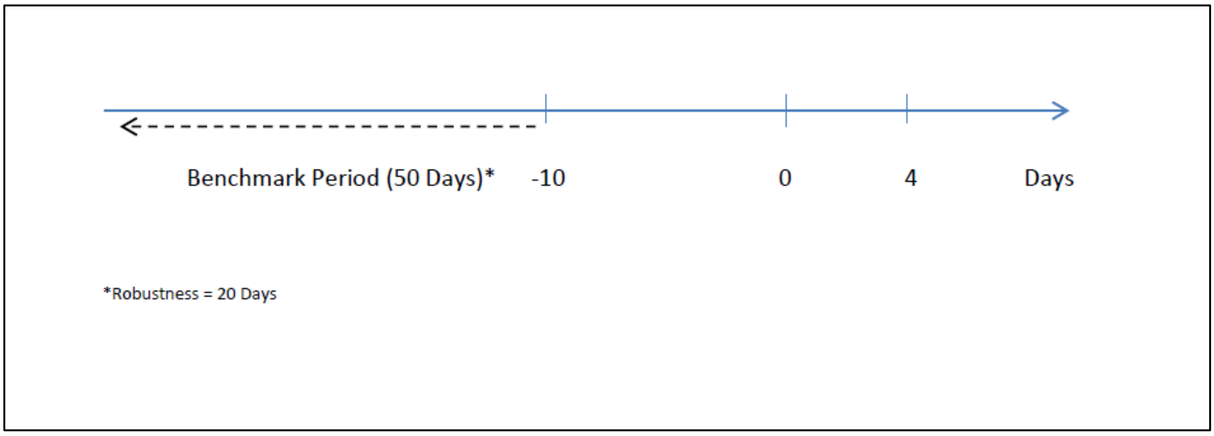
$$UATVI_{(i,j,t)} = UTVI_{(i,j,t)} - Benchmark\ UTVI_{(i,j,\overline{50})} \qquad (4.3).$$

$$DATVI_{(i,j,t)} = DTVI_{(i,j,t)} - Benchmark\ DTVI_{(i,j,\overline{50})} \qquad (4.4).$$

[63] For robustness, all analyses are reported with benchmark traded volume calculated as the broker's average daily TVI for 20 trading days *before* day -10 of the event. Results are qualitatively similar.

Figure 4-3
Illustration of Timeline around Analyst Recommendations

This figure presents a timeline of event days around the issue of analyst recommendations, with Day 0 representing the day that analyst recommendations are released publicly.



The first pair of hypotheses tested in this chapter concern the asymmetry in abnormal buy and sell volume between upgrade and downgrade recommendations across market settings ($H_{4,1}$, $H_{4,2}$). The *t*-statistic is calculated for the *UATVI* (*DATVI*) over the nine-day event period, to evaluate if the broker-analysts' buy (sell) volume imbalance is significantly different from their benchmark buy (sell) volume imbalance.

Womack (1996) and Jegadeesh, Kim, Krische and Lee (2004) suggest that the level of recommendation revision is indicative of the intended level of private information communicated. Extreme levels of recommendation revisions (e.g., strong buy to strong sell) provide higher investment value than smaller recommendation revisions (e.g., strong buy to sell). The level of recommendation revision communicated in the tip is thus anticipated to have an impact on investors' propensity to act. Furthermore, stocks that are well-covered by analysts should trade in a less asymmetric information environment. Consequently, analyst research on stocks that are well-covered should incorporate less new information to the market. This will also have an impact on investors' propensity to act when additional information in this environment is tipped.

The following multivariate analysis, controlling for underlying market conditions, firm size and the level of recommendation revision, is carried out to test hypothesis $H_{4,3}$. Specifically, in this section, the following regressions are estimated:

$$UATVI_{(i,j,m,t+k)} = \beta_1 Log(MarketCap)_i + \beta_2 Log(Turnover)_i + \beta_3 \Delta Level_m$$

$$+\beta_4 AnalystCoverage_i + \beta_{5,6,7} Dummy_{Bull,Neutral,Bear} + \varepsilon \qquad (4.5)$$

$$DATVI_{(i,j,m,t+k)} = \beta_1 Log(MarketCap)_i + \beta_2 Log(Turnover)_i + \beta_3 \Delta AbsLevel_m$$

$$+\beta_4 AnalystCoverage_i + \beta_{5,6,7} Dummy_{Bull,Neutral,Bear} + \varepsilon \qquad (4.6)$$

where the dependent variables are buy and sell abnormal trading volume imbalances around upgrade and downgrade recommendations respectively, for stock *i*, broker *j*, recommendation event *m*, on trading day *t*. *k* represents the value of days (within the event period) relative to recommendation release. Independent variables include the natural logarithm of market capitalisation of stock *i*; natural logarithm of average daily turnover of stock *i;* $\Delta Level_m$ is the level of recommendation revision for recommendation *m;* reflects the absolute change in recommendation level for downgrade revisions (for example, a change from a prior recommendation of strong buy to strong sell will take the value of 4)[64]; $AnalystCoverage_i$ is a count of the number of broker-analysts who cover stock *i*. Dummy variables are included for each market setting, to reflect the market condition in which the recommendation is issued. Coefficients β_1 and β_3 from estimated equations (4.5) and (4.6) facilitate the test of

[64] As detailed in section 4.2.

hypothesis $H_{4,3}$. Specifically, if firm size is negatively related to abnormal trading volume prior to recommendation release day, it is anticipated that coefficient β_1 is negative and statistically significant; if recommendation revision level is related to abnormal trading volume prior to recommendation release day, it is anticipated that the coefficient β_3 is positive and statistically significant.

4.3.2 Abnormal Returns

In order to quantify the trading profitability around analyst reports under different circumstances to test for hypothesis $H_{4,4}$, daily abnormal returns are computed over the five trading days before and after a recommendation (see Lepone, Leung and Li, 2012). The choice of reporting 11 days of abnormal returns around the event period is to draw inferences, where possible, from stock movement on the day prior and after the reported nine days of abnormal broker-analysts' trade volume imbalance. Specifically, excess returns are calculated as follows:

$$Return(Close)_{i,m,t} = \left(Close_{i,m,t} - Close_{i,m,t-1}\right) - (AORD_t - AORD_{t-1}) \qquad (4.7)$$

where *Close* is the closing price of stock i, on trading day t attributed to recommendation m, and *AORD* is the index value of the All Ordinaries Index on trading day t. For robustness, abnormal returns are also computed based on a stock's volume-weighted average price over a trading day. *Close* in equation (4.7) is replaced with volume-weighted average price, VWAP. Specifically, returns (VWAP) are computed as VWAP of the attributed day relative to VWAP of the day prior, on the stock being recommended. Reported returns are also adjusted by daily changes in the All Ordinaries Index to control for market movements.

Additionally, the fourth hypothesis tested in this chapter ($H_{4,4}$) contends that broker-analysts' abnormal trading volume prior to recommendation release date is positively related to the abnormal returns. To examine this hypothesis, a comparison is made between abnormal trading volume imbalance over the reported nine-day event period and daily abnormal returns (i.e. anticipated profitability). With reference to abnormal volumes by broker-analysts, this section draws inferences on how likely investors are to reward the attributed broker based on their anticipated profitability.

4.3.3 Short-Selling and Institutional Ownership

The last two hypotheses ($H_{4,5}$, $H_{4,6}$) tested in this chapter relate to determining whether recipients of downgrade recommendations respond by exiting their long positions or actively short-sell in accordance with the provided tip. Data to examine short-selling activity around recommendations are sourced from Data Explorers, which contains information on the amount of stock available for loan and stock lending. A limitation of the data employed in this test is the inability to attribute the institutional activity reflected in these data to the attributed recommending broker.[65]

From Data Explorers, daily information on the quantity of shares available for lending, volume and price for loan transactions is available at individual security-level.

[65] Analysis in this section provides an overview of the institutional activity around the event period, presenting an indication of activity by recipients of tips.

Consistent with Berkman and McKenzie (2012) and Jain, Jain, McInish and McKenzie (2013), this chapter infers the daily level of institutional ownership by the quantity of shares available for lending. Widely adopted in the extant literature (see Lecce, Lepone, McKenzie and Segara, 2012; Jain, Jain, McInish and McKenzie, 2013), the availability of trading information on both institutional investors and short-sellers provides a simultaneous view of trading by potentially the largest groups of informed market participants. Information on loan transactions provides the level of short interest and is calculated in this study as the total number of shares lent, divided by the number of shares outstanding.[66] Following Christophe, Ferri and Angel (2004), a measure for *normal* short-selling activity is computed to observe the abnormal short-selling activity over the period of a downgrade recommendation. Specifically, abnormal short-selling activity ($ABSS_{i,t}$) is the difference between (i) $SS_{i,t}$, stock *i*'s level of short interest on day *t*, around the downgrade recommendation and (ii) $Benchmark\ SS_{(i,\overline{50})}$, the stock's average level of short interest over a benchmark period of 50 days[67], consistent with section 2.2. Formally, a stock's abnormal short-selling activity, computed in percentages, is measured as:

$$ABSS_{i,t} = SS_{i,t} - Benchmark\ SS_{(i,\overline{50})} \qquad (4.8).$$

Like the computation of abnormal return, *ABSS* is computed over 11 days, centred on the day of public release of the analyst recommendation. The *t*-statistic is calculated for

[66] This method follows Jain, Jain, McInish and McKenzie (2013), where institutional ownership is inferred from the availability of stock on loan.

[67] Like section 2.2, this analysis is repeated with benchmark average level of short interest for 20 trading days *before* day -10 of the event.

ABSS, to evaluate whether institutional short-selling activity in this period is significantly different from its benchmark short-selling activity.

4.4 Results

4.4.1 Descriptive Statistics

Table 4-1 confirms that sample examined in this chapter exhibits the bias in analyst recommendations documented by extant research; there are significantly more issues of buy and strong buy recommendations relative to sell and strong sells. In contrast to Jegadeesh, Kim, Krische and Lee (2004) and Womack (1996), the discrepancy between the issuance of positive and negative recommendations is less severe, as strong sell and sell recommendations are approximately 16.75 per cent of all recommendations.[68] This chapter utilises a total of 8,533 recommendation revisions. Of these revisions, 1,396 recommendations are issued as strong buys and 1,826 recommendations are buys, while negative recommendations include only 1,011 sell recommendations and as low as 422 strong sell recommendations. Hold recommendations constitute the highest number of calls in the sample period, with 3,898 issuances. Table 4-1 Panel A reports more calls for strong buy, in comparison to strong sell and sell recommendations, which only amounted to approximately 30 per cent of total recommendations issued in each market period. An examination of recommendation revisions in Table 4-1 Panel B shows that more downgrades (4,511) than upgrades (4,042) are observed across the three sample periods. Not surprisingly, regardless of upgrades or downgrades, one-level revisions are nearly 1.5 times as popular as two-level changes. A total of 145

[68] In Jegadeesh, Kim, Krische and Lee (2004), the authors document that sell or strong sell recommendations made up less than 5 per cent of all recommendations. Womack (1996) document seven issuances of new buy recommendations for every new sell recommendation.

Table 4.1
Descriptive Statistics of Analyst Recommendations

This table presents the descriptive statistics of analyst recommendations, over the three sample periods, (i) Bull - 29 November, 2004 to 29 November, 2006; (ii) Neutral - 1 September, 2009 to 28 February, 2011 and (iii) Bear - 1 April, 2011 to 30 September, 2012. Panel A presents the count of recommendations issued by analysts in the sample, in aggregate and in isolation of the three market periods. Panel B presents the count of recommendation revisions by analysts in the sample, in aggregate and in isolation of the three market periods. Statistics in Panel B are separated by Upgrades and Downgrades, and the level of recommendation revision.

Panel A: Recommendations Issued			
All		8,553	
Strong Buy		1,396	
Buy		1,826	
Hold		3,898	
Sell		1,011	
Strong Sell		422	
	Bull Market	**Neutral Market**	**Bear Market**
All	3,409	2,168	2,976
Strong Buy	507	372	517
Buy	721	449	656
Hold	1,539	1,025	1,334
Sell	441	226	344
Strong Sell	201	96	125

Panel B: Recommendation Revisions						
	Upgrade			**Downgrade**		
All	4,042			4,511		
One-Level	2,459			2,667		
Two-Level	1,519			1,763		
Three-Level	25			36		
Four-Level	39			45		
	Bull Market		**Neutral Market**		**Bear Market**	
	Upgrade	**Downgrade**	**Upgrade**	**Downgrade**	**Upgrade**	**Downgrade**
All	1,667	1,742	1,013	1,155	1,362	1,614
One-Level	1,071	1,075	570	664	818	928
Two-Level	574	643	432	476	513	644
Three-Level	9	11	2	2	14	23
Four-Level	13	13	9	13	17	19

three-level and four-level upgrades and downgrades are identified. Based on market conditions, there are more occurrences of downgrades. The largest difference between downgrade and upgrade recommendations occurs in the bear market, where total downgrades exceed total upgrades by 252 issues, relative to bull markets, where the difference is only 75 issues.

Table 4-2 reports descriptive statistics for the sample of firms examined over the sample period 2004 to 2012. In the earliest period, 29 November 2004 to 29 November 2006, the average market capitalisation of firms is approximately $3.7 billion. This increased to approximately $5.9 billion over the period of 1 September 2009 to 28 February 2011, and $6.1 billion in the more recent period of 1 April 2011 to 30 September 2012. Concurrently, the daily turnover of stocks also increased over the sample period. At the beginning of the sample period, the mean daily turnover of stocks was approximately $7.1 million, this increased substantially in the Neutral and Bear markets to approximately $19 million.

Table 4-2
Descriptive Statistics of Firms

Table 4-2 presents the descriptive statistics of firms in the sample dataset. The table reports the descriptive statistics of firm market capitalisation and daily turnover in aggregation and also in quartiles of market capitalisation. Panel A reports these statistics computed in the Bull market of 29 November, 2004 to 29 November, 2006; Panel B reports the Neutral market of 1 September, 2009 to 28 February, 2011 and Panel C reports the Bear market of 1 April, 2011 to 30 September 2012.

Quartile	Number of Firms	Market Capitalisation ($ mil)				Daily Turnover ($ mil)			
		Mean	25th Percentile	Median	75th Percentile	Mean	25th Percentile	Median	75th Percentile
Panel A: Bull Market (Nov '04 - Nov '06)									
All	397	3,721.14	478.94	1,374.28	3,567.83	7.13	0.66	1.92	6.41
1	101	7,967.52	2,672.37	4,454.76	7,813.88	15.60	4.43	7.89	16.67
2	100	1,014.95	651.93	973.25	1,314.45	1.74	0.79	1.35	2.32
3	99	306.03	225.46	295.06	389.84	0.47	0.16	0.38	0.70
4	97	97.40	57.22	105.04	130.28	0.09	0.04	0.08	0.12
Panel B: Neutral Market (Sept '09 - Feb '11)									
All	350	5,895.31	749.59	1,728.78	4,031.35	19.77	1.96	7.01	19.10
1	123	10,006.14	2,177.18	3,846.91	8,334.65	33.55	8.84	16.36	28.82
2	104	939.94	693.00	911.69	1,205.18	3.78	1.51	2.94	4.55
3	78	257.24	198.15	249.83	298.99	1.02	0.38	0.68	1.41
4	45	84.06	51.28	95.36	109.46	0.29	0.06	0.19	0.45
Panel C: Bear Market (Apr '11 - Sept '12)									
All	427	6,170.97	604.51	1,648.30	4,096.52	19.96	1.56	5.81	16.47
1	121	11,033.21	2,126.57	3,846.91	9,054.60	35.82	8.52	15.88	31.97
2	113	922.38	661.72	932.61	1,168.13	3.23	1.64	2.79	4.61
3	104	278.50	215.38	286.08	327.67	0.74	0.29	0.52	0.95
4	89	93.42	61.17	107.10	120.35	0.19	0.07	0.12	0.24

4.4.2 Volume Imbalance

Table 4-3 and Figure 4-4 report the mean percentage abnormal volume imbalance of broker-analysts over the nine-day event period for Bull, Neutral and Bear markets respectively, around analyst recommendations. Specifically, buy traded volume imbalance is reported for upgrade recommendations and sell traded volume imbalance is reported for downgrade recommendations, for the markets respectively.

Results indicate there are no statistically significant abnormal buy volumes prior to the public release of upgrade recommendations in Bull markets, suggesting that recipients do not necessarily provide order flow to broker-analysts who provide an upgrade tip. Buy volume only begins to increase on the event day (Day 0), and continues until Day +2. Similar results hold in Neutral markets. However, in Bear markets, there is no evidence of any additional buying activity around the release of upgrade recommendations. Negative market sentiment in bear markets appears to prevail despite positive analyst research, suggesting that recipients generally exercise caution in down-trending markets.

Results for downgrade recommendation in the Bull market demonstrate that abnormal sell volume starts three days before the public release of downgrade recommendations. This persists until four days after the public release day (i.e., abnormal sell volume is observed from Day -3 to Day 4). In Neutral market conditions, results demonstrate abnormal sell volumes two days before recommendation announcement, persisting until day four. Similar to results in the Neutral market, abnormal sell volumes occur on day -2.

Table 4-3

Abnormal Buy and Sell Trading Volume Imbalance of Recommending Brokers around Upgrades and Downgrades

Table 4 presents the percentages of broker-analysts trading volume imbalance as per section 2.2. The table reports mean percentage of abnormal buy volume imbalance for upgrades and abnormal sell volume imbalance for downgrades respectively. Panel A reports volume imbalance around recommendations in the Bull period, Panel B reports Neutral period, and Panel C reports the Bear period.

Days	Abnormal Buy Volume Imbalance (Upgrades)	Abnormal Sell Volume Imbalance (Downgrades)	Abnormal Buy Volume Imbalance (Upgrades)	Abnormal Sell Volume Imbalance (Downgrades)	Abnormal Buy Volume Imbalance (Upgrades)	Abnormal Sell Volume Imbalance (Downgrades)
	Panel A: Bull Market (29 Nov '04 - 29 Nov '06)		**Panel B: Neutral Market (1 Sept '09 - 28 Feb '11)**		**Panel C: Bear Market (1 Apr '11 – 30 Sept '12)**	
	Freq 1667	**Freq 1742**	**Freq 1012**	**Freq 1155**	**Freq 1429**	**Freq 1745**
-4	-3.81 ***	0.66	1.62	3.53 **	-1.70	-0.54
-3	-0.87	4.54 ***	1.60	2.73 *	-1.38	-0.14
-2	0.91	3.88 ***	2.73 *	5.00 ***	-0.63	2.13 **
-1	0.39	6.92 ***	2.83 *	5.50 ***	-0.82	1.14
0	2.76 **	6.20 ***	5.15 ***	4.67 ***	-1.13	2.11 **
1	5.20 ***	8.17 ***	2.43	4.17 ***	1.31	3.42 ***
2	1.61	5.51 ***	2.94 *	3.32 **	0.05	1.84 *
3	0.86	4.18 ***	-0.19	4.05 ***	0.52	1.65
4	1.23	5.29 ***	0.03	4.16 ***	0.05	0.16

*** indicates statistical significance at the 0.01 level
** indicates statistical significance at the 0.05 level
* indicates statistical significance at the 0.10 level

Figure 4-4
Abnormal Buy and Sell Trading Volume Imbalance of Recommending Brokers around Upgrades and Downgrades

Graphs in Figure 4 illustrate the trading volume imbalance of broker-analysts around a recommendation release. This figure displays the variation in average abnormal buy volume imbalance of broker-analysts around an upgrade recommendation and the variation in average abnormal sell volume imbalance of broker-analysts around a downgrade recommendation. Figure 4-4-1 illustrates this for the Bull period, Figure 4-4-2 illustrates this for the Neutral market, and Figure 4-4-3 illustrates this for the Bear period.

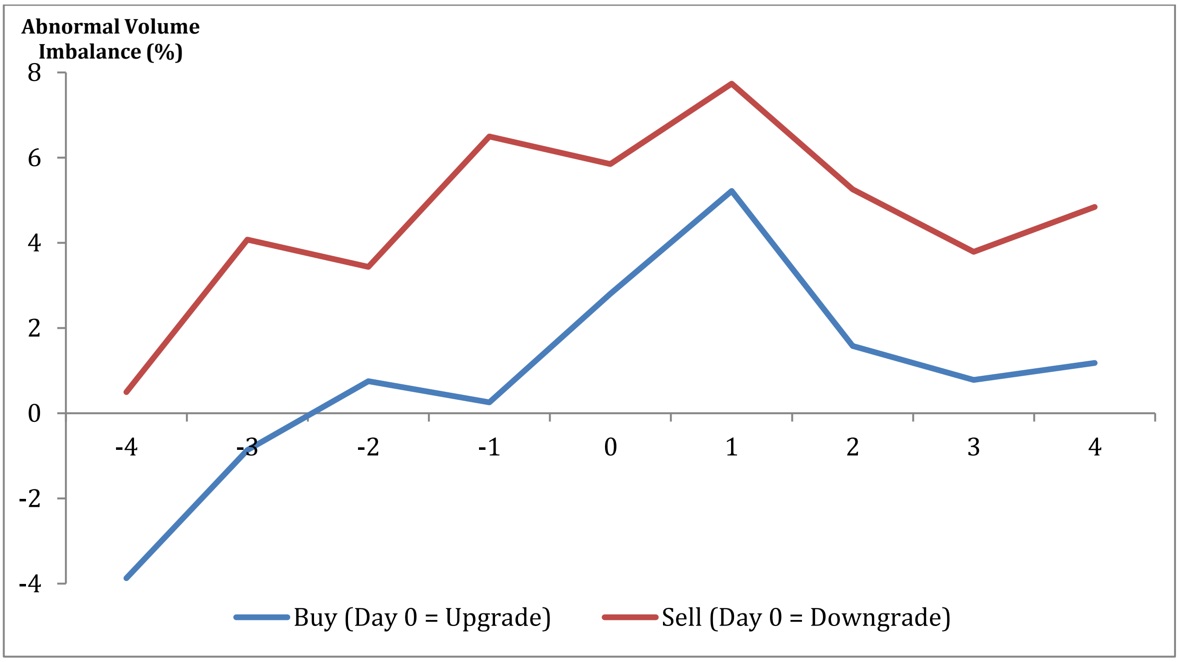


Figure 4-4-1
Abnormal Volume Imbalance of Recommending Brokers in Bull Market, 29 November 2004 –29 November 2006

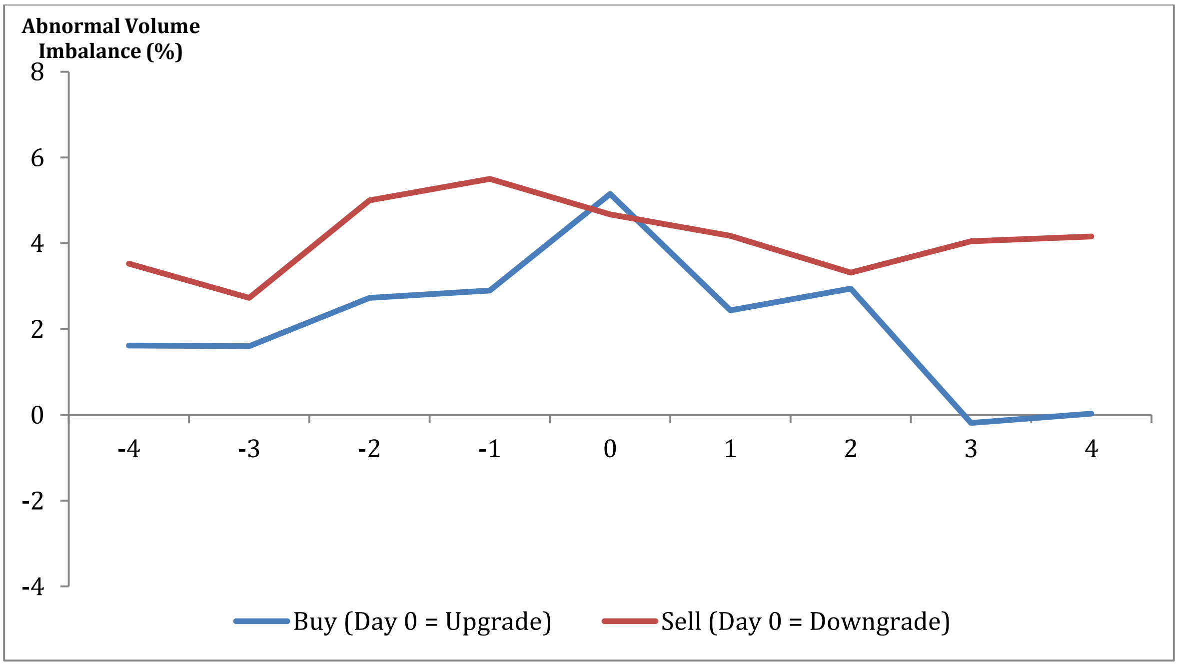


Figure 4-4-2
Abnormal Volume Imbalance of Recommending Brokers in Neutral Market, 1 September 2009 – 28 February 2011

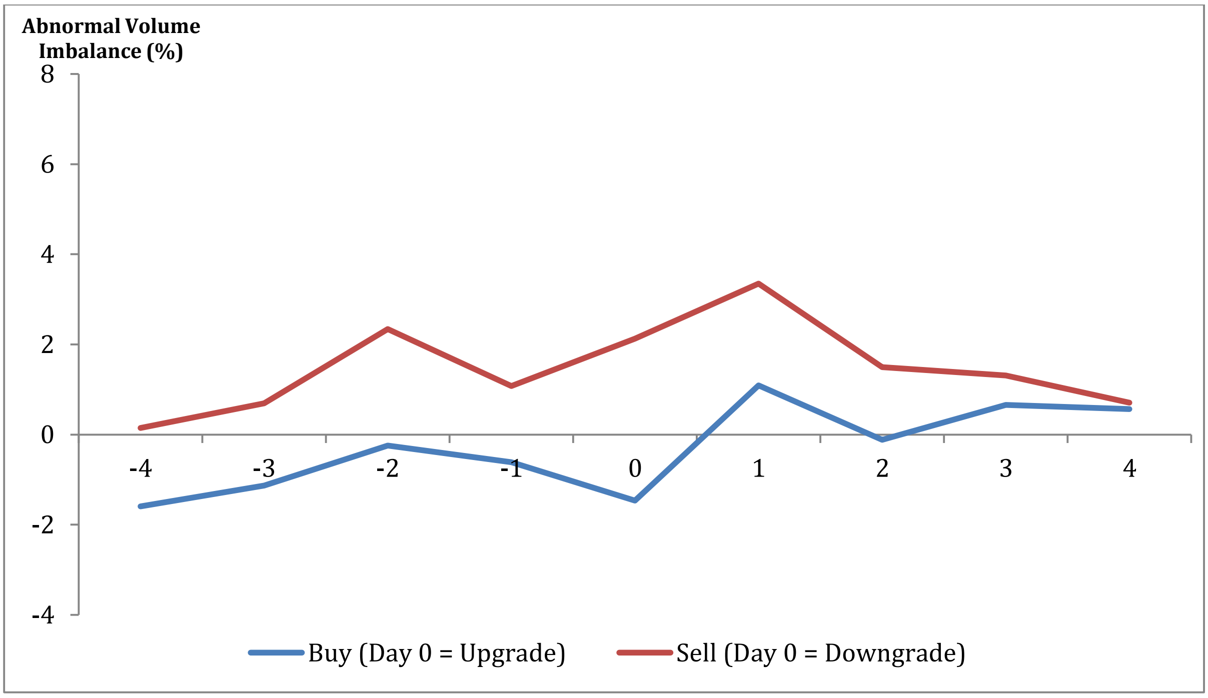


Figure 4-4-3
Abnormal Volume Imbalance of Recommending Brokers in Bear Market, 1 April 2011- 30 September 2012

in the Bear market but only for two days after the release of a downgrade recommendation

Across the three markets, the Bull period experiences the largest sell volume imbalance around the event day (6.20 per cent). On Day -1, the abnormal sell volume is as high as 6.92 per cent in the Bull period, and on Day +1, the abnormal sell volumes rose to 8.17 per cent. The size of volume imbalance decreases in the Neutral market, and further in the Bear market. Unless institutions/investors held a long position in the attributed stock, a tip on downgrade recommendation would require the institution/investor to participate in short-selling. Results in Table 4-3 suggest that recipients are opportunistic in bullish market conditions, but are more risk-averse in bearish market conditions. Unlike the bull market, where tips in contrarian analyst recommendations attract abnormal trading volume, investors appear to exercise caution around positive analyst research. Results in this section provide support for hypotheses $H_{4,1}$ and $H_{4,2}$. Prior to release day, market conditions and upgrade recommendation revisions are not associated with broker abnormal buy volume, but market conditions and downgrade recommendation revisions are associated with broker abnormal sell volume.

4.4.1.1 Abnormal Volume Imbalance – by Firm Size

Table 4-4 reports the results of average buy (sell) trading volume imbalance of broker-analysts over the nine-day event period, by stock market capitalisation quartiles. The results in this section provide little support for statistically significant abnormal buy volumes prior to upgrade recommendations. In the Bull period, abnormal buy volume is observed for Quartile 2 and Quartile 3, either starting from Day 0 or Day 1 of the event window. Panel B of Table 4-4 shows that the Neutral market generally provides insignificant abnormal buy volume before the release of upgrade recommendations, with the exception of Day -2 in Quartile 1 and Day -1 of Quartile 2. Panel C of Table 4-4 demonstrates that upgrades in bear markets generally provide insignificant abnormal buy volume across the event period.

For downgrade recommendations, significant abnormal sell volumes are observed across all market conditions. Panel A in Table 4-3 presents evidence that in the Bull market, abnormal selling activity by broker-analysts in the largest market capitalisation quartile starts on Day -3, persisting up until Day 4. Quartile 2 demonstrates that abnormal sell volume one day prior to the recommendation release

Table 4-4
Abnormal Buy and Sell Trading Volume Imbalance of Recommending Brokers around Upgrades and Downgrades: Quartiles of Market Capitalization

This table reports the mean percentage of abnormal buy volume imbalance report for upgrades ('**Buy UATVI**'), and abnormal sell volume imbalance for downgrades ('**Sell DATVI**'), respectively. Results are segregated by the stock's market capitalisation. Within a cross-section of market conditions (Bull, Neutral and Bear), the sample stocks are divided into four different groups according to the market capitalisation of each stock. Firms with the largest market capitalisation are categorised in '**MC Quartile 1**' and firms with the smallest market capitalisation are in '**MC Quartile 4**'. This table reports mean percentage of abnormal buy volume imbalance for upgrades, '**Buy UATVI**', and abnormal sell volume imbalance for downgrades, '**Sell DATVI**' respectively. Panel A reports abnormal volume imbalance around recommendations in the Bullish period, Panel B reports the Neutral period, and Panel C reports the Bearish period.

	MC Quartile 1		MC Quartile 2		MC Quartile 3		MC Quartile 4	
Days	Buy UATVI	Sell DATVI	Buy UATVI	Sell DATVI	Buy UATVI	Sell DATVI	Buy UATVI	Sell DATVI
Panel A: Bull Market (29 Nov '04 - 29 Nov '06)								
-4	-1.82	2.77	-3.80	-4.12	-15.23**	8.11	-39.79	-6.49
-3	-2.54	7.67***	2.85	0.01	-6.77	6.02	-0.38	-14.56
-2	-0.31	4.48***	3.21	1.78	-2.45	11.24**	-19.85	1.11
-1	0.79	6.23***	0.67	8.25***	-6.69	7.73	50.00	1.14
0	1.48	5.54***	6.69***	5.41**	-6.01	13.36***	2.99	4.98
1	2.64	8.53***	7.11***	7.45***	11.42**	10.71**	32.36	1.42
2	0.74	5.83***	4.73*	5.06**	-4.02	7.70	-11.22	-16.95
3	-1.22	5.72***	5.69**	1.76	-7.95	6.72	-6.90	-1.53
4	0.14	7.48***	3.40	3.51	-1.32	3.94	26.64	-14.89
Panel B: Neutral Market (1 Sept '09 – 28 Feb '11)								
-4	1.33	1.40	2.88	10.93***	-1.85	1.80	35.31	-12.05
-3	2.15	-0.19	-0.17	4.06	0.92	20.51***	27.02	21.53
-2	3.91**	3.63**	1.91	5.73*	-3.04	9.41	17.66	19.04
-1	2.72	3.38**	5.54*	9.75***	-4.24	6.33	2.79	20.66
0	4.91***	3.44**	5.49*	6.11**	7.16	11.36*	11.46	4.10
1	2.69	4.41***	4.82	3.77	-4.89	11.33*	0.24	-21.33
2	2.95*	1.83	3.86	5.14	-6.19	11.50*	61.43*	-0.95
3	-2.15	2.77	3.42	4.55	2.48	9.04	48.30	18.02
4	-0.53	1.85	0.00	8.27***	5.82	13.69**	22.73	-9.37
Panel C: Bear Market (1 Apr '11 - 30 Sept '12)								
-4	-0.53	-0.97	-0.88	-2.51	-8.56	2.92	-38.37**	47.01***
-3	-1.64	0.19	1.79	-1.26	-7.37	-4.43	-4.92	35.24**
-2	-0.43	1.36	-0.40	1.45	-3.69	3.27	4.20	35.83**
-1	-1.39	0.71	0.12	-1.15	-2.53	6.05	25.43	31.41**
0	-0.99	1.22	0.23	2.35	-12.30**	1.12	32.08	40.94***
1	0.72	2.41**	3.77	1.96	0.28	12.20***	-6.88	19.60
2	-0.56	0.87	1.44	2.40	-0.38	3.52	7.96	20.83*
3	-0.76	1.61	3.27	-0.54	-1.81	4.61	31.39	25.94*
4	-1.29	0.13	3.99	0.00	-5.42	-1.75	31.85	11.21

*** indicates statistical significance at the 0.01 level
** indicates statistical significance at the 0.05 level
* indicates statistical significance at the 0.10 leve

Table 4-5
Abnormal Buy and Sell Trading Volume Imbalance of Recommending Brokers around Upgrades and Downgrades

This table is similar to Table 4, reporting the mean percentage of abnormal buy volume imbalance for upgrades (**'Buy UATVI')**, and abnormal sell volume imbalance for downgrades (**'Sell DATVI'**), respectively. Results are segregated by the stock's trading turnover. Within a cross-section of market conditions (Bull, Neutral and Bear), the sample stocks are divided into four different groups according to the trading turnover of each stock. Firms with highest trading activity are categorised in '**TR Quartile 1**' and firms with least trading activity are categorised in '**TR Quartile 4**'. This table reports mean percentage of abnormal buy volume imbalance for upgrades, '**Buy UATVI**', and abnormal sell volume imbalance for downgrades, '**Sell DATVI**', respectively. Panel A reports abnormal volume imbalance around recommendations in the Bullish period, Panel B reports the Neutral period, and Panel C reports the Bearish period.

	TR Quartile 1		**TR Quartile 2**		**TR Quartile 3**		**TR Quartile 4**	
Days	**Buy UATVI**	**Sell DATVI**	**Buy UATVI**	**Sell DATVI**	**Buy UATVI**	**Sell DATVI**	**Buy UATVI**	**Sell DATVI**
Panel A: Bull Market (29 Nov '04 – 29 Nov '06)								
-4	-3.91**	2.20	-3.14	-3.27	-4.76	4.33	-21.92	15.15
-3	-3.55**	7.10***	1.35	2.22	9.29	-3.97	8.45	0.60
-2	-0.70	4.44***	3.21	3.21	2.19	1.76	11.07	12.03
-1	0.20	5.55***	-1.00	9.47***	8.64	2.49	21.26	32.77
0	0.86	5.88***	3.07	6.02**	12.50*	6.20	65.78*	24.35
1	3.16*	7.41***	6.32**	9.10***	13.99**	6.05	29.59	36.24
2	0.92	6.49***	1.88	3.62	4.54	4.68	14.65	20.17**
3	-1.26	5.65***	4.78*	2.52	-0.31	-3.17	-9.75	29.30
4	0.38	6.64***	1.07	4.92*	5.35	-3.38	33.17	9.01
Panel B: Neutral Market (1 Sept '09 - 28 Feb '11)								
-4	-0.07	2.71	5.37	4.13	-0.61	6.68	5.95	2.37
-3	1.03	0.96	3.59	0.28	-4.63	21.13***	15.23	3.35
-2	3.52*	4.67**	0.37	4.25	0.18	6.94	18.75	15.18
-1	2.37	4.23**	5.31	5.89**	-4.83	10.61*	10.89	9.29
0	3.42*	3.02*	6.39	7.41***	8.74	-0.99	22.23	29.50**
1	1.38	3.83**	4.69	5.17**	1.29	2.07	4.65	8.01
2	1.25	2.06	6.34	4.20	1.10	6.33	10.44	6.64
3	-2.24	2.11	-0.43*	4.12	12.27**	13.17**	11.47	13.60
4	-1.33	0.96	-2.38***	6.72**	13.62**	12.67**	13.54	12.79
Panel C: Bear Market (1 Apr '11 – 30 Sept '12)								
-4	-0.61	-0.95	0.46	-2.54	-13.01**	8.35*	-30.40***	-0.11
-3	-1.48	-0.02	1.30	-1.04	-6.58	-1.41	-20.14	11.99
-2	-0.51	1.62	1.59	1.40	-7.74	8.60*	-12.56	-0.19
-1	-1.30	0.91	0.33	-1.69	-4.98	9.52**	9.61	10.59
0	-0.93	1.30	1.25	1.06	-15.34**	9.22**	0.61	8.74
1	0.54	2.35**	4.94**	2.89	-5.04	10.41**	-7.76	11.52
2	-0.65	0.80	2.26	2.55	0.58	8.03*	-9.72	-1.02
3	-0.84	1.21	4.68*	0.42	-8.78	4.94	7.12	15.98*
4	-0.97	-0.14	2.37	-0.53	0.81	6.40	-3.86	-7.37

*** indicates statistical significance at the 0.01 level
** indicates statistical significance at the 0.05 level
* indicates statistical significance at the 0.10 level

persists two days after the event. For Neutral market, Panel B of Table 4-3, shows that Quartile 1 experiences abnormal sell volumes on Day -2, persisting until Day 1; Quartile 2 demonstrates abnormal sell volume one day prior to public release of a recommendation. In the Bear market, as presented in Panel C of Table 4-4, significant abnormal sell volumes are observed prior to a downgrade recommendation release but only for Quartile 4. Starting from Day -4, abnormal sell volumes are approximately 47 per cent higher relative to the benchmark period, persisting until the day of the recommendation release, when abnormal sell volumes decrease to approximately 40 per cent. Results from downgrade recommendations also provide support for hypothesis $H_{4,2}$, that abnormal selling activity is observed prior to the recommendation release day. Specifically, when compared across firm sizes, quartiles with smaller firms exhibit larger magnitudes of abnormal selling activity over the event window. Despite analyst research providing a better information environment for smaller-market capitalisation stocks, the lack of significant results observed across all three panels in Quartiles 3 and 4 of Table 4-4 can be explained by a lack of liquidity.

In Table 4-5, stocks are categorised in quartiles of average turnover for each stock in the corresponding market condition. Results in Table 4-5 demonstrate that low trading turnover in stocks may be one explanation for the lack of significant results in the smaller-market capitalisation stocks in Table 4-4. On trading days within the event period, insufficient turnover in smaller-capitalisation/lower-trading activity stocks weakens the significance of abnormal trading activity, despite having a higher magnitude.

Univariate results documented in this section so far provide preliminary support for hypothesis $H_{4,3}$ that firm size is related to abnormal trading volumes prior to the recommendation release day. According to the results reported, firm size influences recipients' propensity to reward recommending brokers with order flow.

4.4.1.2 Regression Analysis – Volume Imbalance

The level of recommendation change is expected to have an impact on investors' propensity to act. Stocks that are well-covered by analysts should have less asymmetric information; analyst research on stocks that are well-covered should add less new information to the market. This could impact on investors' propensity to act when information is tipped. To investigate these cross-sectional implications, the following regressions are estimated. Table 4-6 presents parameter estimates for equations (4.5) and (4.6). Regression analysis is conducted for three time intervals: (1) four days prior to recommendation release, (2) the day of recommendation release and (3) four days after recommendation release. Panel A suggests that prior to recommendation releases there is no abnormal trading volume by broker-analysts, regardless of the market condition. The lack of abnormal buying activity by recommending brokers documented in this section is similar to the results of Juergen and Lindsey (2009) and Busse, Green and Jegadeesh (2012). Panel A of Table 4-6 presents results for upgrade revisions and shows that broker-analysts only experience abnormal trading volume imbalance on the days after the release of recommendation revisions, consistent for all market periods. In the model for post-recommendation release, the coefficient for *Log(MarketCap)* confirms that recipients have larger reactions for smaller market capitalisation stocks.

Panel B of Table 4- provides regression results for downgrade recommendations, and confirms that prior to recommendation release there is abnormal trading volume imbalance by broker-analysts. Results from dummy variables *Bull, Neutral* and *Bear* demonstrate that the effect of abnormal selling activity before the recommendation release day is greatest in the Bull market, marginally lower in the Neutral market, and lowest in the Bear market. This sequence of effects across Bull, Neutral and Bear markets is also observed in columns ***Day 0*** and ***Day +1 to +4***, as the Bull shows the largest coefficient and Bear has the lowest coefficient. These results imply that the largest abnormal selling activity in the event windows is observed in the Bull market, followed by Neutral and Bear. Comparing columns ***Day -1 to -4***, ***Day 0*** and ***Day +1 to +4,*** the coefficients for Bull, Neutral and Bear are strongest in ***Day 0*** as the market responds most strongly on the day of recommendation release. The magnitudes of coefficients for the three market conditions are larger in column ***Day -1 to -4*** than ***Day +1 to +4***, running counter to intuition. This suggests that broker-analysts receive and trade more sell order flow prior to publicly releasing their downgrade revisions than they do after the recommendations are publicly released, irrespective of market conditions. Across all columns ***Day -1 to -4***, ***Day 0*** and ***Day +1 to +4***, results provide statistical significance for both $\Delta Level_m$ and *Log (MarketCap)*. The positive coefficients of $\Delta Level_m$ in Panel B of Table 4-6 for all three regressions indicate that abnormal

Table 4-6

Regression Results of Abnormal Trading Volume Imbalance

This table presents results of broker-analysts' abnormal trading volume imbalance around analyst recommendations for the periods (i) 29 November, 2004 to 29 November, 2006; (ii) 1 September, 2009 to 28 February, 2011 and (iii) 1 April, 2011 to 30 September, 2012, according to the following equation:

$$UATVI_{(i,j,m,t+k)} = \beta_1 Log(MarketCap)_i + \beta_2 Log(Turnover)_i + \beta_3 \Delta Level_m + \beta_4 AnalystCoverage_i + \beta_{5,6,7} Dummy_{Bull,Neutral,Bear} + \varepsilon$$

$$DATVI_{(i,j,m,t+k)} = \beta_1 Log(MarketCap)_i + \beta_2 Log(Turnover)_i + \beta_3 \Delta AbsLevel_m + \beta_4 AnalystCoverage_i + \beta_{5,6,7} Dummy_{Bull,Neutral,Bear} + \varepsilon$$

where the dependent variables are buy and sell abnormal trading volume imbalances around upgrade and downgrade recommendations respectively, for stock i, broker j, recommendation event m, on trading day t. Independent variables include the natural logarithm of market capitalisation of stock i, natural logarithm of average daily turnover of stock i, $\Delta Level_m$ is the change in recommendation level for recommendation m; this is computed as the absolute change in recommendation level for downgrade revisions; $AnalystCoverage_i$ is the count of the number of broker-analysts who cover that particular stock i, in the market period, attributed to trading day t. The model also controls for the market condition by applying dummy variables for each market period. T-statistics are reported in parentheses.

	Day -4 to -1	**Day 0**	**Day +1 to +4**
Panel A: Upgrades			
Log (MarketCap)	-0.0043	-0.0023	-0.0118
	'(-0.78)	'(-0.21)	(-2.09)**
Log (Turnover)	0.0048	-0.0077	-0.0043
	'(1.07)	'(-0.88)	'(-0.92)
ΔLevel	-0.0002	0.0129	0.0045
	'(-0.03)	'(0.85)	'(0.57)
Analyst Coverage	-0.0007	-0.0028	0.0026
	'(-0.39)	'(-0.81)	'(1.45)
Bull	0.0166	0.1959	0.3181
	'(0.21)	'(1.32)	(4.18)***
Neutral	0.0437	0.2243	0.3185
	'(0.57)	'(1.5)	(4.18)***
Bear	0.0143	0.1625	0.3053
	'(0.19)	'(1.1)	(4.05)***
Number of Observations	9,707	2,513	9,837
R-Square	0.0012	0.0092	0.0042
Panel B: Downgrades			
Log (MarketCap)	-0.0097	-0.0176	-0.0049
	(-1.98)**	(-2.01)**	'(-1.01)
Log (Turnover)	0.0013	0.0005	-0.0029
	'(0.31)	'(0.07)	'(-0.71)
ΔLevel	0.0291	0.0275	0.0265
	(4.09)***	(2.01)**	(3.76)***
Analyst Coverage	-0.0006	-0.0004	0.0008
	'(-0.36)	'(-0.14)	'(0.49)
Bull	0.1962	0.3975	0.1681
	(2.85)***	(3.07)***	(2.47)**
Neutral	0.1950	0.3822	0.1516
	(2.82)***	(2.92)***	(2.21)**
Bear	0.1664	0.3583	0.1290
	(2.44)**	(2.77)***	(1.91)*
Number of Observations	11,095	2,858	11,094
R-Square	0.0097	0.0197	0.0135

*** indicates statistical significance at the 0.01 level
** indicates statistical significance at the 0.05 level
* indicates statistical significance at the 0.10 level

trading volume imbalance is stronger on all days around a recommendation release, if the recommendation change is of a stronger level. Consistent with the aforementioned results, the negative coefficient of *Log(MarketCap)* confirms a stronger propensity to act on tipped information for smaller market-capitalisation stocks, or a higher propensity for investors to reward broker-analysts with order flow when tipped on smaller-market capitalisation firms.[69]

The chapter thus far investigates the trading behaviour of broker-analysts in the nine-day period around the public release of associated analysts' recommendation revisions in the Australian Equities Market. Results provide support consistent with evidence of tipping, specifically for downgrades as documented in extant literature (see Juergen and Lindsey, 2009; Busse, Green and Jegadeesh, 2012). Investors' propensity to act on tips varies with market conditions, firm size and level of recommendation change, consistent with hypotheses $H_{4,1}$, $H_{4,2}$ and $H_{4,3}$. Specifically, investors are more likely to act on tips of stronger levels of recommendation downgrades (e.g., strong buy to strong sell) in smaller and mid-capitalisation stocks provided in the bull market. In a bear market, investors are most likely to act on tips in the smallest-market capitalisation stocks.

To better understand the trading behaviour of tipped investors around the release of analyst recommendations, the chapter continues to investigate abnormal returns, driving profitability for investors, under the various circumstances in which recommendations are issued.

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[69] It is noted that similar results are obtained when Days -10 to -1 are pooled to form observations within regression pre-recommendation; and Days 1 to 10 are pooled to form observations within regression post-recommendation.

4.4.3 Abnormal Returns

Figure 4-5 and Table 4-7 report mean daily abnormal returns earned over the 11 day period around a public recommendation release (five days pre-release and five days post-release). Column ***Upgrades*** illustrates that stocks experience positive abnormal returns from Day -1, through to Day +2 for both Bull and Neutral markets, but only until Day +1 for Bear markets. The highest close-to-close return for upgrades in the Bull market is on Day 0. In Neutral and Bear markets, stocks experience the highest close-to-close return on Day +1 and are nearly twice the return obtained on Day +1 in the Bull market. For upgrade recommendations, positive abnormal returns occur consistently starting from Day -1. On Day -1, Close-to-Close Returns for upgrades are on average 32.67 basis points in Bear markets, 27.88 basis points in Bull markets and as low as 17.69 basis points in Neutral markets. Reported abnormal returns around upgrade recommendations (Day -1 to Day 1) are similar in comparison to previous studies; Lepone, Leung and Li (2012), for example, estimate 29.06 basis points of abnormal returns on Day -1 and 43.61 basis points on Day 1. Similar to upgrades, the Column ***Downgrades*** shows that close-to-close returns for downgrades are strongest on Day 0 for Bull markets and Day +1 for Neutral and Bear markets. The magnitude of returns on Day +1 for Neutral and Bear markets is approximately 1.5 times that of returns on Day +1 for the Bull market. Unlike upgrades, abnormal returns for downgrade recommendations generally persist for longer (Bull market until Day +5, Bear market until Day +2), with the exception of Neutral market where close-to-close abnormal returns also persist up to Day +2. In contrast to upgrades, the abnormal returns around downgrades are generally only earned on Day 0 of recommendation release (with the exception of the Bear market). The magnitudes of abnormal returns

Table 4-7
Abnormal Returns of Stocks around Analyst Recommendation Release

This table presents the mean abnormal returns (in basis points) surrounding changes in analyst recommendations. Returns (Close) are computed as close-to-close returns on the stock being recommended. Returns (VWAP) are computed as the volume-weighted average price (VWAP) of the attributed day relative to VWAP of the prior day, on the stock being recommended. Both measures are the net of close-to-close returns on the All Ordinaries Index. The Column **Difference** provides additional returns earned for stocks issued with downgrades relative to upgrades matched by trading days around the release. Panels A, B and C provide daily returns for recommendations in the Bull, Neutral and Bear markets respectively.

	Upgrades		Downgrades		Difference	
Days	Returns (Close)	Returns (VWAP)	Returns (Close)	Returns (VWAP)	Returns (Close)	Returns (VWAP)
Panel A: Bull Market (29 Nov 04 - 29 Nov 06)						
-5	-18.56 ***	-13.45 ***	25.67 ***	26.73 ***	7.11 ***	13.29 ***
-4	-3.47	-5.42	11.07 **	12.19 ***	7.60 **	6.77 ***
-3	-3.03	-3.86	2.89	-0.51	-0.14	-3.36
-2	3.09	0.26	-4.71	-3.53	1.62	3.27
-1	27.88 **	26.49 **	-7.13	-5.96	-20.75 ***	-20.54 **
0	36.87 ***	34.87 ***	-48.71 ***	-36.88 ***	11.85 ***	2.01 ***
1	33.50 ***	37.77 ***	-43.97 ***	-50.34 ***	10.47 ***	12.58 ***
2	9.83 **	12.51 ***	-23.93 ***	-26.79 ***	14.10 ***	14.28 ***
3	1.15	4.07	-14.81 ***	-17.95 ***	13.66 ***	13.88 ***
4	1.58	0.75	-10.02 **	-7.71	8.44	6.96
5	6.60	5.68	-12.92 ***	-14.75 ***	6.31 ***	9.07 ***
Panel B: Neutral Market (1 Sept 09 - 28 Feb 11)						
-5	-6.73	-13.98 **	8.83	4.16	2.10	-9.82 *
-4	-5.35	-4.96	5.29	-0.29	-0.06	-4.67
-3	-17.85 ***	-15.83 ***	-2.87	4.17	-14.98	-11.66 **
-2	-0.06	-1.27	14.17 *	6.44	14.10	5.17
-1	17.69 **	18.20 ***	1.14	14.97 *	-16.55	-3.23
0	26.39 ***	27.66 ***	-39.71 ***	-36.25 ***	13.32 ***	8.59 ***
1	57.13 ***	54.28 ***	-63.94 ***	-64.06 ***	6.81 ***	9.78 ***
2	15.59 **	14.28 **	-25.25 ***	-32.77 ***	9.66 ***	18.49 ***
3	6.83	2.75	-2.51	-4.75	-4.32	2.00
4	-8.98	0.81	-4.37	-2.02	-4.61	1.21
5	7.52	6.88	1.31	0.01	-6.22	-6.87
Panel C: Bear Market (1 Apr 11 – 30 Sept 12)						
-5	0.03	-2.59	4.90	2.83	4.86	0.24
-4	-5.37	-4.52	-10.33	-11.44	4.96	6.92
-3	5.20	7.91	-0.86	-6.21	-4.33	-1.69
-2	4.25	-3.68	-14.03	-14.58	9.78	10.89
-1	32.67 ***	33.54 ***	-33.38 ***	-36.09 ***	0.71 ***	2.55 ***
0	31.00 ***	20.85 ***	-42.29 ***	-44.72 ***	11.29 ***	23.87 ***
1	54.24 ***	46.03 ***	-64.10 ***	-72.31 ***	9.86 ***	26.27 ***
2	-4.49	9.07	-16.97 ***	-21.55 ***	12.48	12.48 ***
3	13.91 **	7.60	6.78	2.62	-7.12	-4.98
4	-5.32	3.16	-0.31	-1.44	-5.01	-1.73
5	-2.31	-4.87	-3.28	-6.81	0.98	1.95

*** indicates statistical significance at the 0.01 level
** indicates statistical significance at the 0.05 level
* indicates statistical significance at the 0.10 level

Figure 4-5
Abnormal Returns of Stocks around Analyst Recommendation Release

Graphs in Figure 4-5 illustrate stock abnormal returns around the release of upgrade and downgrade analyst recommendations, from Day -5 to Day +5. Figure 4-5-1 illustrates this for the Bull market, Figure 4-5-2 illustrates this for the Neutral market, and Figure 4-5-3 illustrates this for the Bear market.

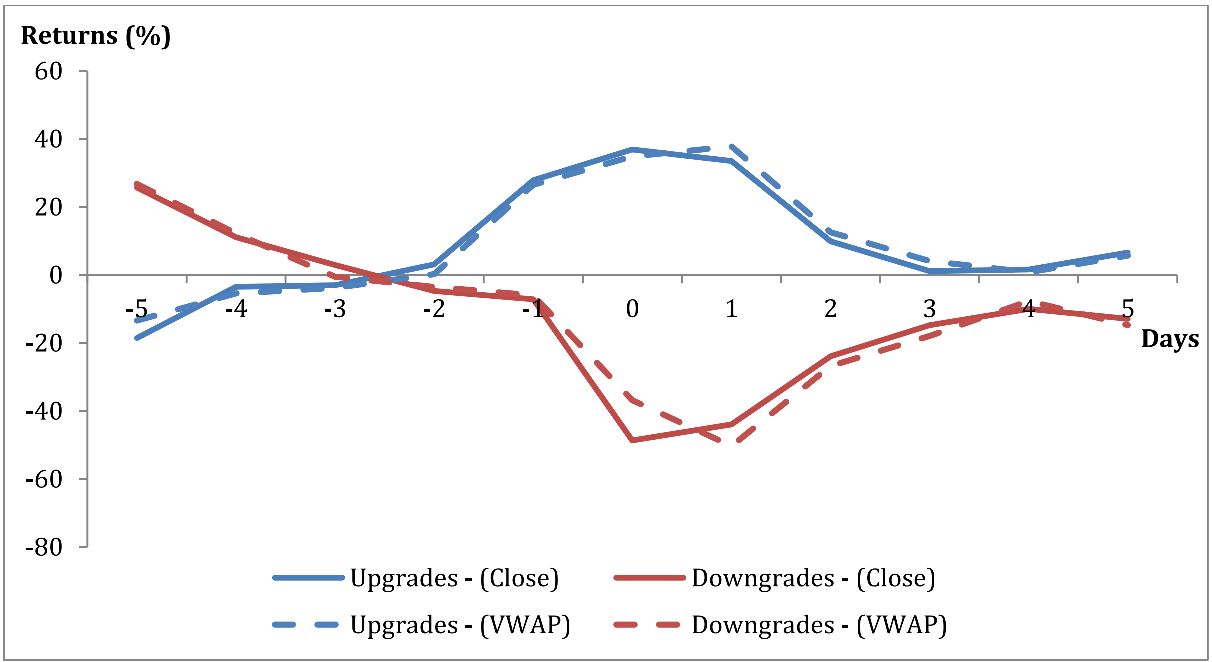

Figure 4-5-1
Abnormal Returns on Stocks around the release of Analyst Recommendations in the Bull Market, 29 November 2004 – 29 November 2006

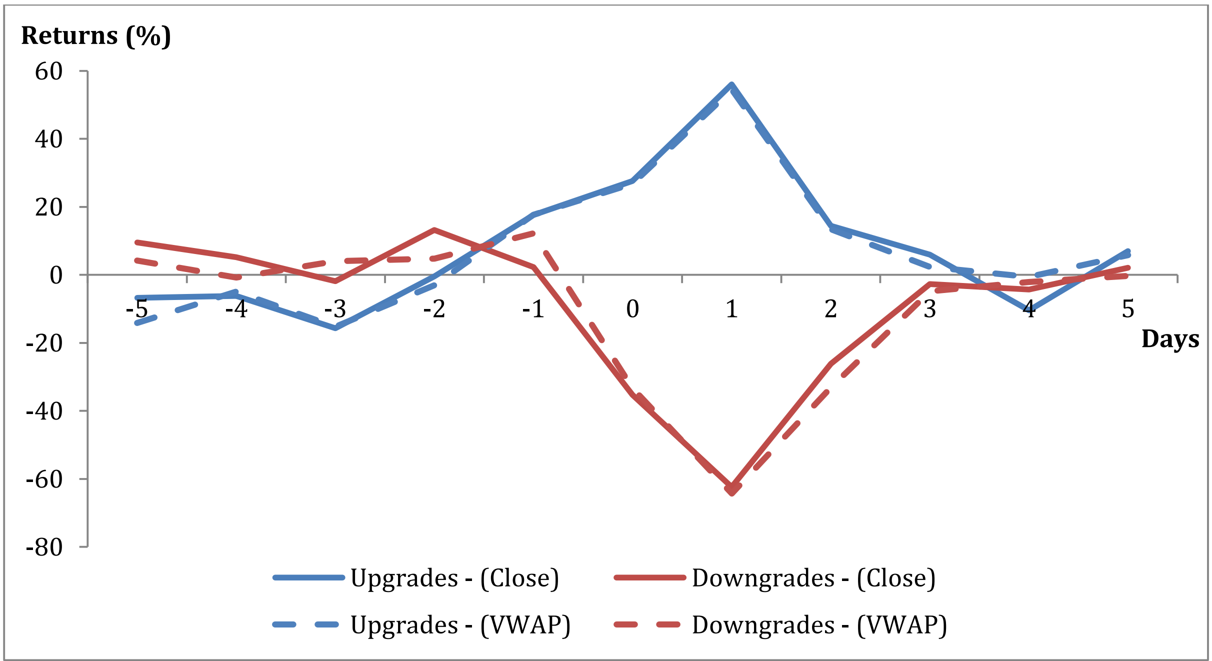

Figure 4-5-2
Abnormal Returns on Stocks around the release of Analyst Recommendations in the Neutral Market, 1 September 2009 – 28 February 2011

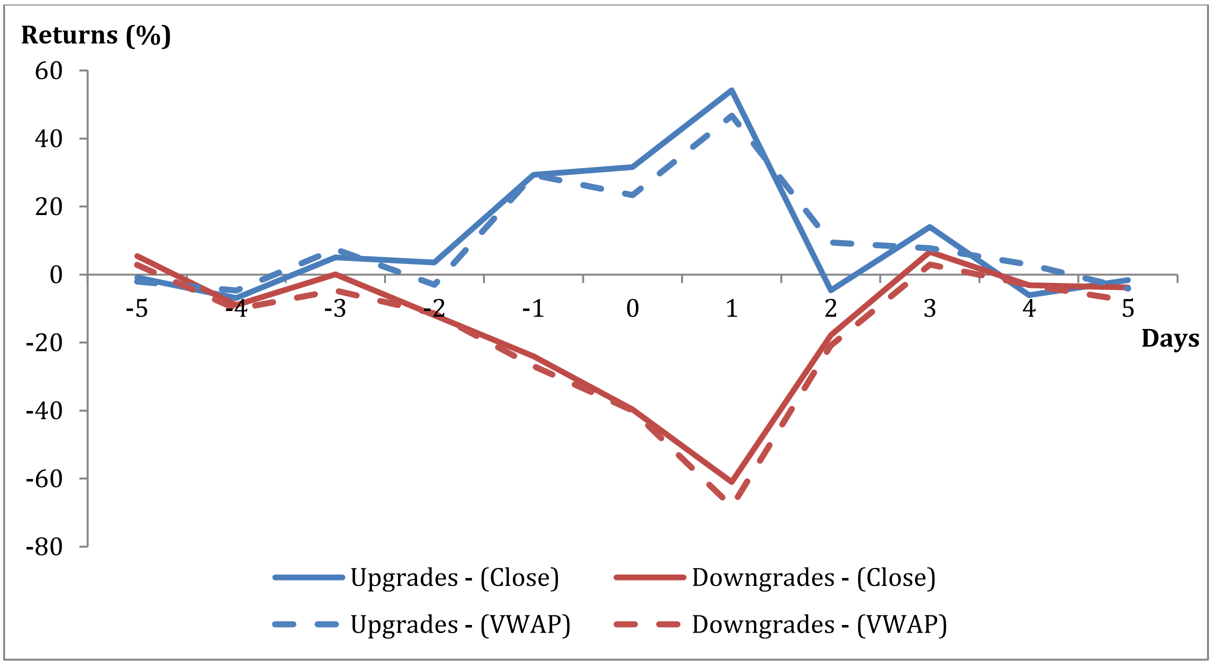

Figure 4-5-3
Abnormal Returns on Stocks around the release of Analyst Recommendations in the Bear Market, 1 April 2011 – 30 September 2012

are generally larger for downgrade recommendations than they are for upgrade recommendations (see Column ***Difference*** in Table 4-7). This difference persists for longer during Bull markets, with differences between returns obtained from downgrades and upgrades statistically significant up until Day +3, (Day +2 during Neutral markets, and Day +1 during Bear markets).

Table 4-8 presents daily average abnormal returns around analyst recommendation releases segmented by firm size. Results indicate that smaller firms provide larger abnormal profit opportunities around the release of analyst recommendations. During Bull markets, significant abnormal returns are most prominent in Quartile 3; during Neutral markets, significant abnormal returns for upgrades are most prominent in Quartile 2, and Quartile 3 for downgrades. The lack of liquidity appears to drive the lack of statistical significance in the smaller firms. When mean daily abnormal returns are computed based on quartiles of average daily turnover, there is a lack of statistical significance in the lower quartiles of turnover. While recipients may be keen to trade in accordance with sentiment in these stocks, these stocks lack sufficient trading turnover to facilitate recipients' trading in response to tips.

The results documented in this section complement the observed trading behaviour earlier presented. Analysis of abnormal returns shows that downgrade recommendations yield significantly higher returns for sellers on the day a downgrade recommendation is released (approximately 11 – 13 basis points more, measured over Day -1 to Day 0), compared to purchasers on the day an upgrade recommendation is released. The drastic difference in market reaction provides a consistent response to analyst bias, the reluctance to issue negative research[70]. Results demonstrate that investors are aware of bias in analyst recommendations and, therefore, more likely react to downgrades. As documented in Barber, Lehavy and Trueman (2007), this reluctance is not subject to avoiding contrarian views from market sentiment. Downgrades are largely associated with the high cost of disseminating negative information and negative impacts on relationships with associated firms. In particular, Barber, Lehavy and Trueman (2007) investigate analyst recommendations in a bear market and finds that investment banks are still reluctant to issue stock downgrades in bear markets[71] (as they are in bull markets). In comparison to the bear markets, results show that downgrades draw more attention (higher broker-analysts' abnormal sell volume imbalance) in the bull and neutral markets. Given equal reluctance to issue

[70] See, for example, Jegadeesh, Kim, Krische and Lee (2004), where sell or strong sell recommendations made up less than 5 per cent of all recommendations in the period 1985 to 1999 in the US . Womack (1996) also found that new buy recommendations occur seven times more often than sell recommendations.

[71] They attribute this bias to external relationships that investment banks have and contrast this to findings of abnormal returns generated by independent research firms during the bear market.

downgrade recommendations by analysts across market conditions, results further indicate that investors are more likely to act on contrarian views in the bull and neutral markets.

Consistent with the implications of Bhushan (1989), the aforementioned results report that small firms experience higher information asymmetry. In such instances, analyst research carries more value, and results reported herein demonstrate that investors do act accordingly. The magnitude of abnormal sell volumes prior to a downgrade recommendation release is consistently strongest in the smaller-market capitalisation firms (regardless of market conditions). Albeit lacking statistical significance, results on volume imbalance of broker-analysts when firms are segregated by quartiles of average turnover confirm that smaller-market capitalisation stocks generally lack trading turnover. These results show that while investors are keen to act on the tipped information prior to analyst release of downgrades, there is generally insufficient trading in these stocks. Yielding the highest returns, in smaller-capitalisation stocks investors can earn up to approximately 75 basis points for upgrades while downgrades provide up to approximately 101 basis points of abnormal profits.

In conjunction with Tables 4-3 and 4-4, results in Table 4-7 and 4-8 confirm the conjecture that recipients behave differently under various combinations of factors that drive profitability. When abnormal returns are examined across the firm quartiles, smaller-market capitalisation and less liquid stocks generate greater

Table 4-8
Abnormal Returns of Stocks around Analyst Recommendation Release: Quartiles of Market Capitalization

This table is similar to Table 4-7 but abnormal returns are averaged by quartile of stock's market capitalisation. Abnormal returns are measured as per section 4.3.2. Largest firms are categorised in '**MC Quartile 1**' and smallest firms in '**MC Quartile 4**'. Panels A, B and C provide daily returns for recommendations in the Bull, Neutral and Bear markets respectively.

Panel A: Bull Market (29 Nov '04 - 29 Nov '06)						
	Upgrades		**Downgrades**		**Difference**	
Days	**Returns (Close)**	**Returns (VWAP)**	**Returns (Close)**	**Returns (VWAP)**	**Returns (Close)**	**Returns (VWAP)**
MC Quartile 1						
-5	-7.6952	-9.5916*	20.0753***	21.1856***	12.3801***	11.5940***
-4	-3.2313	1.2085	15.7423***	17.6979***	12.5110***	16.4894***
-3	-1.0313	-9.0601*	20.8041***	15.2978***	19.7728***	6.2377***
-2	11.2290**	11.9181**	2.3347	4.0359	-8.8943	-7.8822
-1	13.0292**	7.7843	5.1188	4.4939	-7.9104	-3.2904
0	34.2900***	35.3977***	-25.0635***	-14.2022**	-9.2265***	-21.1955***
1	21.5903***	29.9012***	-33.2287***	-33.6816***	11.6384***	3.7804***
2	7.9294	7.4913	-11.2463**	-17.5921***	3.3169***	10.1008***
3	1.7769	4.6467	-4.0580	-6.7589	2.2811	2.1122
4	14.0315**	12.4145**	-5.8752	-2.5036	-8.1563***	-9.9109**
5	9.1016	7.9436	-11.9508**	-11.2691**	2.8492***	3.3255**
MC Quartile 2						
-5	-22.0378***	-12.4195*	43.6844***	38.7279***	21.6466***	26.3084***
-4	-0.9716	-5.5692	11.6748*	16.5611***	10.7032	10.9919**
-3	-7.4831	-4.5856	1.4416	1.9534	-6.0415	-2.6322
-2	-8.8910	-9.4363	3.5193	0.5991	-5.3717	-8.8372
-1	14.2490*	13.4203*	4.8812	11.9351	-9.3678	-1.4852
0	33.9889***	30.3678***	-36.6292***	-23.8099***	2.6403***	-6.5579***
1	39.6864***	42.0944***	-34.5777***	-36.7310***	-5.1087***	-5.3634***
2	17.0503**	23.6392***	-23.5896***	-23.8344***	6.5393***	0.1952***
3	4.4009	5.2964	-16.3425**	-20.8966***	11.9416**	15.6002***
4	0.8385	-1.9192	-9.2615	-6.9683	8.4230	5.0491
5	17.2567***	11.4344*	-10.9792	-14.0258**	-6.2775***	2.5914***
MC Quartile 3						
-5	-32.1677**	-19.0143	-2.5562	17.5539	-29.6115	-1.4604*
-4	3.3156	-7.6611	27.8134**	13.2183	24.4978	5.5572
-3	-12.0432	-7.0401	-14.3694	-10.1698	2.3262	3.1297
-2	5.1472	-5.5840	-26.4845	-31.7653	21.3373	26.1813
-1	15.7089	17.5287	-53.1957***	-50.0336***	37.4868***	32.5049***
0	60.3871***	58.6731***	-121.7427***	-112.5124***	61.3556***	53.8393***
1	34.6252**	42.0494***	-91.3813***	-114.8438***	56.7561***	72.7944***
2	-9.8577	-11.7822	-44.1562**	-48.3043**	34.2985	36.5221
3	3.6549	5.3380	-31.8516*	-25.8264	28.1967	20.4884
4	-9.8308	-10.8321	-7.7336	-10.5555	-2.0972	-0.2766
5	-10.5234	-4.8570	-5.9179	-7.1961	-4.6055	2.3391
MC Quartile 4						
-5	-36.3425	-36.4716	35.9960	23.0562	-0.3465	-13.4154
-4	-33.0249	-43.3029*	-57.0233**	-46.6956*	23.9984	3.3927
-3	40.0133	56.1532	-54.4352	-80.5645**	14.4219	24.4113
-2	14.0143	-11.8040	-40.6934	-8.8524	26.6791	-2.9516
-1	43.9907	53.9420	-37.8006	-58.8201*	-6.1901	4.8781***
0	10.9440	-3.3764	-84.2692	-66.3111	73.3252	62.9347
1	70.4260**	53.6909*	-47.8366	-69.9055**	-22.5894***	16.2146***
2	30.9834	44.5551	-48.0674	-45.8709	17.0840*	1.3158**
3	-25.4407	-11.7634	-34.8662	-48.8410	9.4255	37.0776
4	-52.6643*	-39.4379	-41.5522	-33.4349	-11.1121	-6.0030
5	-33.0766	-17.3581	-36.1769	-47.6492	3.1003	30.2911

Panel B: Neutral Market (1 Sept '09 – 28 Feb '11)						
	Upgrades		Downgrades		Difference	
Days	Returns (Close)	Returns (VWAP)	Returns (Close)	Returns (VWAP)	Returns (Close)	Returns (VWAP)
MC Quartile 1						
-5	11.4604*	11.0176	17.3835**	13.5384*	5.9231	2.5208
-4	-1.2739	0.7048	0.3338	-7.4950	-0.9401	6.7902
-3	-10.6057	-15.2330**	4.7356	11.1703*	-5.8701	-4.0627***
-2	-1.2595	2.8964	18.1267**	16.5499*	16.8672*	13.6535
-1	15.9218**	12.4976	5.4254	17.5306*	-10.4964	5.0330
0	11.7076	16.2967**	-44.8608***	-31.6033***	33.1532***	15.3066***
1	52.9913***	49.5428***	-54.4740***	-60.5796***	1.4827***	11.0368***
2	13.5043*	13.2804*	-14.5131**	-17.4035***	1.0088***	4.1231***
3	2.3040	0.6293	-3.9772	-3.7111	1.6732	3.0818
4	-9.9312	-2.9508	5.1360	4.9998	-4.7952*	2.0490
5	0.3627	0.9861	2.0304	7.2784	1.6677	6.2923
MC Quartile 2						
-5	-43.9859***	-59.4706***	-13.0188	-14.4408	-30.9671*	-45.0298***
-4	-10.0249	-18.7598	19.6592	12.0264	9.6343	-6.7334*
-3	-31.3576**	-15.4714	8.5218	8.1706	-22.8358**	-7.3008
-2	5.5701	5.2027	24.1861**	14.8279	18.6160	9.6252
-1	19.2184	19.5371	11.3647	21.3820*	-7.8537	1.8449
0	31.4137	35.3605*	-47.3769***	-51.6603***	15.9632***	16.2998***
1	72.3213***	66.6765***	-86.9868***	-78.4967***	14.6655***	11.8202***
2	15.7060	11.0282	-42.1470***	-46.8526***	26.4410***	35.8244***
3	14.0625	12.4136	20.1735	5.6932	6.1110	-6.7204
4	-6.9125	4.4994	-11.1355	-4.3147	4.2230	-0.1847
5	14.5904	10.1137	13.0494	1.0001	-1.5410	-9.1136
MC Quartile 3						
-5	-3.3741	-22.2696	-24.9583	-12.9170	21.5842	-9.3526
-4	-15.6478	3.2629	31.0113	13.8651	15.3635	10.6022
-3	1.4495	-18.1600	-68.5697**	-35.1684	67.1202*	17.0084
-2	-10.8704	-21.1136	-46.1130	-74.7977**	35.2426	53.6841
-1	24.3492	35.7876	-62.0944**	-37.6654	37.7452**	1.8778*
0	36.8541	35.2801	10.6207	-3.9177	-26.2334	-31.3624
1	24.9398	13.8667	-72.6266***	-63.3753***	47.6868***	49.5086**
2	-4.0015	-3.0384	-29.0869	-60.6844***	25.0854	57.6460*
3	-7.0679	-16.7556	-25.6622	-25.7345	18.5943	8.9789
4	11.0092	11.7354	0.2245	-0.6782	-10.7847	-11.0572
5	37.9008*	43.6895**	-11.4199	-11.9678	-26.4809	-31.7217*
MC Quartile 4						
-5	-31.4086	-51.7588	172.5486	62.5297	141.1400	10.7709
-4	-0.6121	-19.9038	-125.3791	-29.6384	124.7670	9.7346
-3	-127.8167*	-23.3873	-28.2539	-31.5523	-99.5628	8.1650
-2	15.0602	-81.1493	56.0985	17.5488	41.0383	-63.6005
-1	11.3215	56.3518	45.8211	95.0368	34.4996	38.6850
0	268.8571	175.1187	-43.5790	-97.1962	-225.2781	-77.9225
1	134.6569	214.7358**	6.9147	7.3766	-127.7422	-207.3592
2	151.9701*	151.6630**	-58.8993	-98.5270	-93.0708**	-53.1360***
3	96.0647	34.3908	-110.1572*	-50.7294	14.0925*	16.3386
4	-96.5106	0.2944	-145.2399**	-125.0462**	48.7293	124.7518
5	-32.3829	-48.2762	-82.3930	-113.0818	50.0101	64.8056

Panel C: Bear Market (1 Apr '11 – 30 Sept '12)						
	Upgrades		Downgrades		Difference	
Days	Returns (Close)	Returns (VWAP)	Returns (Close)	Returns (VWAP)	Returns (Close)	Returns (VWAP)
MC Quartile 1						
-5	-2.7200	-7.3749	8.0596	5.6244	5.3396	-1.7505
-4	-15.0425**	-9.1968	6.5075	3.3951	-8.5350***	-5.8017
-3	-3.3451	-2.2916	13.9951**	12.1409*	10.6500*	9.8493
-2	-1.8695	-8.4560	-13.5162*	-11.6448*	11.6467	3.1888
-1	16.7964*	18.4597**	-27.0647***	-23.1137***	10.2683***	4.6540***
0	20.6022**	4.1236	-33.8641***	-41.5602***	13.2619***	37.4366***
1	40.5002***	40.2668***	-64.8791***	-66.3398***	24.3789***	26.0730***
2	-0.9733	6.2238	-7.8502	-16.8942***	6.8769	10.6704***
3	9.3390	9.3599	2.8568	-0.3088	-6.4822	-9.0511
4	-8.3059	-1.0081	4.2332	6.7810	-4.0727	5.7729
5	-0.5767	-4.9655	6.4262	2.3491	5.8495	-2.6164
MC Quartile 2						
-5	4.9539	5.2475	5.0015	1.2617	0.0476	-3.9858
-4	3.4899	9.0953	-23.2621**	-15.8298	19.7722*	6.7345*
-3	-4.0282	1.7204	-6.0465	-16.3076*	2.0183	14.5872
-2	-0.9041	-7.7194	-24.9173**	-24.8754**	24.0132	17.1560
-1	37.3181***	21.0485*	-24.2524*	-27.6448**	-13.0657***	6.5963***
0	29.1989**	31.7393**	-64.6851***	-59.6551***	35.4862***	27.9158***
1	80.1973***	64.9395***	-78.9248***	-83.6928***	-1.2725***	18.7533***
2	-2.5703	12.7748	-28.5224***	-33.8591***	25.9521*	21.0843***
3	11.0612	1.9798	-3.4148	-9.5391	-7.6464	7.5593
4	1.5792	10.0963	-7.2655	-8.2762	5.6863	-1.8201
5	-0.2992	-6.3209	-3.5179	-11.3537	3.2187	5.0328
MC Quartile 3						
-5	21.7681	26.6009	4.5885	6.1791	-17.1796	-20.4218
-4	37.6316	21.9213	-37.3800	-41.1309*	-0.2516**	19.2096*
-3	59.0602**	68.9482***	-21.1138	-37.9489	-37.9464*	-30.9993***
-2	9.7949	15.8299	18.0734	11.4472	8.2785	-4.3827
-1	34.6248	37.0666	-24.3669	-54.5798	-10.2579	17.5132*
0	87.4463**	82.6261***	-25.4893	-36.3130	-61.9570*	-46.3131**
1	48.0771**	35.2954	-82.0545***	-93.1219***	33.9774***	57.8265***
2	-29.8759	-15.2933	-26.1666	-16.8649	-3.7093	1.5716
3	17.1685	0.7083	57.0140	59.3067	39.8455	58.5984
4	25.1991	17.9968	17.9689	-0.9687	-7.2302	-17.0281
5	-19.8233	-1.4428	-45.5270**	-27.7909	25.7037	26.3481
MC Quartile 4						
-5	-43.1372	-56.6158**	-18.9690	-17.5440	-24.1682	-39.0718
-4	-47.5501	-84.0703*	-29.0935	-48.5751	-18.4566	-35.4952
-3	21.7882	10.0623	-52.2474*	-40.2649	30.4592	30.2026
-2	75.3304*	21.2600	-29.3735	-39.5766	-45.9569	18.3166
-1	152.2098	228.1598**	-139.7983*	-138.4062*	-12.4115**	-89.7536***
0	22.5159	-3.2218	-37.6783	-17.7018	15.1624	14.4800
1	64.4327	26.7692	42.0101	-27.4286	-22.4226	0.6594
2	4.2083	66.4412	-17.2059	-10.4696	12.9976	-55.9716
3	65.2750*	33.8348	-11.6299	-26.5798	-53.6451	-7.2550
4	-75.0954*	-23.1239	-37.8018	-34.1809	-37.2936	11.0570
5	6.7975	-3.3829	2.4978	-16.9465	-4.2997	13.5636

*** indicates statistical significance at the 0.01 level
** indicates statistical significance at the 0.05 level
• indicates statistical significance at the 0.10 level

returns around the event day, particularly on the day of public recommendation release and one day after, spurring higher volume imbalance around event day.

4.4.4 Cross-Sectional Analysis – Trading Volume Imbalance and Returns

Thus far, the analyses on Abnormal Trading Volume Imbalance and Abnormal Returns have been independent. To test hypothesis $H_{4,4}$, Table 4-9 compares the abnormal trading volume imbalance and daily abnormal returns around the event period. Prior to Day 0 of upgrade recommendations, stock prices generally trend upward. This implies that, on average, positive news is better anticipated by the market, largely providing an explanation for the lack of broker-analysts' buy trading volume imbalance preceding upgrade recommendation releases. This could possibly be attributed to two factors: (i) as the market has already moved in the intended direction, recipients act to a lesser extent, or (ii) as the market has already moved in the intended direction, tipped information becomes less valuable and therefore broker-analysts are not rewarded with order flow. The market generally lags for downgrade recommendations, providing a valuable opportunity for tipped downgrade information. Consistently, broker-analysts experience abnormal sell volume imbalance prior to the release of a downgrade recommendation. As the market is lagging in its reaction to negative information, recipients act on the tipped information and reward broker-analysts with the order flow. In the Bear market, stocks anticipating downgrade recommendations trend downwards one day prior to the public release of analyst research. This suggests that the market predicts negative announcements better in a bear market, providing excess supply of the stock prior to the release of analysts' research. This act deters recipients from acting on tipped information.

On days prior to recommendation, it is consistently observed that there is a lack of broker-analysts' abnormal trading volume imbalance if abnormal returns, on average, are larger than 15 basis points in the direction consistent with the attributed recommendation. This comparison is presented in Panel B of Table 4-9. As an example, on day prior to recommendation, there is no abnormal buy volume imbalance in the Bull market as stocks achieve abnormal returns on Day -1. Specifically, on average, abnormal returns are larger than 15 basis points. In contrast, prior to Day 0 for downgrades, stocks do not experience significant abnormal returns, with an average of less than -15 basis points, which is statistically insignificant. Correspondingly, the study finds that broker-analysts experience abnormal sell volume imbalance pre-release of downgrade recommendations. The abnormal buy (sell) volume imbalance observed consistently leads upgrade/downgrade releases if abnormal daily return, on average, is below the threshold of 15(-15) basis points. This threshold holds across both cross-sections of market conditions and quartile sizes (Refer to Table 4-9).[72]

Broker-analysts experience abnormal buy (sell) volume imbalance prior to an upgrade (downgrade) recommendation only when stock prices have not yet moved significantly in the direction of the recommendation. Abnormal returns around upgrade recommendations provide that stocks experience positive abnormal returns one day prior to recommendation release, suggesting that the market anticipates and impounds

[72] The exception to this threshold is stocks in the largest quartile, MC Quartile 1, where this threshold is lower, at a magnitude of 10 basis points. For stocks in quartile 1, it is observed that this phenomenon is more sensitive to lower abnormal returns.

Table 4-9

Abnormal Trading Volume Imbalance and Daily Returns – Consolidation

This table presents a consolidation of Tables 4.3 and 4.7. The table reports abnormal buy volume imbalance and abnormal daily returns, for upgrades; and abnormal sell volume imbalance and abnormal returns, for downgrades. Similar to Table 4-3, abnormal trading volume imbalance is measured as per section 4.3.1. Abnormal daily returns reported in this table are close-to-close returns measured as per section 4.3.2. Panel A reports the Bullish period, Panel B Reports the Neutral period, and Panel C reports the Bearish period.

	Upgrades		Downgrades	
Days	Abnormal Buy Volume Imbalance (%)	Abnormal Daily Returns (Close, bps)	Abnormal Sell Volume Imbalance (%)	Abnormal Daily Returns (Close, bps)
Panel A: Bull Market (29 Nov 04 – 29 Nov 06)				
-5		-18.56 ***		25.67 ***
-4	-3.81 ***	-3.47	0.66	11.07 **
-3	-0.87	-3.03	4.54 ***	2.89
-2	0.91	3.09	3.88 ***	-4.71
-1	0.39	27.88 **	6.92 ***	-7.13
0	2.76 **	36.87 ***	6.2 ***	-48.71 ***
1	5.20 ***	33.50 ***	8.17 ***	-43.97 ***
2	1.61	9.83 *	5.51 ***	-23.93 ***
3	0.86	1.15	4.18 ***	-14.81 ***
4	1.23	1.58	5.29 ***	-10.02 **
5		6.60		-12.92 ***
Panel B: Neutral Market (1 Sept 09 – 28 Feb 11)				
-5		-6.73 **		8.83
-4	1.62	-5.35	3.53 **	5.29
-3	1.60	-17.85 ***	2.73 *	-2.87
-2	2.73 *	-0.06	5.00 ***	14.17 *
-1	2.83 *	17.69 ***	5.50 ***	1.14
0	5.15 ***	26.39 ***	4.67 ***	-39.71 ***
1	2.43	57.13 ***	4.17 ***	-63.94 ***
2	2.94 *	15.59 **	3.32 **	-25.25 ***
3	-0.19	6.83	4.05 ***	-2.51
4	0.03	-8.98	4.16 ***	-4.37
5		7.52		1.31
Panel C: Bear Market (1 Apr 11 – 31 Oct 12)				
-5		-0.02		4.90
-4	-1.70	-5.37	-0.54	-10.33
-3	-1.38	5.20	-0.14	-0.86
-2	-0.63	4.25	2.13 **	-14.03
-1	-0.82	32.67 ***	1.14	-33.38 ***
0	-1.13	31.00 ***	2.11 **	-42.29 ***
1	1.31	54.24 ***	3.42 ***	-64.10 ***
2	0.05	-4.49	1.84 *	-16.97 ***
3	0.52	13.91 **	1.65	6.78
4	0.05	-5.32	0.16	-0.31
5		-2.31		-3.28

*** indicates statistical significance at the 0.01 level
** indicates statistical significance at the 0.05 level
* indicates statistical significance at the 0.10 level

positive information prior to analyst research. This increases general buying pressure in the stock, conversely causing a lack of abnormal buying activity by broker-analysts. In contrast, downgrades exhibit abnormal returns only starting on the day of recommendation release (for Bull and Neutral markets). Hence, the anticipated profitability for tipped investors in this instance leads abnormal selling activity by broker-analysts. Table 4-9 clearly documents an association between abnormal returns and trading volume imbalance by broker-analysts, in support of hypothesis $H_{4,4}$.

4.4.5 Short-Selling

This section reports the results for test of hypotheses $H_{4,5}$ and $H_{4,6}$. In particular, this section seeks to understand if the abnormal sell volume imbalance around downgrade recommendations found in section 4.4.1 is explained by institutions exiting their long positions or actively short-selling in accordance with the provided tip.

Panel A of Table 4-10 presents results of abnormal short-selling activity, by quartiles of market capitalisation, around the 11-day event period in sample data.[73] While this section seeks to understand institutional activity around downgrade recommendations to test hypotheses $H_{4,5}$ and $H_{4,6}$, the chapter presents relevant results for upgrade recommendations. Results for short-selling activity around upgrade recommendations demonstrate the occurrence of statistically significant abnormal short-selling activity on days after release of a public recommendation in Quartile 1 and on all event days for

[73] The Dataexplorers data available for this chapter are for the period July 2006 – July 2013, while the Bull market is defined for the period 29 November 2004 – 29 November 2006. As the short-selling data include only a limited portion over the Bull market, this section does not investigate the effect of abnormal short-selling activity and institutional ownership by cross-section of market conditions.

Quartile 2. Results from Quartiles 3 and 4 are not statistically significant. For downgrade recommendations, results demonstrate that abnormal short-selling activity occurs for Quartiles 1 and 2, for the entire 11-day period centring on a downgrade recommendation. While Table 4-10 demonstrates that abnormal short-selling also occurs for Quartile 2 around an upgrade recommendation, the magnitude of abnormal short-selling for downgrades is larger for every day across the event, with the exception of Day -3 where abnormal short-selling of upgrades exceeds that of downgrades by 0.0058 per cent. After Day 0, the magnitude of abnormal short-selling for Quartile 2 for downgrades gradually exceeds twice the magnitude of abnormal short-selling for upgrades, where upgrades resulted in abnormal short-selling on Day +4 of 0.1483 per cent while downgrades on Day +4 saw 0.3187 per cent of abnormal short-selling.

As presented in Panel A of Table 4-10, results for Quartiles 1 and 2 show that institutions actively participate in short-selling of stocks prior to analyst recommendations. The results, however, show no significant abnormal short-selling activity over the 11-day period around downgrade recommendations for Quartiles 3 and 4. Results in Quartiles 3 and 4 may be driven by one of the following two reasons: (i) Quartiles 3 and 4 are smaller market capitalisation stocks, which are less liquid[74]. Due to the difficulty in borrowing these stocks, recipients may find it harder to act; (ii) the number of observations in Quartiles 3 and 4 is much less than Quartiles 1 and 2, causing a lack of significance. The small number of observations also provides support for the conjecture that institutions experience difficulty in borrowing these stocks.

[74] This lends support to the findings of D'Avolio (2002). The study finds that the portion of stocks available to short-sell, but are never short-sold, is small and highly illiquid stocks.

Around downgrade recommendations, for the largest quartile of stocks, abnormal short-selling activity begins on Day -4 of the event period, at approximately 0.0973 per cent. This increases monotonically over the 11-day event period, to 0.3529 per cent of abnormal short-selling activity on Day +5. In Quartile 2, abnormal short-selling activity is significant, starting five days before public release of downgrade recommendations. The magnitude of abnormal short-selling activity is consistently higher than that of results in Quartile 1. Results here imply that short-sellers react more to downgrade recommendations in smaller-market capitalisation stocks, in Quartile 2 relative to Quartile 1.

Panel B of Table 4-10 presents results on the level of institutional ownership around upgrade and downgrade recommendations, for stock market capitalisation quartiles. Results show that over the 11-day event period, there is no evidence of institutional exit, in response to analyst recommendations, on any particular day. It is noteworthy that the proxy used for the level of institutional ownership is based on the number of shares held by beneficial owners, which are predominantly mutual funds and pension funds. As these funds generally have a longer-term view of stock holdings, they are usually unconcerned about fluctuations in share-prices due to short-term performance. In addition, these institutions generally hold large positions in listed firms, which makes it difficult and costly to exit a company in response to a temporary fluctuation in prices. Consistent with this, it is observed that institutional ownership remains relatively unchanged across the entire 11-day observation period, which supports the notion that these institutions are reluctant to act on minor changes in short-term company performance pre-or-post downgrade recommendations.

Results on abnormal short-selling activity and institutional ownership in this section further describe recipients' reaction to analyst recommendations, in particular downgrades, following on results documented in previous sections. This chapter documents (i) significant abnormal short-selling activity around the public release of downgrade recommendations and, (ii) no evidence of institutions exiting their long positions in accordance with a downgrade recommendation. The implications of this show that results on abnormal sell volume around downgrade recommendations are largely driven by recipients actively participating in short-selling and not institutional selling activity upon receipt of an upcoming downgrade recommendation, in support of hypothesis $H_{4,5}$ and $H_{4,6}$.

Table 4-10

Abnormal Short-Selling Activity and Institutional Ownership

This table reports the average abnormal short-selling activity and level of institutional ownerships around event days for the periods 1 September, 2009 to 28 February, 2011 and 1 April, 2011 to 30 September, 2012. The sample data are divided into four different groups in accordance with market capitalization of stocks in the dataset; the largest firms are placed in '**MC Quartile 1**' and the smallest firms in '**MC Quartile 4**'. Panel A of this table reports average abnormal short-selling activity and Panel B reports the raw institutional holdings. **Freq** reports the number of downgrade recommendations attributed to the reported results.

Days	**MC Quartile 1**		**MC Quartile 2**		**MC Quartile 3**		**MC Quartile 4**	
	Upgrade	**Downgrade**	**Upgrade**	**Downgrade**	**Upgrade**	**Downgrade**	**Upgrade**	**Downgrade**
	Freq 453	**Freq** 532	**Freq** 220	**Freq** 266	**Freq** 78	**Freq** 88	**Freq** 24	**Freq** 27
Panel A: Abnormal Short Selling Activity								
-5	0.0196	0.0744 *	0.0934 **	0.1096 ***	-0.02124 **	-0.0166	-0.0014	-0.0200
-4	0.0043	0.0973 **	0.0973 **	0.1163 ***	-0.01371 ***	-0.0096	-0.0032	-0.0183
-3	0.0039	0.1030 **	0.1212 ***	0.1154 ***	-0.02245 **	-0.0161	-0.0031	-0.0131
-2	0.0242	0.1111 ***	0.1345 ***	0.1622 ***	0.00916	-0.0315	0.0048	-0.0084
-1	0.0350	0.0964 ***	0.1166 ***	0.1771 ***	0.00814	-0.0257	0.0037	-0.0068
0	0.0318	0.1111 ***	0.1203 ***	0.1659 ***	0.00293	-0.0164	-0.0027	-0.0053
1	0.0745	0.1438 ***	0.1022 **	0.1795 ***	-0.01742	0.0042	0.0051	-0.0076
2	0.0997 *	0.1988 ***	0.1257 ***	0.2326 ***	-0.02303	-0.0018	0.0159	0.0025
3	0.1138 **	0.2288 ***	0.1349 ***	0.2664 ***	-0.02996	0.0516	0.0138	0.0151
4	0.1235 **	0.2684 ***	0.1483 ***	0.3187 ***	-0.05282	0.0406	0.0121	0.0208
5	0.1252 **	0.3529 ***	0.1652 ***	0.3080 ***	-0.02756	-0.0079	0.0197	0.0147
Panel B: Raw Institutional Holding								
-5	14.3117	14.6640	11.8784	11.5632	5.6846	5.3128	2.5432	3.1519
-4	14.3042	14.6114	11.8678	11.4755	5.7265	5.3098	2.5703	3.1742
-3	14.2838	14.6685	11.8814	11.4492	5.8137	5.3067	2.5671	3.1312
-2	14.2781	14.7121	11.8507	11.5321	5.6177	5.2963	2.5576	3.1471
-1	14.2502	14.7012	11.7708	11.5315	5.6811	5.2842	2.5611	3.1756
0	14.2395	14.6644	11.8923	11.5272	5.6224	5.2280	2.5841	3.1978
1	14.2348	14.6801	11.8251	11.5365	5.6175	5.2244	2.5615	3.1436
2	14.1898	14.6374	11.8284	11.5475	5.5653	5.2742	2.5607	3.1156
3	14.2056	14.6598	11.8927	11.4762	5.5600	5.2498	2.5516	3.1016
4	14.2416	14.6137	11.9425	11.4977	5.5726	5.2352	2.5556	3.0915
5	14.2687	14.6251	11.8615	11.5575	5.6612	5.1592	2.6704	3.0902

*** indicates statistical significance at the 0.01 level
** indicates statistical significance at the 0.05 level
* indicates statistical significance at the 0.10 level

4.5 Summary

This chapter provides the first comprehensive discussion of the characteristics which influences recipients' propensities to act on tipped information, using several datasets that allow an accurate observation of broker trading activity around the release of their analyst reports. Analysis in this chapter extends empirical research on tipping by identifying factors driving profitability around analyst recommendations and recipients' behaviour in response to the underlying circumstances.

First, the analysis in Chapter 4 provides further evidence in support of tipping in Australia, but specifically, that recipients provide more abnormal sell volume preceding downgrade recommendations. Drawing support from empirical literature, downgrade recommendations are perceived to be more valuable, as they are generally scarcer. Examining daily abnormal returns, the analysis confirms the value asymmetry of downgrades compared to upgrades. This asymmetry is consistent across all three market conditions examined, with the strongest price responses to downgrades observed in bull and neutral markets, compared to bear markets. Correspondingly, recipients' responses to downgrade tips are the strongest in bull markets, indicating a stronger propensity to act when analyst research exhibit contrarian views of the underlying market condition. Examining across market capitalisation quartiles, abnormal returns are largest among smaller-market capitalisation firms, supporting views that analyst research of smaller firms conveys greater information. Analysis of abnormal trading volume provides larger abnormal sell volumes in response to tips for this subset of stocks, consistent across all market conditions. Results on short-selling activity and institutional holding around downgrade recommendations suggest that recipients who respond to downgrade tips are predominantly short-sellers.

The study also finds that investors' propensity to act on tips is driven by the relative information value attributed to the analyst reports. Stock prices impounding external information shocks prior to the analyst reports reduce the information value of the tips provided. Integrating the results of abnormal trading volume and daily returns, the study consistently finds that broker-analysts' abnormal trading volumes lead abnormal daily returns. Specifically, recipients only respond to tips when the underlying stocks have not impounded information in the direction of the attributed analyst research. In situations where stocks experience abnormal daily returns prior to public release of analyst recommendations, this dissertation finds that there is no abnormal trading volume for broker-analysts.

Chapter 5: The Impact of Co-Location on Institutional Execution Costs

5.1 Introduction

The general findings of empirical research discussed in Section 2.5 report that AT positively contributes to market quality via tighter bid-ask spreads, greater depth and enhanced price discovery (see Hendershott, Jones and Menkveld, 2011; Hasbrouck and Saar, 2013; Brogaard, Hendershott and Riordan, 2014). Despite findings of improved liquidity, the theoretical literature around algorithmic and high frequency traders predicts higher price impact costs imposed on other market participants, as their faster access to information allows algorithmic and high frequency traders to avoid such costs, and pass them on to their counterparties (see Cartea and Panelva, 2012; Rosu, 2014; Biais, Foucault and Moinas, 2014; Hoffman, 2014).

In this chapter, hypothesis $H_{5,1}$ is tested, specifically whether technological upgrades at exchanges lead to an increase in Algorithmic and High Frequency Trading activity. The technological upgrades investigated in this chapter are co-location services hosted by exchanges. Over the period of 2007 to 2011, 12 exchanges are identified as having invested in providing market participants with co-location services. Garvey and Wu (2010) find that distance from an exchange plays a large role in how quickly orders interact with the exchange. In effect, co-location reduces latency, enabling co-located algorithmic trading participants to interact more rapidly with the market. Utilising this exogenous event, hypothesis $H_{5,2}$ is tested to determine whether the level of algorithmic and high frequency trading is positively related to the execution costs incurred by institutions.

The remainder of this chapter is organised as follows. Section 5.2 describes the data employed in this chapter, and the effect of co-location on proxies of algorithmic trading adopted from the empirical literature. The research design is discussed in section 5.3 and results reported and discussed in section 5.4. Section 5.5 provides robustness tests and section 5.6 concludes.

5.2 Data

This chapter utilises two sets of data to examine the impact of AT activity on institutional execution costs. Trade and order data for 12 equity exchanges are obtained from the Thomson Reuters Tick History (TRTH) database, sourced by the Securities Industry Research Centre of Asia-Pacific (SIRCA). The TRTH database contains more than five million equity and derivatives instruments around the world. Securities within the dataset are identified by a unique Reuters Instrument Code (RIC). The data obtained from TRTH are trade and quote data including: (1) number of bids, (2) number of asks, (2) volume of trade, and (4) turnover for each security trading day

As opening and closing session mechanisms differ across exchanges[75], all exchange-specific opening and closing times are identified and data during these periods is removed to ensure the effects are only captured during continuous trading. Consequently, this leaves orders submitted during continuous trading in the subsequent analysis, which more accurately capture any effects of changes in latency.

Data on institutional trades are sourced from Abel Noser Solutions. Abel Noser Solutions is a consulting firm that works with institutional clients to monitor trading costs. Clients of Abel Noser Solutions include pension plan sponsors, retirement funds, and money managers such as Lazard Assets Management and Fidelity.[76] The data provided by Abel Noser Solutions have been utilised by various academic studies, including Goldstein, Irvine, Kandel and Weiner (2009), Goldstein, Irvine and Puckett (2011) and Anand, Irvine, Puckett and Venkataraman (2013a, 2013b). For each trade execution, the database reports anonymised identity codes for the institution and the broker involved in each trade, the CUSIP and ticker for the stock. Several reference prices are included in the dataset: (1) the stock price when the

[75] As an example, the Australian Securities Exchange conducts a random opening auction, in which orders are submitted in the 'Pre-Open' phase of 7:00am – 10:00am. At 10:00am, trading for stocks is opened at staggered times, dependent on the first alphabet of the stock trading ticker. In contrast to this, the Borsa Italiana also runs an opening auction. However, the pre-auction phase takes place from 8:00:00 am to 9:00:59am, for the securities in the Blue Chip and Star segments.

[76] See Anand, Irvine, Puckett and Venkataraman (2013a; 2013b).

Table 5-1
Co-Location Dates
This table presents co-location dates for the 12 exchanges included in the analysis of this chapter.

Exchange	Country	Co-Location Date	Reference for Co-Location Date
Australia Securities Exchange	Australia	Nov-08	http://www.asx.com.au/documents/investor-relations/annual_report_2008.pdf
XETRA Germany	Germany	Aug-06	http://deutsche-boerse.com/dbg/dispatch/en/notescontent/dbg_nav/press/10_Latest_Press_Releases/20_Deutsche_Boerse/INTEGRATE/mr_pressreleases?notesDoc=0759C7A6A8C0BE8EC12578C500337D8B&newstitle=deutscheboerseoperatesxetracas&location=press
National Stock Exchange India	India	Jan-10	http://www.nseindia.com/technology/content/tech_intro.htm
Borsa Italiana	Italy	Sep-09	https://europeanequities.nyx.com/sites/europeanequities.nyx.com/files/327777.pdf
London Stock Exchange	UK	Sep-09	http://www.londonstockexchange.com/about-the-exchange/media-relations/press-releases/2010/lsegmakescolocationdirectlyavailabletovendorsandserviceproviders.htm
Kuala Lumpur Stock Exchange	Malaysia	9-Nov-09	http://bursa.listedcompany.com/newsroom/Media_Release__09Nov09.pdf
New York Stock Exchange	US	Apr-08	https://europeanequities.nyx.com/sites/europeanequities.nyx.com/files/327777.pdf
Oslo Stock Exchange	Norway	Apr-10	http://www.oslobors.no/ob_eng/Oslo-Boers/Trade/Delta/The-strategic-partnership-with-the-London-Stock-Exchange-Group
Paris Euronext	France	Apr-08	https://europeanequities.nyx.com/sites/europeanequities.nyx.com/files/327777.pdf
Lisbon Euronext	Portugal	Apr-08	https://europeanequities.nyx.com/sites/europeanequities.nyx.com/files/327777.pdf
Tokyo Stock Exchange	Japan	4-Jan-10	http://asiaetrading.com/tse-colocation-trading-growing-rapidly/
Toronto Stock Exchange	Canada	30/06/2010	http://www.tmx.com/en/news_events/news/news_releases/2010/6-17-2010_TMXGroup-Co-Location.html

broker receives the order, (2) the open price of the stock on the day of order placement, (3) execution price and date, direction and size of trade.

The sample period in this analysis is taken in view of the corresponding introduction of co-location services by the respective exchanges. The co-location dates for the 12 exchanges are based on documents issued by the exchanges and listed in Table 5-1. The month in which co-location is being implemented for each exchange is excluded from the analysis to allow for take up of co-location services, and consequently the event window examined for each exchange covers a period of 12 months before and 12 months after co-location.

5.3 Research Design

This section outlines the research design employed to test the two hypotheses developed for this chapter. First, the variables in question are defined and the measure adopted for computation is delineated. The section then describes the multivariate tests to evaluate the relation between the intensity of algorithmic trading activity, co-location and institutional execution costs.

5.3.1 Variables

5.3.*1.1 Algorithmic Trading Proxy*

According to Hasbrouck and Saar (2010), high frequency activity is ordinarily associated with rapid order submission and cancellation strategies. In light of a lack of explicit identification of algorithmic traders in available data, a proxy of algorithmic trading developed by Hendershott, Jones and Menkveld (2011) is adopted. Specifically, variable *AT Proxy* measures message traffic normalised by dollar turnover, where message traffic is a count of the frequency of orders submitted to the market. For stock *i* on day *t, AT Proxy* is calculated as:

$$AT\ Proxy_{it} = \frac{{}^{-Dollar\ Turnover_{it}}\!/_{100}}{Message\ Traffic_{it}} \tag{5.1}$$

Dollar Turnover is converted into US dollars, to ensure comparability across exchanges. *AT Proxy* provides the negative of the dollar volume, in US dollars, associated with each message. An increase in algorithmic and high frequency trading activity is identified by an increase in this measure. The computed measure is winsorised 5 per cent to remove extreme values that are likely erroneous.[77]

5.3.*1.2 Institutional Execution Costs*

To measure execution costs, the execution price relative to opening price of the stock for the trading day is computed. In contrast with order placement price, the use of open price as a pre-trade benchmark accounts for the price drift between the decision time (open) and the order placement time with a broker. This pre-trade benchmark price follows the approach documented in empirical studies (see, for example, Chan and Lakonishok, 1995; Keim and Madhavan, 1997; Jones and Lipson, 2001; Anand, Irvine, Puckett and Venkataraman, 2013a; 2013b). To compute a time-series of institutional execution costs, the value-weighted institutional execution cost is measured on a daily

[77] Consistent with Hendershott, Jones and Menkveld (2011).

basis for every stock in the sample dataset. The daily institutional execution cost for each stock is $Execution\ Cost_{it}$,

$$Execution\ Cost_{it} = \sum_{n=1}^{N} \omega_{itn} \left[D_{itn} \left(\frac{P_{itn} - P_{it,o}}{P_{it,o}} \right) - R_{mt} \right] \quad (5.2)$$

where P_{itn} is the value-weighted execution price of order *n*, for stock *i*, on day *t*; $P_{it,o}$ is the opening price of stock *i* on trading day *t*; D_{itn} is a variable that takes the value of 1 for buy orders, and -1 for sell orders; ω_{itn} is the value weight of order *n*. Consistent with Keim and Madhavan (1995), the subsequent analysis controls for market movements, R_{mt}, by adjusting the measured execution costs for market returns of market *m* on trading day *t.* Execution costs are aggregated by institutions for a stock on the same side (buy/sell) for any one trading day. Orders submitted by one institution across various brokers are stitched into one trade to ensure analysis is done on a holistic order.

5.3.2 Multivariate Tests

5.3.*2.1 Co-Location and Algorithmic trading*

Co-location refers to a facility provided by the exchange for market participants to co-locate their computer servers in the same room as the computer server, which operates the trading system of an exchange. The reduction in distance between an institution's server and an exchange's matching engine means that there is a reduction in distance travelled by an order from the computer server of a broker (previously located in the broker's office) to the trading system of the exchange and back. This time lapse is referred to as *exchange latency*. An upgrade in *exchange latency* inevitably provides a homogenous speed advantage to all trades submitted to the exchange via co-location services. This exchange-wide technological upgrade should be distinguished from *trader latency,* where the benefits of improved speed are achieved as traders subscribe to enhance their trading engines. The events examined in in this chapter, however, only relate to exchange latency..

To examine the relation between algorithmic trading and institutional execution costs, this chapter first presents evidence on the impact of co-location on algorithmic trading activity. As discussed in section 5.2.1, co-location is a technological upgrade implemented by exchanges to enhance trading speed, and should be utilised by those who require speed the most, namely algorithmic traders. Hypothesis $H_{5,1}$, which seeks to identify the impact of co-location on algorithmic trading, is tested by estimating Equation (5.3) below:

$$AT\ Proxy_{it} = \alpha_i + \gamma_t + \beta_i CoLo_{it} + \delta_i Log(Turnover)_{it} + \rho_i Volatility_{it} + ExDummy_j + \varepsilon_{it} \quad (5.3)$$

where $AT\ Proxy_{it}$ is the proxy for algorithmic trading intensity, as defined in section 5.2, for stock *i* on day *t*; $CoLo_{it}$ is a dummy variable which takes the value of one if day *t* is after the implementation of co-location for the attributed exchange in which stock *i* is trading, and takes the value of zero if day t is before the implementation of co-location for the attributed exchange; $Log(Turnover)_{it}$ is the natural logarithm of turnover for stock *i* on day *t*; $Volatility_{it}$ is the natural logarithm of high price to low price on trading day t for stock *i*; $ExDummy_j$ is a list of dummy variables for each exchange. All continuous variables in the above regression are standardised every day to have a mean of zero and a standard deviation of one within each exchange. The above panel regression is estimated with stock and day fixed effects, α_i and γ_t, respectively.

5.3.*2.2 Co-Location and Execution Costs*

As hypothesis $H_{5,1}$ identifies a relation between co-location and algorithmic trading intensity, hypothesis $H_{5,2}$ investigates the relation between co-location and institutional execution costs. Taken together, both hypotheses provide a relation between algorithmic trading and institutional execution costs. Specifically, hypothesis $H_{5,2}$ also controls for known stock effects, including volatility and stock turnover (see Chan and Lakonishok, 1995; Anand, Irvine, Puckett and Venkataraman, 2013a). The model adopted is a fixed effects panel model controlling for exchanges, stocks and days, according to the following specifications:

$$Cost_{it} = \alpha_i + \gamma_t + \beta_i CoLo_{it} + \delta_i Log(Turnover)_{it} + \rho_i Volatility_{it} + ExDummy_j + \varepsilon_{it} \quad (5.4)$$

where α_i is firm fixed effects, γ_t is day fixed effects, $Cost_{it}$ is the daily value-weighted institutional execution costs as defined in section 5.2.1, for stock i on day t; $Log(Turnover)_{it}$ is the natural logarithm of mean turnover 40 days prior to trading day i; $Volatility_{it}$ is the natural logarithm of high price to low price on trading day t for stock i; $ExDummy_j$ is a list of dummy variables for each exchange. All continuous variables are standardised each day, to have a mean of zero and a standard deviation of one, to ensure that the resulting coefficients are comparable across exchanges. Equation (5.4) is estimated via a fixed effects model controlling for exchanges, stocks and days.

5.4 Results

5.4.1 Descriptive Statistics

Table 5-2 reports summary statistics of execution costs for each of the 12 exchanges included in this study. The daily trading cost is estimated for each stock on each trading day over the one-year event window centred on co-location. The average institutional execution cost documented in Table 5-2 ranges from -7.5 basis points (Milan Stock Exchange) to 25.4 basis points (New York Stock Exchange). Negative average execution costs at the Milan Stock Exchange suggest that institutions are able to consistently obtain executions at prices better than their pre-trade benchmarks. Keim and Madhavan (1997) argue that liquidity-supplying institutions can achieve such a result. Compared to previous studies examining institutional execution costs, reported costs in Table 5-2 are similar; Anand, Irvine, Puckett and Venkataraman (2013a), for example, estimate institutional execution costs for NYSE and NASDAQ stocks to be approximately 24.5 basis points and Brogaard, Hendershott, Hunt and Ysusi (2014) estimate institutional execution costs in LSE stocks of approximately 15 basis points. Across the 12 exchanges, the average institutional execution cost is 10.3 basis points.

Table 5-2
Descriptive Statistics - Exchange

This table presents institutional trading costs: both execution and adverse selection costs for the period of 12 months before and after the month in which co-location is being implemented in each exchange. The average institutional trading cost is computed daily and segregated by the 12 exchanges. The daily trading cost is estimated for each stock on each trading day. The reported statistics in this table are the equally weighted average for all stock-days in each exchange.

	Institutional Execution Cost			Market Capitalization	
Exchange	**Mean**	**Std**	**Median**	**(USD$'mil)**	**Number**
Australia Stock Exchange	0.090	10.140	0.000	1,160	59,648
XETRA Germany	0.019	1.740	-0.063	475	24,269
National Stock Exchange India	0.178	2.252	0.093	897	33,059
Milan Stock Exchange	-0.075	2.759	-0.129	4,812	51,866
London Stock Exchange	0.123	3.867	0.038	358,708	191,676
Kuala Lumpur Stock Exchange	0.038	1.320	-0.007	286	13,343
New York Stock Exchange	0.254	16.632	0.078	9,787	1,705,309
Oslo Stock Exchange	0.019	2.380	-0.072	857	15,268
Euronext Paris	0.203	3.519	0.126	3,219	54,724
Lisbon Stock Exchange	0.227	4.549	0.044	3,404	3,822
Tokyo Stock Exchange	0.076	37.352	0.068	1,577	330,000
Toronto Stock Exchange	0.087	2.090	0.019	1,067	113,444
Average	0.103				

5.4.2 Co-Location and High Frequency Trading

Figure 5-1-1 shows the average electronic messages per minute across the 12 exchanges on a weekly basis. For each algorithmic trading measure employed, cross-sectional means are taken as the average across exchanges, for each trading day. Over the two-year period, electronic messages per minute, on average, nearly tripled from a level of 10 electronic messages submitted per minute to approximately 30 electronic messages per minute, for the markets examined. Figure 5-1-2 Panel B depicts *AT Proxy;* before co-location was implemented the average dollar volume executed per electronic

Figure 5-1
High Frequency Trading Measures

Figure 5-1 graphs the trend for High Frequency Trading measures over two years around the implementation date of co-location, for 12 exchanges worldwide. Figure 5-1-1 depicts the number of electronic messages per minute. Figure 5-1-2 depicts a measure developed by Hendershott, Jones and Menkveld (2011), defined as the negative trading volume divided by the number of messages.

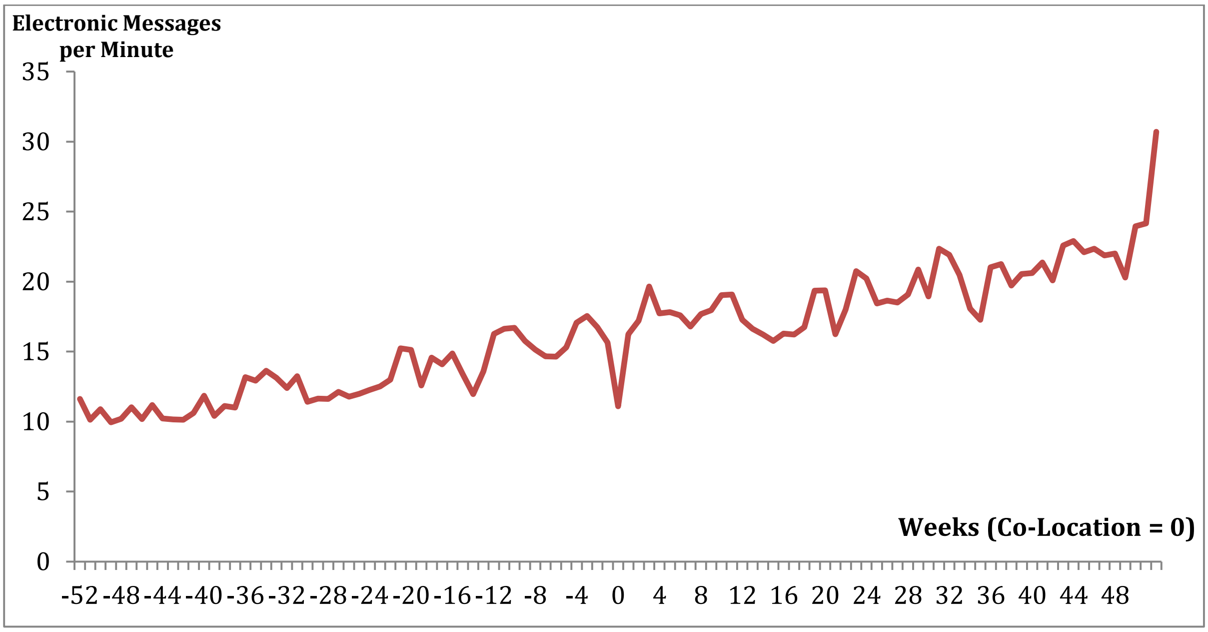

Figure 5-1-1

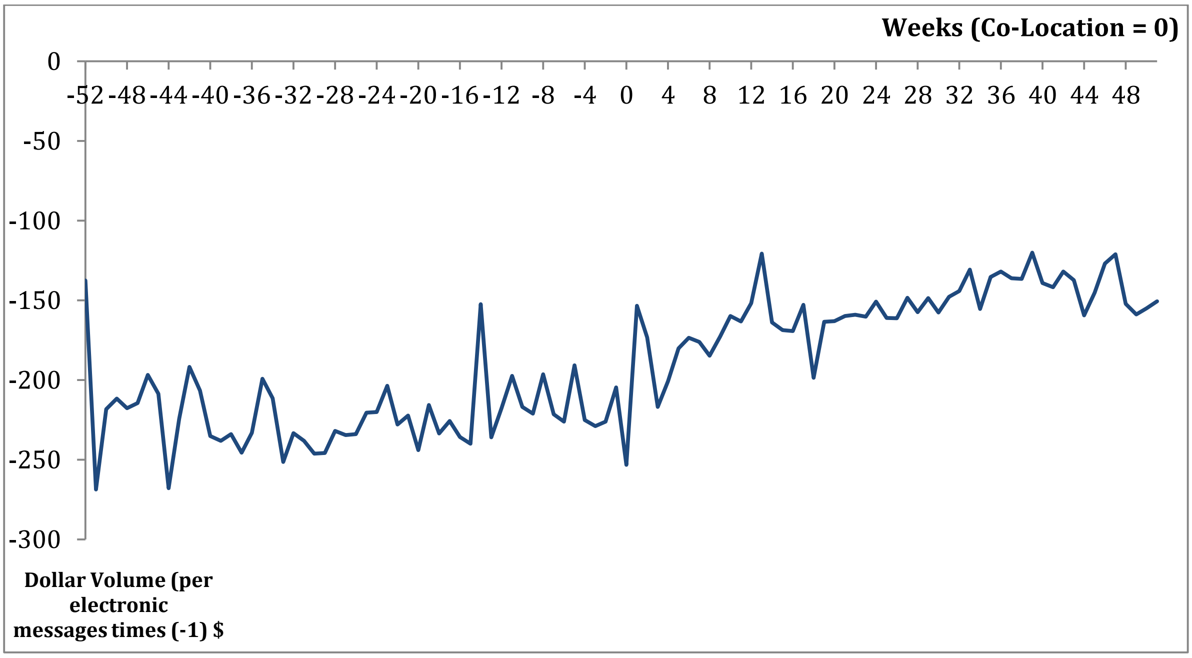

Figure 5-1-2

message submission is in the range of approximately $200-$250. Following co-location, the average dollar volume executed per electronic message submission decreased to a range of $150-$200. By the end of first year after co-location is implemented, this measure showed that across the 12 exchanges the average size of trade has decreased below $150 for every order submission.

Table 5-3 reports summary statistics of *AT Proxy* pre and post co-location for each of the 12 exchanges examined. Reported statistics in Table 5-3 are value-weighted interday, and averaged across stock-days during the event window. Results demonstrate that all exchanges exhibit an increase in *AT Proxy* after the implementation of co-location, with the exception of the Kuala Lumpur Stock Exchange. The differences between *AT Proxy* in the pre and post periods are also statistically significant for all exchanges. In the year prior to co-location, *AT Proxy* in the sample ranged from -1,111.7 (London Stock Exchange) to -5.5608 (Toronto Stock Exchange). Post-implementation of co-location, *AT Proxy* for the London Stock Exchange increased to -880.9 and Toronto Stock Exchange increased to -4.1922. While the London Stock Exchange experienced the largest difference in *AT Proxy* (230.9) around co-location, the Toronto Stock Exchange experienced the smallest difference in *AT Proxy* at 1.3686. The Kuala Lumpur Stock Exchange presents an anomaly around the implementation of co-location, as variable *AT Proxy* declined from -84.5701 to -98.0963, implying a reduction in algorithmic trading activity. This could be a result of stock selections for this exchange, as it is worth noting that in Table 5-2, Kuala Lumpur Stock Exchange exhibits the smallest average market capitalisation across all 12 exchanges (USD$286

Table 5-3
Exchange-Specific Algorithmic Trading Measures Centred on Co-Location

This table presents statistics of *AT Proxy* over the period 12 months before and 12 months after the implementation of co-location in each exchange. This table reports the average for the pre- and post- co-location periods, including the differences, experienced by each equity exchange in the analysis. The reported statistics in this table are the equally weighted average for all stock-days in each exchange, in pre- or post- periods respectively. The column **Difference** reports the mean difference between **Pre** and **Post**. T-statistics of mean differences are reported in parentheses.

	AT Proxy		
Exchange	**Pre**	**Post**	**Difference**
Australia Stock Exchange	-41.6975	-20.3311	21.3664 (69.72)***
XETRA Germany	-119.5000	-111.2911	8.2089 (4.45) ***
National Stock Exchange India	-14.6449	-7.4354	7.2095 (26.48) ***
Milan Stock Exchange	-28.1328	-16.4557	11.6772 (18.07) ***
London Stock Exchange	-1,111.7000	-880.9000	230.8999 (14.5) ***
Kuala Lumpur Stock Exchange	-84.5701	-98.0963	-13.5262 (-4.03) ***
New York Stock Exchange	-7.2093	-3.4136	3.7957 (227.18) ***
Oslo Stock Exchange	-33.7463	-14.8003	18.9460 (43.49) ***
Euronext Paris	-66.3856	-28.3228	38.0628 (34.19) ***
Lisbon Stock Exchange	-163.1000	-43.7731	119.3269 (26.15) ***
Tokyo Stock Exchange	-30.2770	-13.5288	16.7482 (136.29) ***
Toronto Stock Exchange	-5.5608	-4.1922	1.3686 (26.19) ***

*** indicates statistical significance at the 0.01 level
** indicates statistical significance at the 0.05 level
* indicates statistical significance at the 0.10 level

million), a fraction of the average of USD$358,708 million for the London Stock Exchange.

5.4.3 Univariate Results

Table 5-4 presents summary statistics of *AT Proxy,* institutional execution costs, and control variables, around co-location, across all stocks and stock market capitalisation quartiles. Control variables include volatility, measured as the natural logarithm of high price to low price for the attributed stock, and *Log(Turnover)*, measured as the natural logarithm of turnover for the attributed stock. Reported statistics in Table 5-4 are first value-weighted interday, and subsequently averaged across stock-days during the pre and post event windows. Results show that in aggregate across all stocks traded in the 12 exchanges, *AT Proxy*, institutional execution costs, and volatility increase in the period after co-location, while the variable *Log(Turnover)* decreases after co-location (Panel D of Table 5-4). The changes across the pre and post co-location period for all variables are statistically significant at the 5 per cent level of significance. Panels A, B and C of Table 5-4 segregate these descriptive statistics by groups of market capitalisation. MC Group 1 reports summary statistics for the group of largest market capitalisation, and MC Group 3 reports for the group of smallest market capitalisation. Results from each MC Group again confirm that *AT Proxy,* institutional execution costs and volatility increase after the implementation of co-location, and *Log(Turnover)* decreases after co-location. Differences between the pre- and post- co-location period for all variables in all MC Groups are also statistically significant.

Table 5-4
Descriptive Statistics – Market Capitalization Groups Centred on Co-Location

This table presents summary statistics of *AT Proxy*, institutional trading costs and control variables around co-location, and segregated by groups of stock market capitalisation, over the period 12 months before and 12 months after the implementation of co-location in each exchange. This table reports the average for the pre- and post- co-location periods, including the differences. The reported statistics in this table are the equally weighted average for all stock-days in each MC Group, in pre- or post- periods respectively. MC Group 1 consists of the largest market capitalisation stocks, and MC Group 3 consists of the smallest market capitalisation stocks. **Difference** reports the mean difference between **Pre** and **Post**. T-statistics of mean differences are reported in parentheses.

	AT Proxy	Institutional Execution Cost	Volatility	Log(Turnover)
Panel A: MC Group 1				
Pre	-162.6	0.0262	0.0318	19.3655
Post	-105.4	0.2295	0.0455	18.4698
Difference	57.2	0.2033	0.0138	-0.8956
	(17.73)***	(2.03)**	(114.82)***	(-104.23)***
Panel B: MC Group 2				
Pre	-64.6	0.0345	0.034	17.9195
Post	-41.9	0.291	0.0549	17.1269
Difference	22.8	0.2565	0.0209	-0.7927
	(25.9)***	(2.85)***	(189.68)***	(-107.46)***
Panel C: MC Group 3				
Pre	-208.1	0.1069	0.044	17.4417
Post	-58.9	0.2912	0.0682	15.8168
Difference	149.2	0.1843	0.0242	-1.6249
	(45.2)***	(24.65)***	(261.02)***	(-252.92)***
Panel D: All				
Pre	-157.7	0.0738	0.0392	18.1148
Post	-67.2	0.2784	0.0607	16.8978
Difference	90.5	0.2047	0.0215	-1.2169
	(51.1)***	(6.94)***	(335.01)***	(-264.99)***

*** indicates statistical significance at the 0.01 level
** indicates statistical significance at the 0.05 level
* indicates statistical significance at the 0.10 level

The results in table 5-4 suggest negative effects from technological upgrades at exchanges. Across all market capitalisation groups, stocks experience higher volatility and lower trading turnover as a result of co-location. These market quality effects increase the difficulty for institutions to execute trade, translating into higher institutional execution costs as a result. Univariate results in Table 5-4 provide preliminary support for hypothesis $H_{5,1}$, suggesting that technological upgrades at the exchange level increase algorithmic trading intensity in the market. Table 5-4 highlights the significant variation in *AT Proxy* and institutional trading costs.

5.4.4 Multivariate Results

Table 5-4 highlights the significant variation in AT and institutional trading costs. To capture this potential variation, this chapter groups the different stocks by market capitalisation, and estimates Equation (5.3) separately for each stock market quartile. Table 5-5 reports results for the test of hypothesis $H_{5,1}$, coefficient estimates of Equation 5-3, to examine the impact of co-location on algorithmic trading activity. After controlling for stock turnover and volatility, results show that co-location is associated with an increase in the level of algorithmic trading activity. Specifically, the increase is strongest in MC Group 1, the largest market capitalisation group, and lowest in MC Group 3, the smallest market capitalisation group.

Table 5-5
Co-Location and High Frequency Trading

This table shows the results from an ordinary least squares panel regression for a two-year window, centred on co-location of 12 equity exchanges included in this chapter:

$$AT\ Proxy_{it} = \alpha_i + \gamma_t + \beta_i CoLo_{it} + \delta_i Log(Turnover)_{it} + \rho_i Volatility_{it} + ExDummy_j + \varepsilon_{it}$$

where $AT\ Proxy_{it}$ is the proxy for AT, as defined in section 5.3.1, for stock *i* on day *t*; $CoLo_{it}$ is a dummy variable which takes the value of one if day t is after the implementation of co-location for the attributed exchange in which stock *i* is trading, and takes the value of zero if day t is before the implementation of co-location for the attributed exchange; $Log(Turnover)_{it}$ is the natural logarithm of turnover for stock *i* on day *t*; $Volatility_{it}$ is the natural logarithm of high price to low price on trading day t for stock *i*; $ExDummy_j$ is a list of dummy variables for each exchange. All continuous variables in the above regression are standardised every day to have a mean of zero and a standard deviation of one within each exchange. The above panel regression is estimated for the 12 markets in this chapter, with stock and day fixed effects, α_i and γ_t, respectively. MC Group 1 consists of the largest market capitalisation stocks, and MC Group 3 consists of the smallest market capitalisation stocks. T-statistics are in parentheses.

MC Quartile	Co-Location	Log (Turnover)	Volatility	Adjusted R-Square
1	0.3322 '(7.85)***	-0.6585 '(-143.46)***	0.0472 '(30.47)***	0.57746
2	0.2592 '(4.53)***	-0.6098 '(-143.46)***	0.0472 '(.)	0.57746
3	0.2398 '(6.96)***	-0.5873 '(-162.09)***	0.0758 '(49.45)***	0.46120
All	0.3322 '(10.35)***	-0.5801 '(-213.69)***	0.0517 '(53.09)***	0.54298

*** indicates statistical significance at the 0.01 level
** indicates statistical significance at the 0.05 level
* indicates statistical significance at the 0.10 level

Table 5-6 subsequently reports coefficient estimates of Equation (5.4), to examine the impact of co-location on institutional execution costs, a test of hypothesis $H_{5,2}$, with results presented for each stock market quartile and across all firms. In aggregate, the positive coefficient for *Co-Location Dummy* indicates that institutional investors pay approximately 23.78 basis points more to execute trades after the implementation of co-location. Moreover, MC Groups 1, 2 and 3 show higher execution costs by institutional investors after co-location of 32.48, 22.74 and 20.49 basis points respectively. The coefficients for *Volatility* across all MC Groups are positive and statistically significant, consistent with expectations as execution costs are also

Table 5-6
Co-Location and Institutional Trading Cost

This table shows the results from an ordinary least squares panel regression for a 2-year window, centred on co-location of 12 equity exchanges included in this chapter:

$$Cost_{it} = \alpha_i + \gamma_t + \beta_i CoLo_{it} + \delta_i Log(Turnover)_{it} + \rho_i Volatility_{it} + ExDummy_j + \varepsilon_{it}$$

where $Cost_{it}$ is the trade value-weighted institutional execution costs as defined in section 5.3.1, for stock i on day t; ; $CoLo_{it}$ is a dummy variable which takes the value of one if day t is after the implementation of co-location for the attributed exchange in which stock i is trading, and takes the value of zero if day t is before the implementation of co-location for the attributed exchange; $Log(Turnover)_{it}$ is the natural logarithm of mean turnover 40 days prior to trading day i; $Volatility_{it}$ for stock i is first computed as the natural logarithm of high price to low price on trading day t; $ExDummy_j$ is a list of dummy variables for each exchange; α_i controls for stock fixed effects and γ_t controls for day fixed effects. All continuous variables in the above regression are standardised every day to have a mean of zero and a standard deviation of one within each exchange. MC Group 1 consists of the largest market capitalisation stocks, and MC Group 3 consists of the smallest market capitalisation stocks. T-statistics are in parentheses.

	MC Group 1	**MC Group 2**	**MC Group 3**	**All**
Co-Location Dummy	0.3248	0.2274	0.2049	0.2378
	'(3.77)***	'(2.2)**	'(2.91)***	'(4.72)***
Log (Turnover)	-0.021	-0.0133	0.0034	0.0044
	'(-2.73)***	'(-1.81)*	'(0.58)	'(1.31)
Volatility	0.0866	0.1036	0.0826	0.0866
	'(8.24)***	'(11.32)***	'(11.79)***	'(17.43)***
Adjusted R-Square	0.326	0.343	0.202	0.252

*** indicates statistical significance at the 0.01 level
** indicates statistical significance at the 0.05 level
* indicates statistical significance at the 0.10 level

adversely affected by higher volatility. Results of MC Groups 1 and 2 provide *Log(Turnover)* with negative and significant coefficients. Consistent with existing research, Table 5-6 reports that firms with higher stock turnover are associated with lower execution costs.

Table 5-5 shows that the implementation of co-location across the 12 exchanges resulted in more AT activity, on average. The magnitude of increased AT activity was strongest for MC Group 1, followed by MC Group 2, and smallest for MC Group 3. At the same time, Table 5-6 shows that the size of execution costs increased for all stocks, but specifically, the magnitudes indicate the highest increase in MC Group 1, followed by MC Group 2, and the smallest increase in MC Group 3. Taken together, results reported in Tables 5-5 and 5-6 find support for hypothesis $H_{5,2}$ that the level of AT is positively related to the execution costs incurred by institutions. However, the causal relation between AT activity and institutional trading costs cannot be directly inferred.

5.5 Robustness Tests

5.5.1 Test of Causality

Results in section 5.4 thus far suggest that algorithmic trading intensity has an impact on institutional execution costs. Following the implementation of co-location, where increased algorithmic trading activity is documented, other factors could coincide and contribute to growth in algorithmic trading activity and the change observed in institutional trading costs. Further, the association between algorithmic trading activity and institutional trading costs may be caused by a change in institutional trading costs, which leads to a change in algorithmic trading activity, and not the posited causal direction as stipulated in hypotheses $H_{5,1}$ and $H_{5,2}$.

In this robustness test, the causal relation between algorithmic trading activity and institutional execution costs as posited is tested by a two-stage least-squares regression and adopts an exogenous instrument, which satisfies two conditions. Firstly, the instrument has to be uncorrelated to execution costs, and secondly it has to be correlated with AT activity. The implementation of co-location in the 12 exchanges in this chapter satisfies both the conditions. While market structures likely differ across exchanges within this chapter, the interpretation and implications of co-location are similar and comparable across exchanges.

In this test, a time series of variables for each exchange is first obtained by computing market value-weighted averages for all variables within each exchange. The resulting time-series is standardised for each exchange to perform the two-stage least-squares method. In the first stage, for each market capitalisation group, the AT proxy is regressed on the instrument of the co-location dummy with day fixed effects as follows:

$$\widetilde{AT}Proxy_{jmt} = CoLo_{it} + \gamma_t \tag{5.5}$$

where γ_t is day fixed effects and $\widetilde{AT}Proxy_{jmt}$ is the market value-weighted average of $ATProxy$ for MC Group *j* in market *m* on trading day *t*.

The estimates of the regression (5.5), the first stage regression, are used to compute $\widetilde{AT}Proxy$. In the second stage, institutional trading costs are regressed on $\widetilde{AT}Proxy$ and control variables, with exchange and day fixed effects. Specifically, the following regression is estimated:

$$Cost_{jmt} = \theta_m + \gamma_t + \beta_i \widetilde{AT}Proxy_{jmt} + \delta_i Log(Turnover)_{jmt} + \rho_i Volatility_{jmt} + \varepsilon_{jmt} \tag{5.6}$$

Table 5-7
2SLS Regression

This table provides results from the second stage of the two-stage least-squares (2SLS) regression of institutional trading costs on instrumented algorithmic trading (AT) activity for co-location for a two-year window, centred on co-location of 12 equity exchanges. The following ordinary least squares regression is performed:

$$Cost_{jmt} = \theta_m + \gamma_t + \beta_i \widetilde{AT}Proxy_{jmt} + \delta_i Log(Turnover)_{jmt} + \rho_i Volatility_{jmt} + \varepsilon_{jmt}$$

where $Cost_{jmt}$ is institutional execution costs as defined in section 5.3.1, for MC Group *j*, in exchange *m*, on trading day *t*. θ_m and γ_t are the exchange and day fixed effects respectively. $\widetilde{AT}Proxy_{jmt}$ is the predicted *AT Proxy* as estimated from the first stage. $Log(Turnover)_{it}$ is the natural logarithm of turnover for stock *i* on day *t;* $Volatility_{it}$ for stock *i* is the natural logarithm of high price to low price on trading day *t.* All continuous variables are first market-value weighted to provide an exchange-level time series. Subsequently, the resulting time series is standardised to have a mean of zero and a standard deviation of one within each exchange. T-statistics are in parentheses.

	Institutional Execution Cost
Predicted AT Proxy	0.0413
	'(2.1)**
Volatility	0.1385
	'(8.31)***
Log (Turnover)	0.0486
	'(3.36)***
Intercept	-0.3562
	'(-1.89)*
Adjusted R-Square	0.1334

*** indicates statistical significance at the 0.01 level
** indicates statistical significance at the 0.05 level
* indicates statistical significance at the 0.10 level

where $Cost_{jmt}$ is institutional trading costs for MC Group *j*, in exchange *m*, on trading day *t*. θ_m and γ_t are the exchange and day fixed effects respectively. $\widetilde{AT}Proxy_{jmt}$ is the predicted *AT Proxy* as estimated from the first stage. As per the first stage, control variables $Log(Turnover)_{jmt}$ and $Volatility_{jmt}$ are market value-weighted.

Table 5-7 presents results from regression (5.6). The variable of interest $\widetilde{AT}Proxy$ is positive and statistically significant for the model with dependent variable institutional execution cost. This implies a positive causal effect of algorithmic trading activity on institutional execution costs of approximately 4.13 basis points. The evidence here confirms hypothesis $H_{5,2}$ that the level of algorithmic trading is positively related to the execution costs incurred by institutions.

5.5.2 Trading Costs of Stitched Orders – Across Trading Days

In their endeavours to limit execution costs and adverse selection, institutions typically split their trades into smaller sizes and even across brokers. Especially with orders of large magnitudes, this active order management strategy could cause one parent order to be worked across multiple days. To reflect this, this dissertation implements an algorithm to stitch smaller orders with similar characteristics to form a multiday parent order consistent with Anand, Irvine, Puckett and Venkataraman (2013a; 2013b). A stitched parent order consists of all tickets submitted by the same institution across brokers for a given stock, and which are on the same side of a trade (buy or sell) over adjacent days, starting and ending on the same days.[78] For the purposes of stitched parent orders, this robustness test uses the opening price on the first day of a stitched parent order as the pre-trade benchmark price for all small subsequent orders within the parent order, and closing price on the last day of stitched parent orders as the post-trade benchmark price. Equation (5.3) is re-estimated for stitched orders and modified control variables measured over the period of execution. For

[78] Unlike Anand, Irvine, Puckett and Venkataraman (2013), this chapter does not limit stitched parent orders to a maximum of five days. A variable within AbelNoser Solutions provides, for each smaller order, how long the parent order is *alive* for. In addition, this variable is also matched to stitch parent orders. Following this algorithm, stitched parent orders provide an approximately 99 per cent match rate, when a further comparison is made to order variables with which small orders within parent orders should match, including the number of days a parent order is alive for and the open price of the first small order submitted.

Table 5-8

Robustness: Co-Location and Institutional Trading Costs (Across Days Package)

This table shows the results from an ordinary least squares panel regression for a 2-year window, centred on co-location of 12 exchange servers included in this chapter:

$$Cost_{it} \; = \alpha_i + \gamma_t + \beta_i CoLo_{it} + \; \delta_i Log(Turnover)_{it} + \rho_i Volatility_{it} + ExDummy_j + \; \varepsilon_{it}$$

where $Cost_{it}$ is the trade value-weighted institutional execution costs as defined in section 5.3.1, for stock i on day t; ; $CoLo_{it}$ is a dummy variable which takes the value of one if day t is after the implementation of co-location for the attributed exchange in which stock *i* is trading, and takes the value of zero if day *t* is before the implementation of co-location for the attributed exchange; $Log(Turnover)_{it}$ is the natural logarithm of mean turnover 40 days prior to trading day *i*; $Volatility_{it}$ for stock *i* is first computed as the natural logarithm of highest price to lowest price over the multiday parent order, then value-weighted across day t; $ExDummy_j$ is a list of dummy variables for each exchange; α_i controls for stock fixed effects and $\gamma_t$controls for day fixed effects. All continuous variables in the above regression are standardised every day to have a mean of zero and a standard deviation of one within each exchange. MC Group 1 consists of the largest market capitalisation stocks, and MC Group 3 consists of the smallest market capitalisation stocks. T-statistics are in parentheses.

	MC Group 1	**MC Group 2**	**MC Group 3**	**All**
Co-Location Dummy	0.433	0.434	-0.045	0.197
	'(5.72)***	'(3.29)***	'(-0.72)	'(4.19)***
Log (Turnover)	-0.020	-0.024	0.002	0.000
	'(-2.82)***	'(-3.26)***	'(0.28)	'(0.11)
Volatility	0.104	0.118	0.096	0.102
	'(10.76)***	'(13.52)***	'(13.45)***	'(20.72)***
Adjusted R-Square	0.271	0.274	0.165	0.204

*** indicates statistical significance at the 0.01 level
** indicates statistical significance at the 0.05 level
* indicates statistical significance at the 0.10 level

Example, in the case of volatility, if an order is executed over five days, volatility is measured as the natural logarithm of the high price to the low price over the five days.

Table 5-8 reports results of this estimation procedure. The positive coefficient for the variable *Co-Location Dummy* confirms that after the implementation of co-location, institutions incur higher execution costs. As in Table 5-6, these are statistically significant across MC Groups 1 and 2 and in the aggregate of all stocks.

Table 5-9
Robustness: 2 SLS Regression (Across Days Package)

This table provides results from the second stage of the two-stage least-squares (2SLS) regression of institutional trading costs on instrumented algorithmic trading (AT) activity for co-location for a two-year window, centred on co-location of 12 equity exchanges. The following ordinary least squares regression is performed:

$$Cost_{jmt} = \theta_m + \gamma_t + \beta_i AT'Proxy_{jmt} + \delta_i Log(Turnover)_{jmt} + \rho_i Volatility_{jmt} + \varepsilon_{jmt}$$

where $Cost_{jmt}$ is institutional execution costs as defined in section 5.3.1, for MC Group j, in exchange m, on trading day t. θ_m and γ_t are the exchange and day fixed effects respectively. $AT'Proxy_{jmt}$ is the predicted AT Proxy as estimated from the first stage. $Log(Turnover)_{it}$ is the natural logarithm of turnover for stock *i* on day *t;* $Volatility_{it}$ for stock *i* is first computed as the natural logarithm of highest price to lowest price over the multiday parent order, then value-weighted across day *t.* All continuous variables are first market-value weighted to provide an exchange-level time series. Subsequently, the resulting time series is standardised to have a mean of zero and a standard deviation of one within each exchange. T-statistics are in parentheses.

	Institutional Execution Cost
Predicted AT Proxy	0.0303
	'(1.78)*
Volatility	0.1406
	'(8.34)***
Log (Turnover)	0.0508
	'(3.97)***
Intercept	-0.4217
	'(-2.92)***
Adjusted R-Square	0.1566

*** indicates statistical significance at the 0.01 level
** indicates statistical significance at the 0.05 level
* indicates statistical significance at the 0.10 level

Adopting the two-stage least-squares method as discussed in section 5.3.2, to confirm the direction of causality and robustness for hypothesis $H_{5,2}$, table 5-9 presents results from the second-stage, for institutional trading costs of orders stitched within one trading day. The positive and statistically significant coefficients for *Predicted AT Proxy* imply an increase in institutional execution and adverse selection costs with the introduction of higher levels of AT.

5.6 Summary

In light of changing market structures over the last decade, stock exchanges worldwide provided market participants with co-location services. In effect, this reduces the latency for co-located AT participants, enabling more rapid interactions with financial markets. Results from the first hypothesis tested in this chapter demonstrate that AT activity increased following the implementation of co-location across 12 exchanges. Moreover, this dissertation documents differing incremental effects of AT intensity after co-location across varying stock market capitalisation groups. The strongest increase in AT activity is observed in the largest stock group, and the increase is incrementally less for smaller groups of stocks by market capitalisation.

Using institutional trades data sourced from the Abel Noser Solutions database, this chapter examines the impact of co-location on institutional trading costs. In aggregate for all stocks, results provide evidence of an increase in institutional trading costs. Results document the strongest increase for stocks in the largest market capitalisation group, and the smallest increase for stocks in the smallest group of stocks. Further, representing exogenous shocks to AT, this dissertation utilises co-location as an instrument and finds consistent results. Taken together, this chapter concludes that heightened AT activity increases institutional trading costs. Overall, the results provide empirical evidence in support of theoretical models (Jovanovic and Menkveld, 2011; Cartea and Panelva, 2012; Biais, Foucault and Moinas, 2014; Hoffman, 2014), which predict that AT imposes higher transaction costs on other fundamental investors.

Chapter 6: Conclusion

The issues examined within this dissertation relate to sources of information asymmetry in financial markets. Topics discussed attempt to provide a better understanding of the determinants and consequences of the two dimensions of information asymmetry in markets: *depth* and *breadth.* Earnings management by narcissistic CEOs, privileged information release by market intermediaries and technological enhancements related to direct market access instigate information asymmetry in financial markets. An understanding of the causes of information asymmetry in equity markets is relevant to regulators, practitioners and, in particular, corporations in their endeavours to minimise the cost of capital and efficiently allocate scarce resources.

The volume of existing literature presented in Chapter 2 on earnings management, analyst recommendations and computerised trading illustrates the enormous role academics have played in understanding these phenomena in financial markets. As financial reporting is the key information source used by managers to keep investors informed, it is imperative for market participants to understand the ability to manage earnings and, consequently, its determinants. Perhaps more pertinent is the identification of a relation between earnings management and individual manager characteristics (see Graham, Harvey and Rajgopal, 2013; Schrand and Zechman, 2012; Srinidhi, Gul and Tsui, 2011; Huang and Kisgen, 2013). Also Chapter 2 identifies that analyst recommendations play a key role in reducing information asymmetry in financial markets. However, the value in such reports presents the opportunity to provide certain investors with early access to this information (Green, 2006; Lepone, Leung and Li, 2013). In the race for early access to information, the growth of computerised trading in the last decade has enabled a new market participant, high frequency traders, to submit, cancel, amend and execute orders almost instantaneously. There is now growing empirical evidence of the effect of computerised trading on traditional market quality indicators but research on their impact for institutional investors has been mixed. In reviewing these three topics in the literature, three gaps are identified: (1) the impact of CEO narcissism on earnings management; (2) the factors in firm and analyst recommendations which influence investors' propensity to act on tips; (3) the effect of heightened levels of computerised trading on institutional execution costs. This dissertation presents three separate pieces of analysis, which address each of these issues.

The first set of results presented in Chapter 3 examines the impact of CEO narcissism on firms' earnings management. While financial reporting provides a mediating channel between managers and investors to communicate firm performance, the ability of managers to exercise judgment allows for the phenomenon of earnings management. Recently, there has been increasing evidence that strong managerial personality has an effect on corporate decisions (Graham, Harvey and Rajgopal, 2013; Schrand and Zechman, 2012). A leading personality trait that has been attracting widespread interest in leadership research is narcissism (Amernic and Craig, 2010; Chatterjee and Hambrick, 2011; Aktas, Bodt, Bollaert and Roll, 2016). Following methodology delineated in previous research, Chapter 3 measures and scales CEO narcissism from the speech data of CEO participation at analyst conferences. Results of Chapter 3 find a positive relation between CEO narcissism and earnings management adopted by a firm, constituting the first empirical evidence to establish this relation. The relation documented is robust to numerous robustness tests performed – various earnings management estimation models, a test of endogeneity and CEO verbosity, or the lack of it, at analyst conferences. The test of endogeneity (for direction of causality) confirms that CEO narcissism drives the magnitude of a firm's earnings management and results presented in Chapter 3 also demonstrate that CEOs' verbosity at analyst conferences does not have an effect on the measure of narcissism. While the practice of earnings management may not be illegal, this phenomenon is potentially a prescription for corporate fraud. Results from this dissertation suggest that information asymmetry caused by earnings management can be identified at an early stage by virtue of a CEO's personality.

The second set of results presented in Chapter 4 identifies the firm and analyst recommendation factors when recipients of information leakage react to tips provided from analyst recommendations. Prior literature has thus far established the phenomenon of tipping and provides substantial empirical evidence in support of this hypothesis (see Irvine, Lipson and Puckett, 2007; Juergens and Lindsey, 2009; Busse, Green and Jegadeesh, 2012; Lepone, Leung and Li, 2012). As tipping results in a subset of informed market participants adding to the *breadth* of information asymmetry in markets, this chapter provides the first comprehensive discussion of the characteristics where this activity is more prevalent. Examining broker analysts' trade-by-trade activity, results provide support consistent with evidence of tipping as documented in the literature. Results document that broker-analysts experience elevated sell-trading volume prior to the public announcement date of downgrades by the associated analysts. This supports the view that the less frequently issued downgrade recommendations are perceived to be more valuable by the market (Frankel, Kothari and Weber, 2006; Asquith, Mikhail and Au, 2006). Further, the magnitude of the abnormal sell trading volume is reliant upon the size of the stock in consideration and the market condition in which it is examined. Firstly, in aggregate of all stocks, the magnitude of abnormal sell volume prior to a recommendation downgrade is most pronounced in the Bull period, and least pronounced during the Bear period. Segregated by quartiles of firm size, during bull and neutral markets, mid-capitalisation firms exhibit stronger broker-analyst abnormal volumes prior to recommendation release; in bear markets, this result is strongest in small-capitalisation firms. This chapter, however, finds no statistically significant changes in buy volume prior to upgrade recommendations, consistent across market conditions and quartiles of firm sizes. On further examination of abnormal returns, Chapter 4 confirms the asymmetry in perception of value across upgrades and downgrades. Downgrade recommendations yield significantly higher returns for sells on the day a downgrade recommendation is released, compared to purchases on the day an upgrade recommendation is released. The significant difference in market reaction is consistent with analysts' reluctance to issue negative research (see Jegadeesh, Kim, Krische and Lee, 2004; Womack, 1996). Secondly, when examined across market conditions, the asymmetry holds true with stronger results in the bull market, followed by a neutral market and subsequently the bear market, indicating that investors have a stronger propensity to act when analyst research runs on contrarian views of the underlying market condition. This comes as no surprise, given the findings of Moshirian, Ng and Wu (2009), which document more issuance of positive research in bull markets and more negative research in bear markets. Chapter 4 finds that evidence of tipping is most prevalent in smaller-market capitalisation firms, as analyst research of smaller firms carries more information value. Specifically, investors do not provide broker-analysts with trading volume solely as a result of their providing a tip, but only if an impending tip has large information value as a result of this informational asymmetry event. Results on abnormal short-selling activity and institutional ownership further describe recipients' reaction to downgrade recommendations. The chapter documents that results on abnormal sell volume around downgrade recommendations are largely driven by recipients actively participating in short-selling activity, with no evidence of institutions exiting their long positions, upon receipt of an upcoming downgrade recommendation. Chapter 4 provides the first comprehensive discussion of the characteristics, which influence recipients' propensity to act on tipped information, using several datasets that allow an accurate observation of broker trading activity around the release of their analyst reports. Analysis in this chapter extends empirical research on tipping by identifying factors driving profitability around analyst recommendations and recipients' behaviour in response to the underlying circumstances.

The final set of results presented in Chapter 5 addresses an important element surrounding the debate on computerised traders: is the growth of computerised traders beneficial to institutional investors. The race for speed has seen high frequency trading moving from milliseconds to microseconds, with discussions around latency of nanoseconds becoming the new norm. This phenomenon is aggravated by exchanges offering co-location services – a latency reducing service that enables market participants to decrease the distance travelled by data fed into the exchange trading system. Despite the growing debate around the increased level of computerised trading, the literature on the effects to institutional investors produced mixed results. While Boehmer, Fong and Wu (2014) suggest that algorithmic trading is largely beneficial for market quality and institutional investors. Brogaard, Hendershott, Hunt and Ysusi (2014) failed to establish any relation between increased computerised trading activity on the London Stock Exchange and institutional execution costs. Utilising the exogenous event of co-location across 12 exchanges worldwide, results in Chapter 5 document the first empirical evidence on adverse effects to institutional trading costs as a result of intensified activity by computerised trading participants. First, Chapter 5 establishes that co-location increases the intensity of computerised trading. The reduction in exchange latency across 12 exchanges attracts more activity by algorithmic traders as they exploit this new market structure. Additionally, the advent of co-location across these exchanges is found to cause an increase in institutional execution costs. This is consistent with views expressed by the theoretical literature that the presence of high frequency intermediaries heightens volatility in financial markets, adversely impacting end investors (Cartea and Panelva, 2012). While market-wide quality measures appear to be improving (see for example, Hendershott, Jones and Menkveld, 2011; Brogaard, Hendershott and Riordan, 2014), this chapter provides evidence, from a transaction costs view, that institutional investors are adversely affected by heightened algorithmic trading activity.

This dissertation discusses the sources of information asymmetry in financial markets today. The research presented demonstrates that: (1) managerial personality is related to earnings management; (2) firm and recommendation factors drive profitability underlying analyst recommendations, which in turn causes investors to act on a recommendation tip; (3) heightened levels of computerised trading cause higher institutional execution costs. These results add to our understanding of issues surrounding information asymmetry that is present in financial markets today.

Appendix

Market Impact Costs of Off-Market Trades: Evidence from the Australian Securities Exchange

This appendix contains work completed during my candidature, which examines transaction costs incurred by market participants across two venues (dark and lit) in one market. Specifically, analysis in this appendix examines the relation between trade size and execution costs in dark versus lit.

A.1 Introduction

Substantial empirical research examines trades and price behaviour around transactions to measure the costs associated with executing a trade.[79] The significance of transaction costs in assessing trading profitability[80] has driven the emergence of

[79] See, for example, Kraus and Stoll (1972), Holthausen, Leftwich and Meyer (1987, 1990), Keim and Madhavan (1996).

[80] Examples include Keim (1999) and Chiyachantana, Jain, Jiang and Wood (2004).

studies attempting to quantify and analyse the various determinants of transaction costs (see Keim and Madhavan, 1998; Chiyachantana, Jain, Jiang and Wood, 2004). A recent study on fund performance documents that institutions with persistently low transaction costs consistently achieve superior fund performance (Anand, Irvine, Puckett and Venkataraman, 2013). Empirical literature has widely documented a positive relation between trade size and market impact, finding that larger orders incur worse prices (see Glosten and Harris, 1988; Easley, Kiefer and O'Hara, 1997; Bernhard and Hughson, 2002). Kyle (1985) and Easley and O'Hara (1987) support this finding, attributing the larger market impact costs of large trades to more severe adverse selection problems (information) and effects of inventory position (liquidity). If liquidity providers know, on average, that they are informationally disadvantaged relative to investors, particularly of larger orders, they protect themselves by providing less favourable prices.[81] This liquidity explanation suggests that risk-averse liquidity providers demand compensation on larger orders for holding more unbalanced inventory positions.[82] However, when opaque markets are examined, research documents a competing negative relation. Studies of the US corporate bond market (see Schultz, 2001; Bessembinder, Maxwell and Venkataraman, 2006; Edwards, Harris and Piwowar, 2007), the US municipal bond market (see Hong and Warga, 2004; Harris and Piwowar, 2006; Green, Hollifield and Schurhoff, 2007a; 2007b), and the London dealer market (Bernhardt, Dvoracek, Hughson, Werner, 2005) document this finding of an inverse relation. Similar models have been developed for upstairs equity markets; however, the relation between trade size and execution costs in upstairs

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[81] This holds irrespective of whether liquidity providers are competing market-makers (see Admati and Pfleiderer, 1988; Glosten and Milgrom, 1985) or limit order traders (see Glosten, 1994) or a combination (see Parlour and Seppi, 2003).

[82] See Biais (1993), Madhavan and Smidt (1993), and Viswanathan and Wang (2002).

markets has largely been unexplored and not examined, in view of dark pools which permit even small trades to execute at prices away from the best bid and ask. This appendix seeks to examine this relation.

With the proliferation of dark trading venues in financial markets worldwide, regulators have taken particular interest in the debate around market fragmentation. The changing nature of dark liquidity has raised questions about the fairness of dark venues for investors, with concerns about lack of market regulation for trades away from the Central Limit Order Book (CLOB).[83] The proliferation of dark trading, or upstairs markets, stems from diseconomies of scale when executing large trades on CLOB, attributed to adverse selection (information) and liquidity costs (Kyle, 1985; Easley and O'Hara, 1987). Grossman (1992) argues that the pre-trade opacity of dark trades enables upstairs markets to be a cheaper trade execution venue vis-à-vis lit markets; as such, trades are primarily liquidity-motivated. Upstairs brokers are a repository of large investors' unexpressed trading interest, since their trading preferences are not publicly disclosed, as one would see in a traditional limit order book with resting limit orders. Moreover, the relationships that exist in upstairs markets amongst traders may enable the screening out of information-motivated orders (Harris and Piwowar, 2007; Frino, Lepone and Kruk, 2011). This dissertation hypothesises that the lack of transparency and the reliance on the broker-dealer relationship in the upstairs equities markets provide a setting that quite closely mimics the operation of debt markets, and contribute to the literature by examining the

[83] See Report 331 released by ASIC in March 2013. Also see, 'Concept Release on Equity Market Structure', *Release No.* 34-61358, dated 14 January, 2010 by the US Securities and Exchange Commission,
MIFID II, amendments adopted by the European Parliament on 26 October, 2012 repealing Directive 2004/39/EC.

relation between trade size and market impact costs for trades executed off-exchange in the Australian Equities Market.

In their examination of the upstairs markets in Toronto Stock Exchange, Smith, Turnbull and White (2001) documented a negligible relation between trade size and adverse selection costs. The study examined trades executed in June 1997, in a period prior to the proliferation of High Frequency Trading and Dark Pools in financial markets. In the period examined, TSE order execution rules allow TSE member firms up to 15 minutes to fill a public limit order in the upstairs markets. The inability to fill this order upstairs within the given timeframe means the order must be immediately sent to the downstairs market for execution (Griffiths, Smith, Turnbull and White, 2000). This appendix differs from the study of Smith, Turnbull and White (2001), as dark trades executed in the sample are not subject to a restricted resting time in the upstairs markets before being routed downstairs (see Section A.2). This dissertation hypothesises that the *Price Information Hypothesis* conjured in the debt markets' literature can be directly tested in equity markets. Schultz (2001) suggests that, if fixed costs of trading are significant, trading costs could decrease with trade size. The first factor contributing to this is whether or not the institution is actively involved in the trade. Institutions that trade frequently possess superior knowledge of transaction prices by actively calling dealers for quotes often, relative to less active institutions. Given the structure of opaque markets, which lack a central source for quotes and trade information, inactive institutions are at an informational disadvantage, resulting in higher costs to trade, due to the lack of transparency. Institutions which are active in dark markets are better able to gauge transaction prices in this venue. Their superior knowledge of transaction prices enables them to trade at better execution costs, consistent with the *Price Information Hypothesis.*

A.2 Institutional Details

The Australian Securities Exchange (ASX) is an automated order-driven market that observes strict price and time priorities during its trading hours from 10:00 am to 4:00 pm, with random opening and closing auction. Prior to November 2011, the ASX was the only public exchange that operated in Australia. The ASX operates a transparent CLOB in which orders are matched based on price, then time priority. However, there are exceptions for trades executed away from the CLOB with reduced pre-trade transparency, which includes dark venues and block trades execution.

The ASX does not stipulate explicit trading mechanisms for executing block trades on the limit order book. Off-market trades, commonly known as upstairs trades in the literature, are trades that occur outside of the exchange's regular trading venue, involving market maker-like entities. Off-market block trades may be negotiated away from the CLOB at any price and are reported to the ASX via three mechanisms, including *Block Special Crossings (BSC)*[84] and *Portfolio Special Crossings (PSC)*[85], which

[84] Trades in excess of AUD$1million, a fixed threshold independent of stock characteristics. Immediate trade reporting is required, unless executed after the closing session, when trade reporting must be no later than 15 minutes prior to the opening of the next trading session. The exchange identifies *Put-Through Special Crossings* within *Block Special Crossings* as trades in securities that have been transferred from one fund to another on the instruction of a single fund manager.

[85] Trades must comprise at least 10 equity securities, with each security trading at turnover no less than AUD$200,000, with a total portfolio value no less than AUD$5million.

must be immediately reported to the ASX[86], and *Facilitated Specified Size Block Special Crossing (FSSBSC)*[87], which must be reported no later than 15 minutes prior to the opening of the next trading session if the trade occurred before 1:00pm, and if executed after 1:00pm, must be reported no later than 1:00pm on the next trading day. Dark trades smaller than the minimum block trade size also enjoy reduced pre-trade transparency in ASX via the ASX operated dark pool 'Centre Point'. ASX operates the Centre Point dark pool as a separate trading venue to its Lit CLOB 'Trade Match'. Centre Point offers anonymous matching services at the prevailing midpoint of the national best bid and offer and accounts for approximately 4.8 per cent of on-market trading (ASX, 2013). 'Centre Point Sweep' orders allow for an interaction between Dark and Lit ASX liquidity, whereby these orders are first routed to ASX Centre Point, then to ASX Trade Match if they are not fully filled.[88] ASX will have the ability to set a minimum order value for Centre Point orders and Centre Point Crossings. Centre Point Block orders may only be entered if the value of the order is equal to or greater than $50,000. Any Centre Point Block order entered with a value less than $50,000 will be rejected by the central system.

[86] ASX Operating Rule 3500.

[87] In addition to a size threshold, FSSBSC requires a broker to act as principal to the trade. On a monthly basis, the ASX updates the trade size thresholds for eligible stocks dependent on changes in the stocks' characteristics.

[88] Sweep orders are first routed to the Centre Point order book and then to the Trade Match order book and continue cycling through the two order books until all available matching opportunities are exhausted (ASX Trader Workstation Release Notes – version 1.12.2.7523,2012).

While Centre Point trades can be executed at or within the best bid or ask prices in the market[89], the formation of prices generally differs across dark pools. In report 331 by ASIC, a majority of dark pools operating in Australia match orders on some form of price-time priority. The remaining dark pools adopt time and size priority and client orders over principal orders.

A.3 Data

The data for this appendix are a proprietary dataset obtained from the ASX, which includes a flag for trades that were executed away from the CLOB, referred to in this appendix as off-market trades. The dataset also provides buyer- and seller-initiated flags for on-market trades. Initiators for off-market trades are inferred in accordance with the tick rule (Lee and Ready, 1991). Trades are classified as buyer-initiated if the transaction price is higher than the prevailing trade price, and trades are classified as seller-initiated if the transaction price is lower than the prevailing trade price.[90] The sample dataset spans the period 1 January 2012 to 30 June 2012. This appendix examines the 100 most actively traded stocks, ranked by daily average turnover[91], in the ASX200, after removing stocks which traded below $1.00 for 99 per cent of the time in the data period.

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[89] ASX Operating Rule 4.2.3. On 26 May 2013, ASIC amended Rule 4.2.3, effectively requiring dark trades to be done with meaningful price improvement of one price increment within the bid-offer spread or the midpoint.

[90] A robustness check is also performed on this rule by applying the tick rule based on trade price, using the trade price of five trades prior to the off-market trade.

[91] The average daily turnover was computed based on the period 1 October 2011 to 31 December 2011. This method is consistent with Chan and Lakonishok (1995), which computed daily trading activity based on a period that is exclusive of when the trades of interest are executed.

Table A-1 presents the descriptive statistics of the 100 firms in the sample data, for the analysis period of 1 January 2012 to 30 June 2012. Firms within the sample period are segregated equally into five groups based on trading activity computed in the period 1 October 2011 to 31December 2011. Quintile 1 includes the most actively traded stock and quintile 5 includes the least actively traded stocks. Panels A and B describe statistics of trades executed on- and off-market respectively. Table A-1 shows that approximately 10 per cent of the daily turnover for a stock is executed in off-market venues. The average trade size executed off-market is $40,411, approximately twice the average trade size executed on-market, $21,941. However, median trade sizes reveal the opposite scenario, where trade size executed off-market is approximately half the value traded on-market. This implies that a majority of trades executed off-market are significantly smaller than trades executed on the lit exchange. The differences in distribution of trade sizes in both markets are illustrated by the standard deviation, where off-market venues consist of trade sizes with larger standard deviation. Panels B1 and B2 report median and average trade sizes of off-market trades in the analysis. Trades executed on Centre Point are the smallest group of trades amongst all off-market executions. The average trade size executed on Centre Point, as illustrated by Panel B2 of Table A-1, is $14,619, while the median trade size is only $1,665. Portfolio Special Crossings have an average trade size of $513,479. The dataset identifies Put-Through Special Crossing (a type of Block Special Crossing) in addition to other Block Special Crossings. Statistics for Put-Through Special Crossings are quite similar to those of other Block Special Crossings, with average trade sizes of approximately $3.2 million and $3.8 million respectively.

Table A-1
Firm Descriptive Statistics

This table presents descriptive statistics of all 100 firms in the analysis period of 1 January 2012 to 30,June 2012, for all the 100 firms. Panel A1 presents statistics for off-market trades and Panel A2 presents statistics for on-market trades. Panel B1 and Panel B2 provide further statistics on the distribution of trade sizes across the different types of off-market trading mechanisms. Firms are categorised by ranking of trading activity in the pre-analysis period of 1 October 2011 to 31 December 2011. The sample comprises all trades for the 100 firms, stocks classified in quintile 1 are the most actively traded stocks and stocks classified in quintile 5 are the least actively traded.

	All	1	2	3	4	5
Panel A1: Off-Market						
Number of Stocks	100	20	20	20	20	20
Daily Number of Trades	71	136	79	59	49	33
Daily Dollar volume of trades($	2,868	9,406	2,202	1,352	744	634
Daily Number of shares traded	365.8	639.6	415.2	393.2	210.1	170.7
Average Volume per trade	5,099	4,712	5,300	6,415	4,294	5,103
Median Dollar Value per Trade ($)	3,216	6,575	2,744	2,009	1,591	1,395
Average Dollar Value per Trade	40,411	69,456	27,974	22,491	15,166	18,813
Std Deviation Trade Size ($ '000)	1,305.5	2,022.2	660.5	284.9	217.4	405.9
Panel A2: On-Market						
Number of Stocks	100	20	20	20	20	20
Daily Number of Trades	1,151	2,535	1,113	868	679	559
Daily Dollar volume of trades($	25,216	85,387	18,926	10,667	6,570	4,529
Daily Number of shares traded	2,935.0	5,750.9	3,370.7	2,660.0	1,688.9	1,204.3
Average Volume per trade	2,545	2,265	3,034	3,044	2,486	2,148
Median Dollar Value per Trade ($)	6,550	12,138	5,238	3,742	3,031	2,346
Average Dollar Value per Trade	21,941	33,693	17,001	12,285	9,673	8,077
Std Deviation Trade Size ($ '000)	90.1	113.3	79.4	64.6	43.9	51.0
Panel B1: Median Dollar Value per Trade ($)						
Centre Point	1,665	3,688	1,798	1,130	1,252	1,036
Portfolio Special Crossing	148,979	864,888	189,936	123,203	65,894	57,332
Put Through Special Crossing	2,285,117	2,362,629	2,392,853	2,445,118	1,849,709	2,302,957
Block Special Crossing	2,127,225	2,329,049	1,786,519	1,830,000	2,067,750	1,732,694
Panel B2: Average Dollar Value per Trade ($)						
Centre Point	14,619	18,925	17,064	14,306	7,656	11,244
Portfolio Special Crossing	513,479	1,601,199	306,112	212,639	102,309	100,182
Put Through Special Crossing	3,220,772	3,517,042	2,718,568	2,445,118	3,062,104	3,000,248
Block Special Crossing	3,803,560	4,229,269	3,094,179	2,712,127	3,441,932	2,822,891

Table A-2
Mean and Fractiles of Distribution of Trade Sizes

This table presents summary statistics for off- and on-market trades executed over the sample period of 1 January 2012 and 30 June 2012. Results are presented for all trades, and classified by the ranking of trading activity. Ranks of trading activity are computed in the pre-analysis period of 1 October 2011 to 31 December 2011. The sample comprises all trades for the 100 firms, stocks classified in quintile 1 are the most actively traded stocks and stocks classified in quintile 5 are the least actively traded.

	All Buys	1	2	3	4	5	All Sell	1	2	3	4	5
Panel B1: Off-Market ($'000)												
Mean	38.40	66.31	24.77	20.99	15.04	20.45	42.41	72.59	31.17	23.98	15.29	17.19
Median	3.24	6.62	2.77	2.01	1.61	1.40	3.19	6.53	2.71	2.01	1.57	1.39
25%	1.29	3.08	1.21	0.99	0.77	0.75	1.28	3.04	1.20	1.00	0.76	0.75
75%	8.67	16.03	6.53	4.64	3.66	3.37	8.55	15.93	6.41	4.77	3.56	3.30
95%	47.92	65.27	34.65	24.40	20.20	22.42	49.81	69.74	33.70	28.02	20.21	22.87
99%	686.0	1,550.0	426.36	320.58	195.75	181.15	737.5	1,610.16	489.74	351.78	179.31	179.25
Panel B2: On-Market ($'000)												
Mean	22.38	34.05	17.81	13.34	10.25	8.73	21.41	33.28	16.00	10.99	8.95	7.25
Median	6.12	11.50	4.97	3.51	2.91	2.19	7.09	12.91	5.61	4.07	3.25	2.56
25%	2.34	5.18	1.97	1.46	1.12	0.97	2.74	5.82	2.24	1.63	1.28	1.04
75%	16.82	29.89	12.52	9.15	7.29	5.77	19.19	33.16	14.24	10.17	8.26	6.87
95%	84.29	124.97	61.85	41.58	32.88	26.16	8.62	12.50	6.24	4.06	3.35	2.76
99%	251.2	330.50	210.85	146.72	113.75	90.08	217.5	292.23	166.85	106.25	92.43	70.19

Table A-2 describes the summary statistics of trade sizes executed off- and on-market respectively. The average trade size executed off-market, as shown in Panel B1, is approximately $38,400 and $42,410 for buys and sells respectively. Panel B2 shows that trade sizes executed on-market are on average approximately $22,380 for purchases and $21,410 for sales. For all groups of stocks, the average purchase trade size is larger than the average sale trade size. The distribution of trade sizes is highly skewed to the right, and at the extreme, the largest 1 per cent of trade sizes is in excess of $250,000. For all five groups of firms, trade sizes within the 95th percentile executed off-market are smaller than the trade sizes executed on-market within the 95th percentile. This implies that trades executed away from the CLOB are predominantly smaller in size than trades executed on-market. The right-skewed distribution of trade sizes is also evident for trades executed off-market. The top 1 percentile of trades executed off-market is in excess of \$1.6 million. The trade sizes executed across the 100 stocks decrease with a decreased ranking of stock trading activity; a stock that has less trading activity is found to have smaller trade sizes, on average.

A.4 Methodology

The analysis examines three measures ubiquitous in the price impact literature: total, temporary and permanent.[92] Post-trade transparency regulations for off-market trades pose a significant difficulty for identifying the accurate trade time. As such, this dissertation employs a pre-trade and post-trade benchmark consistent with Chan and Lakonishok (1995), using the open price of the security for the attributed trading day, while the close price of the security is used as the post-trade benchmark.

The three measures of price impact used are mathematically defined as follows:

$$Total\ PI_{i,t} = \frac{TradePrice_{i,t} - OpenPrice_{i,t}}{OpenPrice_{i,t}}\ x\ Initiator_{i,t}\ x\ 100\% \tag{A.1}$$

$$Temporary\ PI_{i,t} = \frac{ClosePrice_{i,t} - OpenPrice_{i,t}}{OpenPrice_{i,t}}\ x\ Initiator_{i,t}\ x\ 100\% \tag{A.2}$$

$$Permanent\ PI_{i,t} = \frac{ClosePrice_{i,t} - OpenPrice_{i,t}}{OpenPrice_{i,t}}\ x\ Initiator_{i,t}\ x\ 100\% \tag{A.3}$$

[92] Refer to section 2.5 for a more detailed discussion of execution costs.

To eliminate the effects of market movements, equation (A.1) is modified to:

$$Total\ PI_{i,t} - Market\ Return_t = \frac{TradePrice_{i,t} - OpenPrice_{i,t}}{OpenPrice_{i,t}}\ x\ Initiator_{i,t}\ x\ 100\% \qquad (A.4)$$

where $Market\ Return_t$ is the market return on the ASX200 Index for the day *t*. Equation (A.4) attempts to remove market-wide movements that may potentially drive total price impact measured in a particular direction. Market return is measured by the percentage difference between close to open of the attributed trading day.

The lack of an accurate timestamp for trades executed off-market poses a measurement error issue in computing the price impact for off-market trades, since proxies for benchmark prices are used. This is also an issue for temporary price impact, as closing price is taken as a post-trade benchmark proxy for when security prices have adjusted for the occurrence of the off-market trade. Additionally, Table A-2 demonstrates that the distribution of trade sizes is right-skewed, as trades at the 99th percentile are as large as $1.6 million and median trade size is $3,240 for off-market trades. Consistent with the measurement errors of cross-sectional tests faced and methodology adopted by Black, Jensen and Scholes (1972), the research design in this chapter adopts a similar grouping methodology to eliminate this issue.[93] Trades in the sample data are grouped in $1,000 buckets[94], with bucket groups ranging from $1,000 to $5,000,000. Trades between $0 and $1,000 traded values are classified in the $1,000 bucket group, while trades between $1,000.01 and $2,000 traded values are classified

[93] See also Blume (1970) and Blume and Friend (1973).

[94] A robustness test is performed for groups of up to $2,500 value per buckets, with bucket groups ranging from $2,500 to $5,000,000. Results are found to be robust.

in the $2,000 bucket group. This is repeated until the $5,000,000 bucket, which includes all trades with values in excess of $4,999,000.01. Averages of total, temporary and permanent price impacts are computed for each security bucket.

To examine the relation between market impact costs and trade sizes, a cross-sectional regression is estimated controlling for a variety of factors including the proportion of off-market trades executed (in turnover) and daily price volatility for security *i*.

Specifically, the following firm level fixed effects regression equation is estimated:

$$\left(TI_{i,t} - MarketReturn_t\right)_{i,b,Buy} = \propto + \beta_1 Buy + \beta_2 Off_{i,b,Buy} + \beta_3 Vol_{i,b,Buy} + \beta_4 Bucket + FE_i + \epsilon \qquad \text{(A.5)}$$

$$\left(TTI_{i,t}\right)_{i,b,Buy} = \propto + \beta_1 Buy + \beta_2 Off_{i,b,Buy} + \beta_3 Vol_{i,b,Buy} + \beta_4 Bucket + FE_i + \epsilon \qquad \text{(A.6)}$$

$$\left(PI_{i,t}\right)_{i,b,Buy} = \propto + \beta_1 Buy + \beta_2 Off_{i,b,Buy} + \beta_3 Vol_{i,b,Buy} + \beta_4 Bucket + FE_i + \epsilon \qquad \text{(A.7)}$$

where $TI_{i,t}$ is the Total Price Impact measured as $(P_{i,t} - O_{i,t})/\ O_{i,t}$ for buyer-initiated trades and $(O_{i,t} - P_{i,t})/\ O_{i,t}$ for seller-initiated trades, in percentages, for security *i* on trading day *t*; $TTI_{i,t}$ is the Temporary Price Impact measured as $(C_{i,t} - P_{i,t})/\ P_{i,t}$ for buyer-initiated trades and $(P_{i,t} - C_{i,t})/\ P_{i,t}$ for seller-initiated trades, in percentages, for security *i* on trading day *t*; $PI_{i,t}$ is the Permanent Price Impact measured as $(C_{i,t} - O_{i,t})/\ O_{i,t}$ for buyer-initiated trades and $(O_{i,t} - C_{i,t})/\ O_{i,t}$ for seller-initiated trades, in percentages, for security *i* on trading day *t*; $P_{i,t}$ is the trade price of security *i* on trading day *t*; $O_{i,t}$ is the open price of security *i* on trading day *t*; *Buy* is a dummy variable which takes the value of 1 if the dependent variable is computed from buyer-initiated trades for that security bucket and 0 if computed from seller-initiated trades; $Off_{i,b,Buy}$ is the proportion of turnover of buyer- or seller-initiated trades for security *i* within bucket *b* executed off-market relative to total buyer- or seller-initiated turnover for the trading day; $Vol_{i,b,Buy}$ is Average of logarithm (high/low) of a trading day for trades within security *i,* bucket *b* and initiator *buy. Bucket* represents trade sizes in multiples of $1,000, ranging from $1,000 to $5,000,000. The dependent variables of all three regressions are the security bucket mean of total (excess) from equation (A.1) after subtracting market return, temporary and permanent impact costs, by buyer- or seller-initiator.

A.5 Results

A.5.1 Univariate Results

Table A-3 presents results for total, temporary and permanent price impacts of off-market trades in the data. Results are presented based on average of price impacts of security within 50th, 50th-75th, 75th-95th and the 95th percentile of trade sizes and segregated into groups of security based on trading activity as described in Table A-1. The Column *All* presents results for all securities in the sample data for the attributed trade size percentile. Results for total price impact show that the relation with trades

Table A-3

Average Price Impact Costs Classified by Trading Activity Groups and Dollar Value Sizes

Table A-3 reports summary statistics on total, temporary and permanent price impact costs in percentages for off-market trades classified by trading activity quintiles and percentiles of dollar value sizes. Ranks of trading activity are computed in the pre-analysis period of 1 October 2011 to 31 December 2011. Results are also segregated into percentiles of 50, 50-75, 75-95 and above 95. The sample comprises all trades for the 100 firms, stocks classified in quintile 1 are the most actively traded stocks and stocks classified in quintile 5 are the least actively traded.

Groups	1	2	3	4	5	All
Panel A: Bottom 50 Per cent of Trade Size						
Total Price Impact (%)	0.12971***	0.18686***	0.27854***	0.27055***	0.38752***	0.20922***
Temporary Price Impact (%)	-0.16732***	-0.23394***	-0.40329***	-0.41081***	-0.51136***	-0.28416***
Permanent Price Impact (%)	-0.05909***	-0.0604***	-0.16141***	-0.17189***	-0.17610***	-0.10138***
Panel B: 50th - 75th Percentile of Trade Size						
Total Price Impact (%)	0.20689***	0.20642***	0.17797***	0.18461***	0.26885***	0.20554***
Temporary Price Impact (%)	-0.3837***	-0.50808***	-0.48831***	-0.53784***	-0.62023***	-0.47041***
Permanent Price Impact (%)	-0.21705***	-0.34914***	-0.36380***	-0.37598***	-0.38637***	-0.30615***
Panel C: 75th - 95th Percentile of Trade Size						
Total Price Impact (%)	0.10273***	0.14802***	0.09835**	0.10945***	0.22023***	0.12444***
Temporary Price Impact (%)	-0.30775***	-0.32682***	-0.26924***	-0.26085***	-0.22291***	-0.29153***
Permanent Price Impact (%)	-0.24137***	-0.20644***	-0.18562***	-0.16588***	-0.03074	-0.19452***
Panel D: Top 5 Per cent of Trade Size						
Total Price Impact (%)	0.09556*	-0.00760	0.12517	0.12459	0.29366*	0.10022***
Temporary Price Impact (%)	-0.21610***	-0.19292***	-0.19144***	-0.20449***	-0.20333*	-0.20445***
Permanent Price Impact (%)	-0.13757***	-0.2105***	-0.05616	-0.08923	0.08758	-0.11309***

executed off-market is negative.[95] Trades executed within the 50th percentile of trade sizes incur approximately 21 basis points of total price impact, but trades executed in excess of 95th percentile of trade size incur only about 10 basis points of price impact. Larger-sized trades executed off-market incur lower execution costs relative to smaller trade sizes executed off-market. This is in contrast to the established positive relation between trade size and execution costs, which is empirically documented in the literature (see Chan and Lakonishok, 1995; Kraus and Stoll, 1972). Results for temporary price impact show that trades experience price reversals. Trades in the 50th-75th percentile experience -0.47041 per cent of temporary price impact, the largest in magnitude. This implies that these trades incur the highest liquidity premium in the off-market setting. Permanent price impact exhibits a similar trend, with the largest magnitude also for trades within the 50th-75th percentile of trade sizes. Not surprisingly, for all percentiles of trade sizes, the off-market trades executed yield negative permanent price impact, on average, implying a lack of informational effects in trades executed off-market.

Total price impact for all five groups of firms shows that the top 5 per cent of trade sizes incur lower costs relative to the smallest 50 per cent of trades. The general trend across the five groups also shows that execution costs decrease as trade sizes increase in the off-market venues. Panels A, B and C illustrate this, consistent across all groups of stocks; total price impact decreases as trade sizes increase across the

[95] Total price impact is measured as the excess price impact costs after controlling for market return for the trading day. Results for total price impact without controlling for market return yield qualitatively similar inferences.

panels. With the exception of groups 1 and 5, total price impact for the top 5 per cent of trade sizes in Table A-3 lacks statistical significance. An extreme case in Table A-4 illustrates the variation in impact costs; the smallest trade sizes executed off-market in the least actively traded stock incur 38.752 basis points, the highest total price impact cost relative to the other groups of trade size and firm groups. Results for temporary price impact again suggest that all trades executed in the off-market venues experience price reversals. For the smaller dollar value trade sizes, the magnitude of this reversal increases, as there is decreased trading activity in the stock, that is, from groups one to five. This implies that the inherently lower liquidity in these stocks is reflected even in the off-market setting, with a higher liquidity premium demanded for trades in stocks of lower liquidity. The majority of the results documented for permanent price impact illustrate negative impact costs, reflecting the predominantly non-information-driven nature of trades executed off-market. The exception is the largest trades executed in the least actively traded groups of stock, whereby permanent price impact is documented insignificantly. Since upstairs markets are predominantly able to screen out information-motivated trades (Smith, Turnbull and White, 2001), this positive permanent price impact implies that liquidity in the least actively traded stocks on the CLOB is insufficient to execute these trades, leaving it informative yet executed off-market. As counterparties to these trades, upstairs brokers are better compensated, as reflected in the relatively larger total price impact costs incurred by this subset of trades. The largest permanent price impact in terms of magnitude is within the 50^{th} – 75^{th} percentile of dollar value trade sizes, implying the least informational content in these trades.

A.5.2 Multivariate Results

Table A-4 presents coefficient estimates of Equations (A.5) to (A.7) for total, temporary and permanent price impact. Panels A and B report results for on- and off-market trades respectively. The table presents four different regression models: first the baseline model inclusive of all control variables, and subsequent results are reported excluding one control variable each time. Evident from the R-Square reported in Table A-5, the baseline model reported for total, temporary and permanent price impact scores the best fit. Consistent with results from Tables A-2 and A-3, results in Panel A report a negative relation between trade size and market impact costs, even after controlling for market-wide movements, turnover proportion trades executed off-market and daily price volatility for the firm. Despite better execution costs obtained for larger trade sizes, the coefficient of bucket for the permanent price impact regression in models (1) and (3) suggests that for the off-market venue, smaller trade sizes contain less information relative to a larger trade size. Given that all groups of trade sizes exhibit price reversals (refer Table A-3), the positive coefficient for bucket in the temporary price impact regression for off-market shows that the price of larger trade sizes reverses at a smaller magnitude, incurring less liquidity premium. Similarly, since all groups of trade sizes exhibit negative permanent price impact (refer again to Table A-3), the positive coefficient for bucket in the permanent price impact regression for off-market implies that larger trade sizes provide less information in the off-market venue. Results for temporary and permanent price impact in the on- market venue are consistent with prior literature. The positive coefficients of *Bucket* for

Table A-4
Regression Results for Price Impact Costs

This table presents estimates for total impact costs as per the following equation:

$$\left(MI_{i,t} - MarketReturn_t\right)_{i,b,Buy} = \propto + \beta_1 Buy + \beta_2 Off_{i,b,Buy} + \beta_3 Vol_{i,b,Buy} + \beta_4 Bucket + FE_i + \epsilon$$

where the dependent variable is total (excess) price impact costs after controlling for market return for the trading day. Temporary and permanent price impact costs are estimated as per the equation:

$$\left(MI_{i,t}\right)_{i,b,Buy} = \propto + \beta_1 Buy + \beta_2 Off_{i,b,Buy} + \beta_3 Vol_{i,b,Buy} + \beta_4 Bucket + FE_i + \epsilon$$

where *Buy* is a dummy variable which takes the value of 1 if the dependent variable is computed from buyer-initiated trades for that security bucket and 0 if computed from seller-initiated trades; $Off_{i,b}$ is the proportion of turnover of buyer- or seller-initiated trades for security *i* within bucket *b* executed off-market relative to total buyer- or seller-initiated turnover for the trading day; $Vol_{i,b}$ is computed as the average of logarithm (high/low) for trades within security *i* bucket *b* and initiator *buy, Bucket* denotes the trade sizes in multiples of $1,000, ranging from $1,000 to $5,000,000; Panel A presents regression estimates for trades executed off-market and panel B presents regression estimates for trades executed on-market.

	Total				Temporary				Permanent			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Panel A: Off-Market												
Intercept	0.22453 *	0.28645 **	0.22129 *	0.28313 **	-0.30265 **	-0.68610 **	-0.30290 **	-0.68647 **	-0.04722	-0.40489 **	-0.05116	-0.40907 **
Buy	-0.01088 *	-0.01304 **	-0.01102 *	-0.01317 **	-0.00346	0.00991 *	-0.00347	0.00990 *	-0.01711 **	-0.00464	-0.01728 **	-0.00480
Off Proportion (%)	0.08838 **		0.08824 **		-0.54732 **		-0.54733 **		-0.51053 **		-0.51070 **	
Volatility	-0.12250 **	-0.12178 **			-0.00914	-0.01357			-0.14903 **	-0.15316 **		
Bucket	-2.57E-08 **	-1.02E-08	-2.55E-08 **	-1.00E-08	7.26E-08 **	-2.37E-08 **	7.26E-08 **	-2.37E-08 **	5.30E-08 **	-3.69E-08 **	5.32E-08 **	-3.66E-08 **
R-Square	0.01286	0.01208	0.01265	0.01187	0.07595	0.03435	0.07594	0.03434	0.02389	0.00754	0.02369	0.00734
Panel B: On-Market												
Intercept	0.25861 **	0.25806 **	0.25971 **	0.25917 **	0.03057	0.02987	0.03034	0.02965	0.28946 **	0.28821 **	0.29053 **	0.28929 **
Buy	-0.01459 **	-0.01472 **	-0.01461 **	-0.01474 **	-0.00657 **	-0.00674 **	-0.00657 **	-0.00673 **	-0.01168 **	-0.01198 **	-0.01170 **	-0.01200 **
Off Proportion (%)	-0.16583		-0.16614		-0.21362 **		-0.21356 **		-0.38117 **		-0.38148 **	
Volatility	0.03763	0.03777			*-0.00786*	-0.00767			0.03666	0.03699		
Bucket	6.25E-08 **	6.25E-08 **	6.26E-08 **	6.26E-08 **	1.33E-08 **	1.33E-08 **	1.33E-08 **	1.33E-08 **	7.80E-08 **	7.81E-08 **	7.80E-08 **	7.81E-08 **
R-Square	0.01140	0.01136	0.01138	0.01134	0.00644	0.00622	0.00644	0.00622	0.01287	0.01272	0.01286	0.01270

*** denotes statistical significance at the 0.01 level
** denotes statistical significance at the 0.05 level
* denotes statistical significance at the 0.10 level

temporary and permanent price impact in Panel A suggest that larger trade sizes on-market incur higher liquidity premia and have more informational value. In contrast to empirical findings (see, for example, Chan and Lakonishok, 1993; Keim and Madhavan, 1996), results from Table A-4 find larger price effects from seller-initiated trades, as is evident from the negative coefficient of *Buy.* The positive coefficient for *Volatility* in the total price impact on-market regression implies that trades executed during periods of higher price volatility incur more price impact costs. This is consistent with the findings of Domowitz, Glen and Madhavan (2001) as trades of more volatile firms are associated with greater dispersion in beliefs, causing reduced participation by risk-averse traders and, hence, resulting in greater price impact or price concessions. The argument is supported by the negative coefficient for *Volatility* in the temporary price impact regression, but overall the coefficients for this variable do not show statistical significance. Interestingly, results show the price impact of trades executed off-market are negatively related to *Volatility*, implying that when stocks experience high on-market volatility, the trades executed off-market incur smaller execution costs. Results for *Volatility* in the on- and off-market regressions show that in periods of high volatility trades executed off-market incur lower transaction costs.[96] Domowitz, Glen and Madhavan (2001) find that when stock volatility is high, investors experience higher trading costs. This may cause on-market investors to search for liquidity in off-market venues. If upstairs brokers are reliably able to identify only liquidity-motivated trades (Smith, Turnbull and White, 2001), they are able to offer better price improvements in periods of high volatility to induce investors to trade.

[96] Domowitz, Glen and Madhavan (2001) find that when stock volatility is high, investors experience higher trading costs. This may cause on-market investors to search for liquidity in off-market venues.

A.6 Summary

Empirical studies on equity markets have persistently documented a positive relation between market impact costs and trade size. Contrastingly, research in opaque markets, predominantly debt markets, finds the reverse, providing evidence that larger trades incur lower execution costs. While the importance of upstairs markets as having a cheaper execution cost for institutional investors has been well established in empirical literature, the relation between trade size and price impact of upstairs equities markets is left largely unexplored. This appendix examines trade size as a determinant to execution costs, in a semi-opaque environment. Consistent with opaque market studies, results presented in this appendix show that execution costs in the equity off-market venues decline as trade size increases, controlling for market-wide factors, including market returns, proportion of off-market trading activity and intraday price volatility. Results also support empirical findings that trades executed in upstairs markets are predominantly liquidity-motivated. The appendix documents price impact asymmetry, with larger price impact for seller-initiated trades than buyer-initiated trades, on average, in both on- and off-market venues. This is largely inconsistent with price impact asymmetry empirically documented in prior literature.

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