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An Empirical Investigation On The Post-Earnings Announcement Drift And Algorithmic Trading

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DECLARATION OF AUTHORSHIP

This is to certify that to the best of my knowledge the content of this thesis is my own work. This thesis has not been submitted for any degree or other purposes. I certify that the intellectual content of this thesis is the product of my own work and that all the assistance received in preparing this thesis and sources have been acknowledged.

[redacted]

Joe R. Zhang

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ABSTRACT

Motivated by the widespread adoption of AT in financial markets, this dissertation investigates whether algorithmic trading (AT) reduces the Post-Earnings Announcement Drift (PEAD), the financial anomaly where investors under-react to earnings information. Studies suggest AT is associated with sophisticated trading and lower transaction costs and these two factors contribute to lowering PEAD. I conjecture algorithmic traders have an incentive to profit from (and therefore reduce the presence of) PEAD; however the evidence presented in this thesis fails to show that AT attenuates this anomaly.

This thesis is composed of three essays. The first essay (Chapter 2) identifies the factors that explain PEAD and asks two questions: 1) does PEAD still exist; and 2) if so, has it been fully explained. I find PEAD remains a statistically and economically significant anomaly and that low investor sophistication, arbitrage risk and transaction costs are robust but nevertheless incomplete explanations. In other words, one, albeit incomplete, explanation for PEAD is that investors with low sophistication systematically under-react to earnings information and sophisticated traders cannot fully arbitrage the mispricing due to unhedgeable idiosyncratic risks and transaction costs.

The second essay (Chapter 3) considers whether AT's association with lower transaction costs and sophisticated trading implies AT attenuates PEAD. I further conjecture that if sophisticated algorithmic traders are better at extracting trading signals from earnings information AT should also improve price discovery around earnings announcements. After controlling for other explanatory factors, however, my findings show that AT does not contribute to the attenuation of PEAD, but that it is associated with improved price discovery.

The third and final essay (Chapter 4) provides an explanation for why the relation between AT and PEAD may be insignificant. I suggest order-splitting can result in the under-estimation of transaction costs (measured by effective spreads) and I argue one predominant function of AT is to execute large orders via sequences of small transactions. I therefore adjust for a potential bias in the measure of effective spreads by treating sequences of consecutive buy or sell orders as a single transaction. I then revisit a popular study which documents the market impact of AT but show that a structural increase in AT is associated with insignificant improvements in effective spreads.

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ABBREVIATIONS

The following abbreviations are used in this thesis.

3DR = 3-Day Earnings Response

AT = Algorithmic Trading

BHAR = Buy-and-Hold Abnormal Returns

ES = Earnings Surprise

HFT = High Frequency Trading

KM = Kim and Murphy (2013)

PEAD = Post-Earnings Announcement Drift

WPC = Weighted Price Contribution

CHAPTER 1: INTRODUCTION

1.1. Introduction

What has been the impact of electronic trading in financial markets? And specifically has the rise of algorithmic trading (AT) reduced the presence of financial anomalies? To investigate these questions this thesis presents three empirical essays on the post-earnings announcement drift (PEAD) and algorithmic trading (AT). PEAD (the phenomenon whereby investors under-react to earnings information) represents the earliest and best-documented financial anomaly. At the turn of the 21st century PEAD, remains statistically and economically significant; AT embodies the new form of electronic trading used by sophisticated investors dealing in financial exchanges. A large body of literature suggests the characteristics embedded in AT are contributing factors towards attenuating PEAD; however the evidence in this thesis fails to show that AT lowers PEAD. The first essay provides a motivation for this thesis by showing PEAD is associated with factors linked to AT and therefore is a suitable financial anomaly for examining the impact of algorithmic traders; the second essay shows that the relation between AT and PEAD is statistically insignificant; and the third essay presents one explanation for this insignificant relation. This thesis aims to contribute both to the literature on PEAD (where a full explanation of the anomaly remains elusive) and to the public policy debate about the role and utility of AT.

While the computerisation of U.S. financial markets began as early as the 1970s the wide implementation of AT is very much recent phenomenon. Recent studies mostly assess the impact of AT by quantifying changes in market quality benchmarks (such as effective spreads, realised spreads, adverse selection etc.) while few studies have examined the role of AT in attenuating financial anomalies. Financial anomalies however can be symptoms of imperfect markets – a sign that real-life frictions faced by traders are unaccounted for in a financial model's assumptions. For example, the common assumption of frictionless markets is unrealistic if investors face significant transaction costs; the assumption of investor rationality can be compromised by behavioural bias and low investor sophistication; and the assumption of perfect information is undone by informational opacity, agency cost and asymmetric information.

In contrast, the proliferation of algorithmic trading and computerised markets is championed as one of the great levellers of market inefficiencies. The literature gives the sense that AT has brought investors closer – more so than ever before – to frictionless markets; that sophisticated algorithms are a step closer to perfect rationality; and that additional provision of exchange order-book data-feed leads sophisticated algorithmic traders closer to perfect information. Repeatedly AT has been argued to improve liquidity; and the origination of AT by institutional investors, as well as the sophisticated embedded algorithms, reinforces the view that AT is associated with sophisticated investors. The expectation for algorithmic traders is therefore, generally speaking, that any mispricing in the financial market which may be profitably arbitraged away *will* be arbitraged away – and done so quickly.

Given the above viewpoint I investigate whether AT attenuates PEAD; the financial anomaly is well-documented to be robust and persistent and has been noted by Nobel Prize Laureate Eugene Fama as "the granddaddy of under-reaction events" (Fama, 1998, p.286). Factors that are argued to reduce PEAD effects are high investor sophistication and low transaction costs, and both are associated with high AT activity. This thesis therefore in essence seeks to understand the role of AT by considering how one of the most recent developments in electronic trading relates to one of the oldest and most robust financial anomalies.

In Chapter 2 I show that high investor sophistication and low transaction cost attenuate PEAD. The chapter considers the anomaly for the sample period July 1995 to June 2011 and addresses the extent to which PEAD effects remain unexplained. My results show PEAD is a stubborn anomaly in the sense that it remains statistically and economically significant half a century after its discovery. Although it cannot be fully explained away, robust explanatory factors are low investor sophistication, unhedgeable idiosyncratic risk and high transaction costs. In other words one, albeit incomplete, explanation is that investors with low sophistication systematically under-react to earnings surprise and sophisticated traders cannot fully arbitrage the mispricing due to arbitrage risk (represented by unhedgeable idiosyncratic risk) and high transaction cost. My analysis also addresses concerns associated with risk-mismeasurement, data-snooping and the over-finding of PEAD.

In Chapter 3 I consider whether AT attenuates PEAD, given the association between AT, high investor sophistication and low transaction cost. I conjecture algorithmic traders will attempt to profit from the PEAD anomaly, and therefore AT activity and PEAD are potentially inversely related. I also argue that if sophisticated algorithmic traders are extracting trading signals from earnings information then price discovery may improve around earnings announcements. My analysis begins by testing whether a significant decline in PEAD during the early 2000s is associated with variations in AT. I then control for alternative explanations and my results show that across different test methods the relation between AT and PEAD is weak and insignificant. This finding contests the view that AT lowers transaction costs. I then further my analysis by constructing a measure for price discovery as a function of PEAD and show AT improves price discovery.

In Chapter 4 I present one explanation for my findings. Interpreted conservatively, Chapter 3 suggests earnings announcements are an exception to the general case that AT reduces transaction costs. However, interpreted more broadly it also suggests AT does not lower transaction costs. I consider the empirical evidence between AT, liquidity and order-splitting (one of the major functions of AT) given one aspect of AT is that it encourages the camouflage of order size by splitting larger orders into sequences of small orders. I question whether increasing incidences of order-splitting cause mis-measurement of the transaction costs borne by traders. I then revisit a well-known study on the relation between AT and liquidity and find AT contributes substantially less to liquidity after the adjustment is made for order-splitting (I treat sequences of consecutive buy or sell orders as a single transaction). My findings also show that algorithmic traders behave opportunistically, taking advantage of their speed to mitigate price impact while imposing higher adverse selection costs on slow traders.

1.2. Contribution

This thesis contributes to the academic literature on PEAD and to the regulatory and public policy debates on the effects of algorithmic trading. Due to a relatively new sample period the first essay serves as an out-of-sample robustness test on previously factors posited to explain PEAD and on the robustness of the anomaly itself. The essay identifies the competing factors with the highest explanatory power for PEAD and therefore reconcile the literature (the first essay jointly considers 13 explanatory factors documented to explain PEAD). The research methods and results also serve as a reference source for future research into the anomaly. The findings add to the critique of asset pricing theory (such as limits of arbitrage arguments) that the assumption of perfectly rational representative investors ignores the frictions faced by traders. My results suggest revealed preferences of rational traders have an association with unhedgeable idiosyncratic risk and transaction costs.

The second essay contributes to the ongoing academic and public policy debate on AT's effects on market liquidity, price efficiency and price discovery. The empirical literature currently suggests that overall AT improves both liquidity and price discovery in equity markets (the exception is for stocks with small market capitalisation). This thesis contributes to the empirical literature by taking an alternative approach and examining the effects of AT via financial anomalies. The relation between AT and PEAD, to this author's knowledge, remains undocumented but the results can shed considerable light on the role and function of AT. My findings suggest AT does not lower transaction costs and therefore contests the view that algorithmic traders improve liquidity. My findings further suggest that a potential event where transaction costs are not reduced are earnings announcement periods. My findings however support the view that AT generally improves price discovery and the improvements are concentrated among firms releasing higher quality earnings information (this supports the idea that obtaining, processing and acting upon new information takes time and AT has the advantage of reducing search costs and rapidly synthesising large quantities of information). One issue to be addressed in the academic literature is whether algorithmic traders uses only limit order book information or do they also incorporate public news announcements into their trading decisions; my findings suggest that news that signals a change in a firm's fundamental value influences algorithmic traders, which is potentially associated with the practice of news agencies providing digitalised corporate announcement information for AT.

The third essay contributes to both academic and public policy debates on AT's effects on transaction costs and the distribution of AT externalities. My results suggest that while order-splitting is intended to reduce market impact and reduce transaction costs, a high incidence of order-splitting may bias transaction cost measures. The study therefore emphasises that differing research methods for measuring liquidity may significantly influence the outcome of empirical market microstructure studies. The study also shows AT shifts transaction costs from fast to slow traders and therefore contributes to the debate on whether fast and slow traders should be subject to different fees and exchange trading rules.

The remainder of this thesis is organised as follows. Chapter 2 is entitled *Entering the 21st Century: Have We Fully Explained the Post-Earnings Announcement Drift?* and sets out to identify the explanatory factors for PEAD. Chapter 3 is entitled *Does Algorithmic Trading Attenuate the Post-Earnings Announcement Drift?* and argues the explanatory factors for PEAD are potentially embedded in AT. It tests the relation between PEAD and AT and finds the relation to be statistically insignificant. Chapter 4 is entitled *Does Algorithmic Trading Improve Liquidity After Adjustment for Order-Splitting?* and serves as an explanation for the finding of an insignificant relation between AT and PEAD. It argues current measures of effective spreads may be over-estimating the positive contribution that AT has on liquidity. Chapter 5 discuss avenues for further research and concludes this thesis. [1]

[1] To alleviate ambiguity formulas and notations have chapter-specific meanings. For example, the notation β expressed in chapter 3 does not share the same interpretation in chapter 4, unless stated otherwise.

CHAPTER 2: ENTERING THE 21ST CENTURY: HAVE WE FULLY EXPLAINED THE POST-EARNINGS ANNOUNCEMENT DRIFT?

2.1. Introduction

Does the post-earnings announcement drift (PEAD) still exist? And if so has PEAD been explained fully? Declared “the granddaddy of under-reaction events” (Fama, 1998, p.286) PEAD is the tendency of post-event abnormal returns to drift in the same direction as earnings surprise (Foster, Olsen and Shevlin, 1984; Bernard and Thomas, 1989). The phenomenon implies new earnings and accounting information is not fully impounded into stock prices, and debate on the financial anomaly has continued for nearly five decades (Ball and Brown, 1968 and 2013). I consider whether PEAD persists at the turn of the century by following the method of Fama and French (2008) with tests controlling for a range of different firm characteristics.[2] This chapter addresses the extent anomalous PEAD effects remain unexplained and it is also an out-of-sample examination of PEAD given the sample test period generally has no temporal overlap with studies published before the early-2000s.

My results show that at the turn of the century PEAD remains statistically and economically significant and resembles size, book-to-market and momentum effects in that it can, beyond firm beta, explain cross-sectional stock returns (see Fama and French, 1992; Carhart, 1997). From 1995 to 2011 the average 60-day PEAD return is 3.67% and this figure is derived by simulating a strategy that takes a long position on firms with the highest earnings surprise and

[2] Fama and French (2008) note a robust test for financial anomalies require two elements: 1) demonstrating robustness in a cross-section of portfolios that capture different firm characteristics; and 2) employing robust test statistics such as applying the Fama and Macbeth (1973) test method.

a short position in firms with the lowest earnings surprise (i.e., buying good news and selling bad news). After jointly controlling for a range of explanatory factors average PEAD declines but remains significant at 1.90%. The results show a portion of the anomaly is associated with low investor sophistication, high arbitrage risk and high transaction costs. In other words one, albeit incomplete, explanation is that investors with low sophistication systematically under-react to earnings surprises and sophisticated traders cannot arbitrage fully the mispricing due to trading risks (such as the high idiosyncratic risk that must be borne by undiversified or partially diversified investors) and high transaction costs.

To conduct my analysis I augment standard event study methods to control for risk-mismeasurement bias. This is because the traditional event study model assumes a constant firm beta which produces model estimates *unconditional* to earnings surprise; earnings announcements however can shift firm risks. *Conditional* on earnings surprise, I find 60-day PEAD range from 3.56% (under the Carhart (1997) four-factor test) to 4.10% (under standard CAPM test). Following Fama and French (2008) I show significant PEAD effects are found across various portfolio classifications although the anomaly attenuate for firms characterised by high investor sophistication, low structural uncertainty, low arbitrage risk and low transaction costs.

To assess whether these factors can jointly explain away PEAD I then implement a multivariate analysis framework based on regression modelling with scaled interaction terms. This method controls for non-linearity between dependent and independent variables and is increasingly a common framework to test financial anomalies. My results show that after jointly controlling for other explanations PEAD is statistically significant, and therefore remains anomalous.

The rest of the chapter proceeds as follows. Section 2.2 discusses the background of this study and Section 2.3 presents the data. Section 2.4 introduces first stage methods and results while

Section 2.5 considers multivariate analysis and regression results. Section 2.6 concludes this chapter.

2.2. Background

First documented by Ball and Brown (1968)[3] and now considered "the best-documented and most resilient capital markets anomaly" (Livnat and Mendenhall, 2006, p.181) PEAD is associated with under-reaction to unexpected earnings news (Bernard and Thomas, 1989).[4] The discovery of this financial anomaly however has been subject to criticisms associated with over-publishing, data-snooping and measurement error bias.[5] For example Schwert (2002) notes there is bias to over-discovery of financial anomalies due to the research community's incentive to accrue citations and publications while Campbell, Lo and MacKinlay (1999) write "there is little theoretical motivation" for the anomalies literature "which opens up the possibility that the evidence against the CAPM is overstated because of data-snooping and sample selection biases" (p. 212). In contrast, one of the strongest counter-arguments is that persistent out-of-sample significance points to the alternative explanation of model inadequacy (see Banz, 1981; Basu, 1977, 1983; Jegadeesh and Titman, 1993; Debondt and Thaler, 1985). In the context of PEAD, criticisms of over-finding or mismeasurement error have been generally discredited (Bernard and Thomas, 1989) and the empirical literature finds robust evidence across time, across markets and across methods (see Bernard and Thomas, 1989; Liu, Strong and Xu, 2003; Gerard, 2012; Bernard and Seyhun, 1997; Livnat and Mendenhall, 2006; Foster, Olsen and Shevlin, 1984; Kothari, 2001; Sadka, 2006; Vega, 2006; Kim and Kim, 2003;

[3] As documented by Ball and Brown (2013), the origin of the discovery of PEAD dates back to Ball and Brown (1968), to the nascent beginnings of modern research in financial economics represented by the "Chicago" School. The introduction of rigorous economic methods to the study of finance and the creation of the first stock price dataset (the University of Chicago's Center for Research in Security Prices (CRSP) data tape was the first to be machine-readable), contributed significantly to new empirical and market-based research.
[4] The magnitude of under-reaction is positively correlated to earnings surprise while the persistence of under-reaction can last up to three quarters (Bernard and Thomas, 1989 and 1990).
[5] Initial reservations about the discovery of the anomaly include Watts (1978) and Reinganum (1981).

Abarbnell and Bernard, 1992; Mendenhall, 2004; Sadka, 2006; Battalio and Mendenhall, 2005; Chordia, Goyal, Sadka, Sadka and Shivakumar, 2009; Boehmer and Wu, 2013).

Three schools of thought have arisen to explain PEAD's existence and persistence: 1) behavioural; 2) structural uncertainty; and 3) limits of arbitrage constraints. Behavioural explanations argue PEAD is a function of investor naivety and anchoring, biased self-attribution and psychological distraction. Structural uncertainty explanations consider the uncertainties of trading against informed participants and argue PEAD compensates for informational uncertainty and opacity. Limits of arbitrage explanations argue the risks and costs borne by rational traders impedes the complete of arbitrage of market mispricing.

2.2.1. Behavioural Explanations

PEAD is documented to be associated with 1) naive investors anchoring on seasonal random walk expectations; 2) biased self-attribution associated with conservatism (over-confidence) of public news (private news); and 3) psychological distraction. Investor sophistication is commonly employed to proxy the level of investor behavioural bias.

Naive investor expectations cause both the existence and persistence of PEAD. The empirical evidence is consistent with investor expectations on firm earnings following a seasonal random walk which ignores earnings momentum effects and therefore manifests as under-reaction to earnings surprise (Bernard and Thomas, 1989 and 1990; Chan, Jegadeesh and Lakonishok, 1996). Analyst forecasts also exhibit a naive seasonal random walk, so that the reliance by investors on analyst forecasts accentuates under-reaction (Abarbenell and Bernard, 1992).[6] Another explanation is that investors anchor on past performance and therefore are subject to systematic conservatism. Barberis, Shleifer and Vishny (1998) consider evidence on the

[6] Naive investor expectation is also consistent with Kahneman and Tversky (1979) who argue that under conditions of uncertainty and imperfect information investor actions can be overwhelmingly a function of heuristics and behavioural traits and biases.

representativeness bias whereby people overweight recent events (Tversky and Kahneman, 1974) and show investors reveal themselves to believe earnings are mean reverting while Narayanamoorthy (2006) shows PEAD is consistent with accounting conservatism. Daniel, Hirshleifer and Subrahmanyam (1998) find investors exhibit biased self-attribution, being conservative with public news but over-confident about private news, leading to under-reaction (over-reaction) to public (private) information.

High investor sophistication is associated with low behavioural bias (Bartov, Krinsky, Radhakrishman, 2000) and a common proxy for high investor sophistication is a large proportion of institutional ownership of company stock. Individuals are generally less sophisticated compared to institutional investors and Kaniel, Liu, Saar and Titman (2012) show in the post-announcement period individual but not institutional traders are 'news-contrarian' and hence slow down the price adjustment process to earnings surprise, generating persistence in PEAD.[7] Bartov et al. (2000) show that firms with large institutional ownership are subject to smaller PEAD attenuation while Ke and Ramalingegowda (2005) show from short-term stock holdings data that institutional investors overall profit from trading away mispricing generated from PEAD. Alternative proxies for investor sophistication demonstrate similar findings: Mikhail, Walther and Willis (2003) consider stocks covered by analysts with superior experience and show reduced PEAD effects; Battalio and Mendenhall (2005) proxy high investor sophistication by large trade size and show only small-size trades exhibit under-reaction. Campbell, Ramadorai and Schwartz (2009) demonstrate institutional trading anticipates both earnings surprise and PEAD because institutional investors trade in the same direction both before and after the corresponding surprise. In other words, institutional investors anticipate both earnings news surprise and the subsequent PEAD.

[7] I note this is in contrast to Hirshleifer, Myers, Myers and Teoh (2002) who find investors are net buyers after both good and bad news.

An alternative behavioural explanation is that PEAD also reflects the constraints of traders in processing large quantities of information. Hirshleifer, Lim and Teoh (2009) consider research in the field of psychology and show PEAD effects are consistent with investor attention being a scarce cognitive resource (Kahneman, 1973). The authors search for days with a high number of earnings announcements and find under-reaction is associated with periods when investors are more likely to be distracted due to a high inflow of new information (see Hirshleifer and Teoh, 2005; Peng and Xiong, 2006; DellaVigna and Pollett, 2009).

2.2.2. Structural Uncertainty Explanations

Structural uncertainty explanations argue variations in informational uncertainty and opacity are a source of investment risk (see Brav and Heaton, 2002; Vega, 2006). Earnings announcements can be periods of structural uncertainty because: 1) announcements can be uncertain or opaque; 2) the announcement period is subject to unexpected variations in the arrival of private information; and 3) announcement periods are also subject to different levels of probability of informed trading.

Yan and Zhao (2011) show high information opacity is associated with high book-to-market ratio (BM) and high PEAD. “Value” stocks proxied by a high BM receive on average less media attention and are followed by fewer analysts relative to low book-to-market “glamour” stocks. Brown and Han (2000) proxy high information opacity with low institutional holdings and low analyst coverage and show the factors are positively correlated to PEAD. Information uncertainty proxied by idiosyncratic volatility is also positively correlated to PEAD (Gerard, 2012). Finally Garfinkel and Sokobin (2006) argue disagreement in investor opinion is an explanatory factor and Kim and Kim (2003) argue analyst disagreements can be proxied by the dispersion of analyst forecasts.[8]

The unexpected arrival of private information is also a source of structural uncertainty. Sadka (2006) shows the variable component of liquidity is correlated to PEAD[9] and argues PEAD returns are therefore compensation for unexpected variation in the ratio of informed trading to noise. Vega (2006) extends the literature by clarifying that there is a distinction between private information and informed trading and that PEAD varies according to the arrival rate of informed trading rather than from the arrival of private information. For example, traders exceptionally skilled at extracting information from public news sources are nevertheless highly informed. Accordingly Vega (2006) shows that a high probability of informed trading (PIN) is associated with low PEAD.

2.2.3. Limits of Arbitrage Explanations

Trading strategies that seek to profit from PEAD effects will involve holding large positions in individual stocks as well as generating high portfolio turnover. Relevant limits of arbitrage constraints are transaction costs and arbitrage risk.

Jensen (1978) argue financial anomalies can rationally persist because transaction costs make the arbitrage of mispricing unprofitable. Ng, Rusticus and Verdi (2008) show in a standard market microstructure context the magnitude of under-reaction is positively correlated to trading commissions and quoted spreads while Bhushan (1994) finds investor heterogeneity in the cost of processing information can explain cross-sectional variation in PEAD. Chordia et

[8] I note it has been argued that analyst dispersion is a market-wide risk factor (Kim and Kim, 2003). Diether, Malloy and Scherbina (2002) however find evidence inconsistent with this assertion.
[9] The variable component of liquidity can be interpreted as being associated with shifts in private information (see, Kyle, 1985).

al. (2009) demonstrate a significant amount of paper profit from a long-short investment strategy of PEAD is removed after controlling for liquidity and transaction costs.

Unhedged idiosyncratic risk contributes to the limits to arbitrage and Mendenhall (2004) identifies this risk as “arbitrage risk”. The author argues unbiased rational arbitrageurs are often specialised traders holding relatively large positions in few stocks and hence do not derive the full benefit of diversification. Following Wurgler and Zhuravskaya (2002) and Shleifer and Vishny (1997), Mendenhall (2004) defines arbitrage risk as the idiosyncratic portion of stock volatility and finds it monotonically increases with PEAD. The author argues arbitrage risk is correlated to factors such as analyst coverage, turnover and firm size and the inclusion of arbitrage risk as a control variable removes the significance of other positively correlated control variables. In other words, other explanations may potentially be indirect proxies of arbitrage risk. I note limits of arbitrage constraints also encompass agency frictions which cause money managers to under-react to price-sensitive information (Shleifer and Vishny, 1997) and short-selling constraints (Berkman, Dimitrov, Jain, Koch and Tice, 2009).

2.3. Data

I obtain the following data: 1) daily stock returns; 2) quarterly disclosures of corporate accounting and stock ownership; 3) quarterly earnings announcements; 4) historical analyst forecasts; 5) daily returns of the risk-free rate; and 6) daily returns of the Carhart (1997) four factors. I follow Hirshleifer et al. (2009) and obtain the CRSP-Compustat merged database and the I/B/E/S database.[10] CRSP provides daily stock price data, Compustat data provides quarterly accounting filings, and I/B/E/S data contains quarterly analyst forecast and earnings

[10] Obtained from the Wharton Research Data Service.

announcement information.[11] CDA Spectrum provides the Form 13F filing for institutional ownership data.

My sample period covers the period 1st July 1995 to 30th June 2011. I select only data after 1994 as it is shown to be robust for event studies (Hirshleifer et al., 2009; DellaVigna and Pollett, 2009). One benefit of selecting this sample period is that there is no temporal overlap with Bernard and Thomas (1989 and 1990) and many core studies published especially prior to the early-2000s. My tests therefore can serve as an out-of-sample examination of these studies (Schwert, 2003s). I select from the CRSP-Compustat merged data all firms with primary stock listing on the New York (NYSE) and American (AMEX) Stock Exchanges.[12] Closed-end funds, Real Estate Investment Trusts, American Depository Receipts and foreign stocks are excluded.[13] The sample data is then matched to the I/B/E/S dataset via a CRSP-Compustat-I/B/E/S matching procedure provided by the Wharton Research Data Service (WRDS). Berkman and Truong (2009) show a substantial number of earnings announcements are made after trading hours and therefore the immediate price response may only be impounded to stock price in the next trading day. To control for this potential forward-looking bias all announcements made after 16:00 hours are assumed to be made the following trading day.[14] I remove the following observations: 1) firm-quarter observations with less than $5 million in market capitalisation (Mendenhall, 2004); 2) firms with stock prices less than $1 before stock-split adjustment (Hirshleifer et al., 2009); and 3) firm-quarter observations where the actual or median earnings per share forecast is higher than the end-of-quarter stock price (Hirshleifer et al., 2009).

[11] I/B/E/S contains data collected every third Thursday of the month from analysts giving forecasts to the next quarter's corporate earnings.
[12] It is common in PEAD studies to consider only NYSE and AMEX stocks (see Bernard and Thomas, 1989 and 1990; Bhushan, 1994; Bartov, Krinksy and Radhakrishhnan, 2000; Sadka, 2006; Ng, Rusticus and Verdi, 2008).
[13] I select for CRSP stock codes of 10 and 11.
[14] If there are discrepancies in announcement time between Compustat and I/B/E/S I select the earlier of the two dates (DellaVigna and Pollett, 2009).

As PEAD is shown to be associated with a large number of explanations I construct thirteen factors as control variables (the construction of each variable is explained in detail in Section A.2 of the Appendix). Briefly, for firm i and quarter q (where $q \in \{1,2,\dots,64\}$) the factors are:

1) $Insti_{i,q}$ the percentage of shares owned by institutional investors, proxying investor sophistication (Campbell et al., 2009);

2) $Distract\_U_{i,q}$ the number of earnings announcements per trading day, proxying investor distraction (Hirshleifer et al., 2009);

3) $Analyst_{i,q}$ the number of analyst forecasts, proxying information diffusion (Brown and Han, 2000);

4) $Volatility_{i,q}$ the volatility of abnormal returns, proxying uncertainty (Gerard, 2012);

5) $ArbRisk_{i,q}$ the residual variance from the stock's one-factor market model regression,[15] proxying unhedgeable risk (Mendenhall, 2004);

6) $ExpRisk_{i,q}$ the explained variance from the stock's market model regression, proxying hedgeable risk (Mendenhall, 2004);[16]

7) $Illiq_{i,q}$ the Amihud (2002) illiquidity factor, proxying stock illiquidity (Sadka, 2006);

8) $Spread_{i,q}$ the average end-of-day bid-ask spread, proxying direct transaction cost (Ng et al., 2008);

9) $Price_{i,q}$ the end-of-quarter stock price, proxying trading commissions (Blume and Goldstein, 1992);

[15] The market model is the returns of the S&P 500 index (inclusive of dividends) adjusted for the risk-free rate.
[16] Inclusion of this variable follows Mendenhall (2004), Livnat and Mendenhall (2006) and Chordia et al. (2009). An insignificant relationship with hedgeable risk affirms PEAD is not compensation for risks that can be hedged away by a market portfolio.

10) $Turn_{i,q}$ the average daily dollar volume of shares traded, proxying indirect trading costs and order processing costs (Bhushan, 1994);

11) $Mcap_{i,q}$ the market capitalisation, proxying size (Foster, et al., 1984; Bernard and Thomas, 1989);

12) $BM_{i,q}$ the book-to-market ratio, proxying informational opacity (Yan and Zhao, 2011); and

13) $Mom_{i,q}$ the cumulative abnormal return for the 40 days prior to earnings announcement, proxying momentum effects (Vega, 2006).[17]

2.3.1. Summary Statistics and Correlation

The summary statistics of the explanatory factors are presented in in Table 2.1 and the computed values align with previous studies. For example, the mean and median of market capitalisation is \$8.17 billion and \$1.829 billion, respectively (the 25th percentile is \$606 million and the 75th percentile is \$5.64 billion). The mean of daily turnover is \$14.46 million and the 25th and 75th percentiles are \$367,000 and \$15.74 million respectively. The 25th and 75th percentiles of stock price are \$16.75 and \$43.09 respectively; and number of analysts is 2 and 9 respectively. These values align with Mendenhall (2004, Table 2, p.885) and Jegadeesh and Livnat (2006, Table 1, p.27). My computed values for arbitrage risk and hedgeable risk are also nearly identical to that of Mendenhall (2004) and Wurgler and Zhuravskaya (2002).[18] The mean of arbitrage risk is 0.0121 and the 25th and 75th percentiles at 0.0041 and 0.0142 respectively; and the mean of hedgeable risk is 0.0025 and the 25th and 75th percentiles at

[17] In Section A.1 of the Appendix I also consider 1) Volume-Synchronised Probability of Informed Trading (VPIN) as a proxy for the level of informed trading (Vega, 2006). The analysis of this factor causes a loss of observations and therefore I consider it separately from the main body of this chapter.

[18] Mendenhall (2004, p.885) shows an arbitrage risk mean of 0.014 and the 25th and 75th percentiles at 0.004 and 0.017 respectively; and shows a hedgeable risk mean of 0.002 and the 25th and 75th percentiles at <0.001 and 0.003 respectively.

0.0004 and 0.0027, respectively. My values are also consistent with Hirshleifer et al. (2009, Table I, p.2300) where the number of earnings announcements per day ranges from 22 to 150 per trading day at the 25th and 75th percentile, respectively. Please note that the distribution of the bid-ask spread is relatively wide and this is attributable to the significant decline in transaction costs over the sample period (see Bessimbinder, 2003b; Chordia et al., 2009).

The factor correlation coefficients also align with the literature (see Table 2.2). The three factors that have noticeably high correlations are analyst following, illiquidity and firm size. For example, analyst following has a ρ = -0.48, 0.48 and 0.46, respectively with $Illi_{i,q}$, $Turn_{i,q}$, and $Mcap_{i,q}$. In other words, firms with a high analyst following tend to be associated with improved liquidity, higher turnover and larger market capitalisation. This is consistent with the correlation matrix in Vega (2006, Table 1, p.110). My values are also consistent with Amihud (2002) in that large firm size has a relatively strong correlation to lower spreads (ρ = -0.35), higher turnover (ρ = 0.76), and higher price (ρ = 0.47). The log of illiquidity is also correlated to the log of bid-ask spread (ρ = 0.49), price (ρ = -0.44) and the log of market capitalisation (ρ = -0.77). Not surprisingly, one of the strongest correlations is between firm turnover and the log of illiquidity with a correlation coefficient of ρ = -0.84. This supports Bhushan (1994) and Bhardwaj and Brooks (1992) who argue turnover is a robust proxy for liquidity. Overall the distribution and correlation of my explanatory factors are consistent with the literature.

Table 2.1: Summary Statistics

The table values are computed summary statistics across NYSE and AMEX firms in the period July 1995 to June 2011. For firm i in quarter q the variables are earnings surprise ($ES_{i,q}$); institutional ownership ($Insti_{i,q}$); number of announcements released on the same day ($Distract\_U_{i,q}$); number of analysts issuing forecasts within the 90 days prior to earnings announcement ($Analyst_{i,q}$); volatility of daily buy-and-hold-abnormal return (BHAR) in the 40 trading days prior to earnings announcement ($Volatility_{i,q}$); arbitrage risk ($ArbRisk_{i,q}$); hedgeable risk ($ExpRisk_{i,q}$); average of Amihud (2002)s illiquidity measured across 40 trading days prior to earnings announcement ($Illiq_{i,q}$); average of quoted spread at closing across 40 trading days prior to earnings announcement ($Spread_{i,q}$); stock price at the end of the quarter q ($Price_{i,q}$); average daily turnover (in millions of dollars) measured from 271 trading days to 22 trading days prior to earnings announcement ($Turn_{i,q}$); market capitalisation ($Mcap_{i,q}$); book-to-market ratio ($BM_{i,q}$); BHAR across 40 trading days prior to earnings announcement ($Mom_{i,q}$); BHAR from the 2nd to the 61st trading day after earnings announcement ($PEAD_{i,q}$); and BHAR from the 1st trading day before earnings announcement to the 1st trading day after earnings announcement ($3DR_{i,q}$). $BHAR_{i,q} = \prod_n^N (1 + r_{i,q,t+n}) - \prod_n^N (1 + r_{i,t+n}^{MM})$ where for announcement date t, $BHAR_{i,q}$ measures BHAR returns, $r_{i,q,t}$ is the daily stock return, $r_{i,t+n}^{MM}$ is the daily return of a market-adjustment portfolio, and n represents the holding period from the nth day after the date of announcement to the Nth trading day. For the adjustment-portfolio $r_{i,t+n}^{MM}$ I use 5x5 size quintile and book-to-market quintile matched portfolios.

	mean	std	1st percentile	25th percentile	median	75th percentile	99th percentile
$ES_{i,q}$	-0.0026	0.09667	-0.05474	-0.00033	0.00036	0.00165	0.02422
$Insti_{i,q}$	0.63	0.22	0.07	0.49	0.66	0.8	0.98
$Distract\_U_{i,q}$	114.62	118.34	4	22	62	150	316
$Analyst_{i,q}$	6.29	5.42	1	2	5	9	24
$Volatility_{i,q}$	0.0207	0.0135	0.0061	0.0122	0.0174	0.0252	0.0709
$ArbRisk_{i,q}$	0.0121	0.0149	0.0012	0.0041	0.0078	0.0142	0.0683
$ExpRisk_{i,q}$	0.0025	0.0046	0.000	0.0004	0.0011	0.0027	0.0224
$Illiq_{i,q}$	0.0835	0.9679	0.00002	0.0004	0.0018	0.0107	1.4534
$Spread_{i,q}$	0.0107	0.0163	0.00026	0.0011	0.0053	0.0140	0.0681
$Price_{i,q}$	32.2	72.85	2.35	16.75	28.11	43.09	102.25
$Turn_{i,q}$	14.46	39.80	0.001	0.367	2.72	15.74	538.37
$Mcap_{i,q}$	8,170	23,893	45	606	1,829	5,640	118,445
$BM_{i,q}$	0.69	0.77	0.06	0.33	0.53	0.82	3.46
$Mom_{i,q}$	-0.002	0.159	-0.371	-0.074	-0.007	0.062	0.421
$PEAD_{i,q}$	-0.001	0.186	-0.442	-0.092	-0.008	0.079	0.524
$3DR_{i,q}$	0.003	0.072	-0.199	-0.028	0.001	0.034	0.203
Number of Observations	65,368						

Table 2.2: Full Sample Correlation Matrix

The table values are computed correlation coefficients across NYSE and AMEX firms in the period July 1995 to June 2011. The variables are, across firm i and in quarter q, earnings surprise ($ES_{i,q}$); institutional ownership ($Insti_{i,q}$); the decile rank based on number of announcements released on same day ($Distract_{i,q}$); number of analysts issuing forecasts within the 90 days prior to earnings announcement ($Analyst_{i,q}$); volatility of daily BHAR in the 40 trading days prior to earnings announcement ($Volatility_{i,q}$); arbitrage risk ($ArbRisk_{i,q}$); hedgeable risk ($ExpRisk_{i,q}$); the logarithm of average Amihud illiquidity measured across 40 trading days prior to earnings announcement ($LogIlliq_{i,q}$); the logarithm of average of quoted spread at closing across 40 trading days prior to earnings announcement ($LogSpread_{i,q}$); stock price at the end of quarter q ($Price_{i,q}$); average daily turnover (in millions of dollars) measured from 271 trading days to 22 trading days prior to earnings announcement ($Turn_{i,q}$); the logarithm of market capitalisation ($LogMcap_{i,q}$); book-to-market ratio ($BM_{i,q}$); BHAR across 40 trading days prior to earnings announcement ($Mom_{i,q}$); BHAR from the 2nd to the 61st trading day after earnings announcement ($PEAD_{i,q}$); and BHAR from the 1st trading day before earnings announcement to the 1st trading day after earnings announcement ($3DR_{i,q}$). $BHAR_{i,q} = \prod_n^N(1 + r_{i,q,t+n}) - \prod_n^N(1 + r_{i,t+n}^{MM})$ where for announcement date t, $BHAR_{i,q}$ measures BHAR returns, $r_{i,q,t}$ is the daily stock return, $r_{i,t+n}^{MM}$ is the daily return of a market-adjustment portfolio, and n represents the holding period from the n^{th} day after the date of announcement to the N^{th} trading day. For the adjustment-portfolio $r_{i,t+n}^{MM}$ I use 5x5 size quintile and book-to-market quintile matched portfolios.

	$ES_{i,q}$	$Insti_{i,q}$	$Distract_{i,q}$	$Analyst_{i,q}$	$Volatility_{i,q}$	$ArbRisk_{i,q}$	$ExpRisk_{i,q}$	$LogIlliq_{i,q}$	$LogSpread_{i,q}$	$Price_{i,q}$	$Turn_{i,q}$	$LogMcap_{i,q}$	$BM_{i,q}$	$Mom_{i,q}$	$PEAD_{i,q}$	$3DR_{i,q}$
$ES_{i,q}$																
$Insti_{i,q}$	0.05															
$Distract_{i,q}$	0.01	0.03														
$Analyst_{i,q}$	0.02	0.2	0.04													
$Volatility_{i,q}$	-0.01	-0.04	-0.05	-0.06												
$ArbRisk_{i,q}$	0.02	0.03	-0.06	-0.09	0.41											
$ExpRisk_{i,q}$	0.05	0.16	-0.02	0.11	0.16	0.29										
$LogIlliq_{i,q}$	-0.03	-0.26	-0.06	-0.48	0.26	0.24	-0.06									
$LogSpread_{i,q}$	-0.06	-0.31	-0.02	-0.24	0.32	0.16	-0.11	0.49								
$Price_{i,q}$	0.01	0.14	0.07	0.23	-0.31	-0.36	-0.11	-0.44	-0.27							
$Turn_{i,q}$	0.03	0.27	0.05	0.48	-0.21	-0.24	0.06	-0.84	-0.44	0.53						
$LogMcap_{i,q}$	0.01	0.15	0.06	0.46	-0.26	-0.31	0.01	-0.77	-0.35	0.47	0.76					
$BM_{i,q}$	0.04	-0.06	0.02	-0.12	0.03	0.05	0.02	0.21	0.07	-0.24	-0.24	-0.22				
$Mom_{i,q}$	0.08	0.03	0.02	0.01	-0.03	-0.01	0.01	-0.05	-0.06	0.07	0.04	0.05	0.00			
$PEAD_{i,q}$	0.04	0.02	0.02	0.02	-0.03	-0.01	0.01	-0.03	-0.03	0.02	0.03	0.03	-0.01	0.00		
$3DR_{i,q}$	0.22	0.02	0.00	0.00	0.00	0.01	0.01	0.00	00.00	0.02	0.01	0.00	-0.01	-0.02	0.03	

2.4. Test for a Significant Alpha

I now assess whether PEAD remains a financial anomaly by testing whether a PEAD-based investment strategy generate robust and economically significant alpha returns. My results show PEAD remains significant after controlling for the common market risk factors but in general attenuates for portfolios characterized by high investor sophistication, low structural uncertainty and low limits of arbitrage. I begin this section by defining measures of earnings surprise and abnormal return before proceeding to the formal tests.

2.4.1. Measures of Earnings Surprise

Measures of earnings surprise (ES) can be earnings-based or analyst forecast-based (Livnat and Mendenhall, 2006). [19] Shortcomings of earnings-based measures include: 1) the quality of information revealed by earnings information can differ across firms, industry and time; and 2) records of historical earnings data are occasionally restated causing a forward-looking bias (see Livnat and Mendenhall, 2006). Throughout this paper I proxy ES by analyst forecast error. Several factors suggest analyst forecast is a robust proxy for ES. First, analysts are incentivised by both career advancement and reputation to provide accurate information to both current as well as prospective shareholders. Second, they are relatively informed due to experience and analytical ability. Third, they maintain personal access with company managers (see Lim, 2001). Analyst forecasts also contain private information (Dimson and March, 1984; and Womack, 1996; Givoly and Kakonishok, 1979; Francis and Soffer, 1997) and the speed at which prices reflect public information tends to increase if firms have analyst coverage (Hong, Lim and Stein, 2000; Elgers, Lo and Pfeiffer, 2001). Forecasts can still be subject to upward analyst bias (I provide a discussion on the matter in Section A.3 of the Appendix). However

[19] In the past five decades many variations and alternative methods of testing PEAD have been considered. My approach builds from the ongoing developments in the PEAD literature.

Lim (2001) argues analysts trade off the bias to improve access and relationships with firm management and therefore analysts ultimately minimise forecast error and improve forecast accuracy.

I define the forecast error equal to the actual earnings minus the median of analyst forecasts (as proxy for expected earnings) and then standardized by the stock price (Brown, 1987):[21]

$$ES_{i,q} = \frac{Actual_{i,q} - MedForecast_{i,q}}{Price_{i,q}} \tag{2.1}$$

Where for firm i in quarter q (where $q \in \{1,2,\dots,64\}$), $ES_{i,q}$ is earnings surprise, $Actual_{i,q}$ is the announced earnings per share[22], $MedForecast_{i,q}$ is the median of the analyst forecasts[23] and $Price_{i,q}$ is the price per share reported at the end of the quarter by Compustat.[24]

2.4.2. Measures of Abnormal Returns

I measure abnormal returns by buy-and-hold abnormal returns (BHAR).[25] Following Barber and Lyon (1997) and Hirshleifer et al. (2009):

$$BHAR_{i,q,t} = \prod_{n=2}^{N}(1 + r_{i,q,t+n}) - \prod_{n=2}^{N}(1 + r_{i,t+n}^{MM}) \tag{2.2}$$

Where for announcement date t, $BHAR_{i,q,t}$ measures PEAD returns, $r_{i,q,t}$ is the daily stock return, $r_{i,t+n}^{MM}$ is the daily return of a market-adjustment portfolio, and n represents the holding period from the n^{th} day after the date of announcement to the N^{th} trading day. BHAR is a popular alternative to the cumulative abnormal return (CAR) and statistical tests on the measure are

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[21] The drawback is that the measure excludes stocks that do not have an analyst following.

[22] To proxy for $Actual_{i,q}$ I use the actual earnings data (primary earnings per share, excluding extraordinary items, adjusted for stock splits and dividends) from I/B/E/S. It should be noted that despite being in both Compustat and I/B/E/S the common practice is to take earnings data from I/B/E/S. The reason being that for some Compustat data, earnings are restated after an announcement while in contrast I/B/E/S includes the originally reported earnings (see Livnat and Mendenhall, 2006; Bradshaw and Sloan, 2002).

[23] Using only the latest forecast for each analyst issued within the 90 days prior to earnings announcement.

[24] Prices are adjusted for stock-splits.

[25] Compared to cumulative abnormal returns (CAR) BHAR more closely represent investor returns from holding a position in an asset.

robust for sufficiently large sample size (Ikenberry, Lakonishok and Vermaelean, 1995; Barber and Lyon, 1997).[26] The market-adjustment portfolio is commonly the 1) return on S&P 500 index; 2) return on S&P 500 exchange traded fund; or 3) a matched size and book-to-market portfolio. The distribution of BHAR is assumed to have a mean of zero if prices fully reflect announcement surprise.

While PEAD effects are documented to last up to three quarters (see, Bernard and Thomas, 1989) I select *N* equal 61 and therefore compute PEAD over 60 trading days. This is because measures of BHAR across long periods contain more noise and reduce the reliability of test statistics (Fama, 1991; Kothari, 2001).[27] It is also common practice among PEAD studies to measure BHAR from 2 trading days to 61 trading days after the date of earnings announcement (see Mendenhall, 2004; Hirshelifer et al, 2009).

2.4.3. Adjusting Standard Event-Study Methods to PEAD

The standard event-study method is a two-stage regression process. The first stage is to estimate the coefficient betas in the pre-earnings period and the second stage is to project the estimated betas onto post-event factor returns (see Campbell, Lo and MacKinlay, 1997). The pre-earnings announcement estimation window is generally between 12 and 48 months while the post-event period generally covers most of the quarter following the announcement date.

[26] One benefit of computing abnormal returns using BHAR is that it yields well-specified test statistics. Via simulation Barber and Lyon (1997) demonstrate that methods for calculating abnormal stock returns (such as CAR) are mis-specified and adjusting buy-and-hold returns by matching sample firms to control portfolios based on similar size and book-to-market ratios yields improved and well-specified test statistics.

[27] The measure of cumulative abnormal returns across a long horizon "require(s) extreme caution" (Kothari and Warner, 1997, p.301) and generally "the analysis of long-run abnormal returns is treacherous" (Lyon, Barber and Tsai, 1999, p.165). Also Fama (1991, p.1602) advocates for the shortest period in order to obtain the "cleanest evidence".

The estimated daily abnormal return for firm i is then computed by the following:

$$\hat{r}_{i,t} = rf_t + \sum_{z=1}^{Z}\left[\hat{\beta}_z RISKFACTORS_{z,t}\right] \quad (2.3)$$

$$AR_{i,t} = r_{i,t} - \hat{r}_{i,t} \quad (2.4)$$

$$PEAD_{i,q,t} = \sum_{n=0}^{N} AR_{i,t+n} \quad (2.5)$$

Where $\hat{r}_{i,t}$ is the expected return for firm i on day t, $r_{i,t}$ is actual return, rf_t is the daily risk-free rate return; $\hat{\beta}_z$ are the coefficients estimated using the pre-event window regressions; $RISKFACTORS_{z,t}$ are the return of risk factors where $z \in \{1, 2, 3... Z\}$. The risk factors are either the daily returns on the 1) risk-free rate adjusted market portfolio; 2) Fama-French three-factor portfolios; or 3) Carhart (1997) four-factor portfolios. The latter two are used to address the critique that the one-factor CAPM market model is an insufficient specification of the true market pricing model (see Fama and French, 1992; Carhart, 1997). $AR_{i,t}$ is the daily abnormal return and $PEAD_{i,q,t}$ is the cumulative abnormal return.

A criticism of this approach is that the two-stage regression produces biased $\hat{\beta}_z$ (Bernard, 1987) given the method ignores earnings announcements shifting firm risk (Chordia et al., 2009). One popular remedy is to use post-event data to estimate firm risk rather than pre-event data (see Ball and Kothari, 1989; Chopra, Lakonishok and Ritter, 1992; Ball, Kothari and Shanken, 1995) and I control for risk-mismeasurement bias by estimating alpha with only post-announcement returns (see Kothari and Warner, 2001; Sadka, 2006; Ng et al., 2008; Chordia et al., 2009). This is analogous to the one-stage "Jensen's alpha" method (Jensen, 1968):

$$ExcessReturn_{i,t} = a_{i,t} + \sum_{z}^{Z}\left[\gamma_z RISKFACTORS_{z,t}\right] + \varepsilon_{i,t} \quad (2.6)$$

Where $ExcessReturn_{i,t} = r_{i,t} - rf_t$ and $RISKFACTORS_{z,t}$ reflects the post-announcement variation of firm risk factors. To remain consistent with my choice of using BHAR, instead of taking daily returns the dependent and independent variables in Equation 2.6 are computed based on 60-day buy-and-hold returns from the 2nd trading day after earnings announcement to the 61st trading day. A significant estimate of $a_{i,t}$ therefore indicates a positive finding of 60-day PEAD.

Throughout this paper I compute robust t-statistics following Fama and Macbeth (1973) (Fama-Macbeth) which is the standard test procedure for market anomalies (Fama and French, 2008). Daily stock returns are assumed to be independent across time but correlated across stocks (Bernard, 1987; and Petersen, 2005) and therefore due to temporal overlap of PEAD panel data pooled-sample tests will generally fail the assumption of independence and result in pooled sample bias (i.e., over-finding bias) (Fama and French, 2008). The Fama-Macbeth test mitigates over-finding bias.

The Fama-Macbeth procedure is as follows. For each calendar quarter q I run pooled OLS following Equation 2.6. The Fama-Macbeth estimate of the mean and variance of $\widehat{\gamma_z}$ is then:

$$\widehat{\gamma_z} = \frac{1}{Q}\sum_{q=1}^{Q} \hat{\gamma}_{z,q} \tag{2.7}$$

$$\sigma^2(\widehat{\gamma_z}) = \frac{1}{Q}Var(\hat{\gamma}_{z,q}) = \frac{1}{Q^2}\sum_{q=1}^{Q}(\hat{\gamma}_{z,q} - \widehat{\gamma_z})^2 \tag{2.8}$$

In other words, the estimated mean is equal to the average of the quarterly estimates of $\hat{\gamma}_{z,q}$ and the variance is computed from the distribution of the quarterly estimates. $\hat{\gamma}_{z,q}$ is assumed to be independently and identically distributed. I note another advantage of the Fama-Macbeth test is that it addresses concerns that returns variance generally increase when conditioned on earnings surprise. Ignoring increased variance leads to an over-rejection of the null hypothesis that abnormal returns are insignificantly different from zero (Brown and Warner, 1985; and Corrado, 1989) and therefore the Fama-MacBeth test again serves to prevent over-finding.

2.4.3.1. Results

To test the significance of PEAD I create quarterly ES quintiles based on break points computed in the previous quarter and obtain quarterly alpha estimates for each ES quintile. Estimated alphas that monotonically increase with respect to ES quintile rank are consistent with the PEAD anomaly. Each quarter's PEAD is proxied by the estimated alpha of the highest ES quintile minus the estimated alpha of the lowest ES quintile (i.e., good news alpha minus bad news alpha).

Results in Panel A of Table 2.3 show PEAD is statistically and economically significant after controlling for common risk factors. Irrespective of model specification PEAD remains significant, and estimated alphas increase monotonically with respect to ES quintile rank. The first row in Panel A shows the computed quarterly means of buy-and-hold returns (without adjustment to other risk factors). For bad (good) news the average of quarterly mean is 1.49% (5.05%); and the average PEAD is 3.56% (significant at the 1% level). The 3rd ES quintile proxies the quarterly drift of market returns for firms with near-zero ES and shows a return of 1.91% (significant at the 10% level). Going down the rows, as returns are adjusted for more risk factors the return of the 3rd ES quintile centres towards zero but the magnitude of PEAD remains almost constant. For example, the second row shows computed BHAR where the adjustment-portfolio $r_{i,t+n}^{MM}$ is the daily risk-free rate. Returns for the 3rd ES quintile decline from 1.91% to 1.22% while estimated PEAD remains almost unchanged at 3.53% (significant at the 1% level). The last three rows show variants of Equation 2.6: 1) CAPM; 2) Fama-French three-factors; and 3) Carhart (1997) four-factors, and show PEAD ranges between 3.56% and 4.10%. Looking at the one-factor CAPM model, across ES quintiles from bad news to good news the mean of quarterly estimated alphas are monotonically increasing. 60-day alpha returns are -2.49% for firms announcing bad news (significant at the 5% level) and

Table 2.3: 60-day PEAD and 3-day Response Across ES Quintiles

Following Fama and Macbeth (1973) I run quarterly regressions for each ES quintile and test whether the mean of quarterly alphas are statistically different from zero. In the right column I take the quarterly difference between top and bottom ES quintile firms' estimated alpha and compute the sample mean. I conduct quarterly regressions following $Excess\_return_{i,t} = \alpha_{i,t} + \sum_{z}^{Z}\left[\gamma_z RISKFACTORS_{z,t}\right] + \varepsilon_{i,t}$ where the dependent variable is measured by $BHAR_{i,q,t} = \prod_{n=2}^{N}(1 + r_{i,q,t+n}) - \prod_{n=2}^{N}(1 + r_{i,t+n}^{MM})$ with $r_{i,t+n}^{MM}$ as the daily risk-free rate. $RISKFACTORS_{z,t}$ represents buy-and-hold (BHR) market risk premium, Fama and French (1992) three-factors or Carhart (1997) four-factors. Panel A measures BHR from one trading day to 61 trading days after earnings announcement and Panel B measures BHR from one trading day prior to earnings announcement to one trading day after. Period: July 1995 to June 2011. ***. **, * represent t-test significance level at 0.01, 0.05 and 0.1 respectively.

	Panel A: 60-day Drift											
	Earnings Surprise Quintile											
	Bad News		2		3		4		Good News		Good News minus Bad News	
BHR	0.0149		0.0107		0.0191	*	0.0290	**	0.0505	**	0.0356	***
BHAR (adjusted by risk-free rate)	0.00805		0.00369		0.0122		0.0220		0.0434	*	0.0353	***
CAPM	-0.0249	**	-0.0109		-0.00244		0.00482		0.0161	*	0.0410	***
Fama-French 3 factor	-0.0228	**	-0.0101	*	-0.00427		0.00548		0.0138	**	0.0367	***
Carhart (1997) 4 factor	-0.0226	**	-0.00550		-0.00184		0.00573		0.0130	**	0.0356	***
	Panel B: 3-day Response											
	Earnings Surprise Quintile											
	Bad News		2		3		4		Good News		Good News minus Bad News	
BHR	-0.0301	***	-0.0145	***	0.00210	**	0.0199	***	0.0353	***	0.0654	***
BHAR (adjusted by risk-free rate)	-0.0305	***	-0.0149	***	0.00174	**	0.0195	***	0.0350	***	0.0654	***
CAPM	-0.0313	***	-0.0157	***	0.000510		0.0182	***	0.0332	***	0.0645	***
Fama-French 3 factor	-0.0308	***	-0.0153	***	0.000994	*	0.0186	***	0.0335	***	0.0643	***
Carhart (1997) 4 factor	-0.0310	***	-0.0151	***	0.00106	*	0.0185	***	0.0330	***	0.0640	***

1.61% for firms announcing good news. The returns for quintile 2, 3, and 4 are -1.09%, -0.244% and 0.482% respectively. The right column shows the average PEAD is 4.10% (significant at the 1% level). In other words PEAD effects are in excess of 4% after controlling for firm beta. Looking further down at the 4^{th} and 5^{th} rows, controlling for Fama-French three-factors, the estimated PEAD is 3.67% (significant at the 1% level) and 3.56% after controlling for momentum effects (significant at the 1% level). These results suggest PEAD remains a statistically robust anomaly.

As a matter of comparison I also show how the market responds to ES around the immediate announcement period vis-à-vis the post-announcement period. Panel B in Table 2.3 compares the 3-day response (3DR) which is defined as the BHAR measured from one trading day before the date of the earnings announcement to one trading day after. Consistent with expectations this measure is also monotonically increasing with respect to ES quintile which is consistent with bigger news surprise impounding more information into stock prices. For example, the last row shows in the Carhart (1997) four factor model the 3DR is 6.40% (significant at the 1% level); the mean of estimated alphas is -3.10% for bad news (significant at the 1% level) and 3.30% for good news (significant at the 1% level). Irrespective of specification the difference on average between good and bad news firms is between 6.40% to 6.54% (significant at the 1% level), which is approximately twice that of PEAD. This result is consistent with the literature.

2.4.4. Portfolios Classified by Firm Characteristics

Following Fama and French (2008) I now assess the robustness of the PEAD anomaly by running Fama-French three-factor regressions across portfolios classified by different firm characteristics. The intuition is that a finding of significant alpha, irrespective of how portfolios are constructed, indicates robust evidence in favour of PEAD. For each of fourteen explanatory variables[30] I compute within-quarter break points at the 33rd and 67th percentile and group firm-quarter observations into "low", "mid" or "high" portfolios based on the break points. This borrows from Fama and French (1992) and seeks to identify whether factor variation can explain PEAD. For each portfolio I then again estimate PEAD by computing the average quarterly difference between estimated alphas for the highest and lowest ES quintiles (i.e., good news alpha minus bad news alpha).

Results in Table 2.4 show that irrespective of firm characteristic at least one of the low or high portfolios exhibit a significant PEAD. Consistent with the literature PEAD is not uniform in the cross-section and is generally larger in portfolios characterised by low investor sophistication, high structural uncertainty, high transaction costs and high arbitrage risk. Take for example, the second panel in the right column which shows PEAD across different sizes of bid-ask spreads. For firms with the narrowest spreads PEAD is 0.636% (insignificant at the 10% level) while for firms with the widest spreads PEAD rises to 3.83% (significant at the 1% level). This suggests the anomaly is associated with transaction costs. Similarly the results show PEAD attenuation is associated with high institutional ownership, high analyst coverage, and high stock price (which proxy high investor sophistication, low information opacity, and low trading costs respectively). PEAD also attenuates with low volatility, low dispersion, low Amihud (2002) illiquidity and low spreads (which respectively proxy for low investor uncertainty, low analyst disagreement, low illiquidity and low transaction costs). High momentum is also associated with smaller PEAD which is consistent with Sadka (2006) and Vega (2006) finding that PEAD is positively correlated to momentum effects. My results

[30] I include the additional analyst dispersion factor which is computed by the standard deviation of analyst forecasts and proxies for investor disagreement. To compute this variable I omit all firm-quarter observations with only one analyst forecast.

Table 2.4: 60-day PEAD and 3-day Response Across Factor Portfolios

I take the difference of estimated alphas between good and bad news across each tercile group for 14 explanatory factors. Ranking of low, mid, high are based on quarterly within-quarter sort. Following Fama and Macbeth (1973) I run quarterly regressions for the top and bottom ES quintile within each tercile. I then take the difference in estimated alpha between the top and bottom ES quintile and test whether the mean is significantly different from zero. I conduct regressions following $Excess\_return_{\mathrm{i,t}} = \alpha_{i,t} + \sum_{\mathrm{z}}^{\mathrm{Z}}\left[\gamma_z RISKFACTORS_{z,t}\right] + \varepsilon_{\mathrm{i,t}}$ where the dependent variable is measured by $BHAR_{i,q,t} = \prod_{n=2}^{N}(1 + r_{i,q,t+n}) - \prod_{n=2}^{N}(1 + r_{i,t+n}^{MM})$ with $r_{i,t+n}^{MM}$ as the daily risk-free rate. The $RISKFACTORS_{z,t}$ represent BHR for Fama and French (1992) three-factors. The variables below are institutional ownership ($Insti_{i,q}$); number of announcements released on same day ($Distract\_U_{i,q}$); number of analysts issuing forecasts within the 90 days prior to the earnings announcement ($Analyst_{i,q}$); the standard Deviation of Analyst Forecast for firm i in quarter q ($Dispersion_{i,q}$) (note: denotes the group of announcements with only one analyst forecast and hence dispersion is zero); volatility of daily BHAR in the 40 trading days prior to earnings announcement ($Volatility_{i,q}$); arbitrage risk ($ArbRisk_{i,q}$); hedgeable risk ($ExpRisk_{i,q}$); average of Amihud illiquidity measured across 40 trading days prior to earnings announcement ($Illiq_{i,q}$); average of quoted spread at closing across 40 trading days prior to earnings announcement ($Spread_{i,q}$); stock price at the end of quarter, q ($Price_{i,q}$); average daily turnover (in millions of dollars) measured from 271 trading days to 22 trading days prior to earnings announcement ($Turn_{i,q}$); market capitalisation ($Mcap_{i,q}$); book-to-market ratio ($BM_{i,q}$); BHAR across the past 40 trading days prior to earnings announcement ($Mom_{i,q}$); Period: July 1995 to June 2011. ***. **, * represent t-test significance level at 0.01, 0.05 and 0.1 respectively.

		Good News minus Bad News						Good News minus Bad News			
		3-day Response		60-day PEAD				3-day Response		60-day PEAD	
$Insti_{i,q}$	low	0.0534	***	0.0399	***	$Illiq_{i,q}$	low	0.0441	***	0.0109	
	mid	0.0604	***	0.0363	***		mid	0.0554	***	0.00940	
	high	0.0639	***	0.0126			high	0.0667	***	0.0451	***
$Distract\_U_{i,q}$	low	0.0662	***	0.0251	**	$Spread_{i,q}$	low	0.0464	***	0.00636	
	mid	0.0553	***	0.0642	*		mid	0.0543	***	0.0195	
	high	0.0499	***	0.0210			high	0.0648	***	0.0383	***
$Analyst_{i,q}$	low	0.0603	***	0.0512	***	$Price_{i,q}$	low	0.0634	***	0.0400	***
	mid	0.0632	***	0.0106			mid	0.0568	***	0.0149	
	high	0.0489	***	0.00437			high	0.0459	***	0.0188	*
$Volatility_{i,q}$	low	0.0441	***	0.0167		$Turn_{i,q}$	low	0.0647	***	0.0443	***
	mid	0.0590	***	0.0139			mid	0.0568	***	0.0105	
	high	0.0654	***	0.0382	***		high	0.0482	***	0.0215	**
$ArbRisk_{i,q}$	low	0.0384	***	0.0143		$Mcap_{i,q}$	low	0.0672	***	0.0393	***
	mid	0.0579	***	0.0200	**		mid	0.0529	***	0.0138	
	high	0.0690	***	0.0352	***		high	0.0438	***	0.0248	*
$ExpRisk_{i,q}$	low	0.0500	***	0.0231	**	$BM_{i,q}$	low	0.0721	***	0.0367	*
	mid	0.0570	***	0.0389	***		mid	0.0579	***	0.0107	
	high	0.0681	***	0.0284	**		high	0.0548	***	0.0364	**
$Dispersion_{i,q}$	low	0.0737	***	0.00831		$Mom_{i,q}$	low	0.0622	***	0.0380	**
	mid	0.0653	***	0.0201			mid	0.0568	***	0.0386	***
	high	0.0489	***	0.0215	**		high	0.0578	***	0.0121	

therefore align with the behavioural, structural uncertainty, and limits of arbitrage explanations.

I note PEAD does not monotonically decrease with respect to market capitalisation, nor monotonically increase with respect to BM, which supports my findings in Table 2.3 that Fama-French three-factors alone cannot explain away PEAD effects. PEAD is also significant across all low, mid and high hedgeable risk portfolios which affirms Mendenhall's (2006) argument that hedgeable risks is unrelated to PEAD and investors will not be compensated for carrying risks that can be hedged away by the market portfolio.

Two factors that are inconsistent with previous studies are turnover and investor distraction. My results show PEAD is significant for both high and low turnover portfolios: low turnover stocks have a PEAD of 4.43% (significant at the 1% level) while high turnover stocks have a PEAD of 2.15% (significant at the 5% level). The mid portfolio has a PEAD of 1.05% and is insignificant at the 10% level. This suggests the indirect cost to processing market information is potentially a poor explanation for cross-sectional variation in PEAD. The results for investor distraction are also inconsistent with Hirshleifer et al. (2009) and I find days with a high number of announcements are associated with insignificant drift. Notwithstanding, later in my multivariate analysis I show regression results for the two factors align with the literature.

For additional robustness I also group my observations into 5x5 portfolios based on ES quintile by factor quintile and take the average of quarterly PEAD for each of the 25 portfolios (see Section A.4 of the Appendix). I compute the quarterly mean rather than estimated quarterly alpha for each portfolio given univariate tests on BHAR are well specified (Barber and Lyon, 1997)[32] and show the computed values are consistent with Table 2.4. For ease of interpretation

[32] Barber and Lyon (1997) empirically demonstrate that common methods for calculating abnormal stock returns are mis-specified and that correcting buy-and-hold returns by matching sample firms to control firms based on similar size and book-to-market ratios yields well-specified test statistics.

I then plot cross-sectional means of PEAD returns for each factor quintile in Section A.5 of the Appendix. Overall the evidence presented suggests low investor sophistication, high structural uncertainty and high limits of arbitrage can explain PEAD attenuation

I note my results relate to the literature on earnings response coefficient (ERC). A comprehensive review on the ERC literature is beyond this chapter however in general, factors that proxy improvements in the quality and reliability of earnings announcements have a positive correlation to 3DR. For example, high institutional ownership proxies for high quality of earnings as institutional investors are better at monitoring company management relative to individual investors (Velury and Jenkins, 2006). Jiambalvo, Rajgopal and Vekatachalam (2002) also argue that institutional investors are better at predicting future earnings from current earnings information, and better at predicting momentum in future earnings surprise. Therefore institutional and sophisticated investors are less likely to under-react to new information released at announcement.

2.5. Explanations for PEAD – Multivariate Analysis

In the previous section I find the alpha of PEAD tends to attenuate for firms characterized by high investor sophistication, low structural uncertainty and low limits of arbitrage. I now jointly test these explanations and conduct a multivariate analysis.

2.5.1. Regression with Scaled Interaction Variables

To account for multiple explanations of PEAD I employ a regression method using scaled interaction variables. The dependent variable is the firm-quarter PEAD following Barber and Lyons (1998): $BHAR_{i,q,t} = \prod_{n=2}^{N}(1 + r_{i,q,t+n}) - \prod_{n=2}^{N}(1 + r_{i,t+n}^{MM})$. For the adjustment-portfolio $r_{i,t+n}^{MM}$ I use 5x5 size quintile and BM quintile matched portfolios and the data is obtained from Professor Kenneth French's website.[33] This is consistent with Mendenhall (2004) and Hirshleifer et al. (2009). The firm size quintile is based on NYSE firm market capitalisation breakpoints calculated in the most recent June; and the firm BM quintile breakpoints are calculated in the most recent December[34]. To create the explanatory factors: 1) I assign a decile rank $Decile_{z,i,q}$ for each explanatory factor based on within-quarter sorting[35]; 2) each factor is then scaled to between -0.5 to +0.5 (see Bhushan, 1994, Chan, Jegadeesh and Lakonishok, 1996, Mendenhall, 2004); and 3) to formulate the independent regressor each explanatory factor is interacted with the scaled ES variable. The rationale for imposing on the independent regressors a min-max range of one unit is to allow for the meaningful interpretation of the estimated coefficients (Mendenhall, 2004). Specifically, the estimated coefficients can be interpreted as the difference in PEAD between firms in the top and bottom factor decile. The regression model is described by the following:

$$ES_{i,q}^{Quintile} \in \{1,2,3,4,5\} \tag{2.9}$$

$$Decile_{z,i,q} \in \{1,2,3,\dots,10\} \tag{2.10}$$

$$ES_{i,q}^{Scaled} = \left(\frac{ES_{i,q}^{Quintile}-1}{4} - 0.5\right) \tag{2.111}$$

$$InteractionTerm_{z,i,q}^{Scaled} = ES_{i,q}^{Scaled}\left(\frac{Decile_{z,i,q}-1}{9} - 0.5\right) \tag{2.12}$$

$$BHAR_{i,q} = \alpha \quad + \beta \quad ES_{i,q}^{Scaled} + \textstyle\sum_{z=1}^{Z}\left[\gamma_z InteractionTerm_{z,i,q}^{Scaled}\right] + \varepsilon_{i,q} \tag{2.13}$$

Where $BHAR_{i,q}$ is the 60-day PEAD for firm i in quarter q; $ES_{i,q}^{Scaled}$ is the scaled measure for ES ranging between -0.5 to 0.5; $InteractionTerm_{z,i,q}^{Scaled}$ is the interaction term between

[33] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data library.html
[34] Following the method of Fama and French (1992).
[35] As an alternative to ranking by the previous quarter's breakpoints within-quarter ranking is also considered a robust method for determining factor breakpoints (see Bernard and Thomas, 1989; Bhushan, 1994; Bartov et al., 2000; Mendenhall, 2004).

$ES_{i,q}^{Scaled}$ and the explanatory factors $Decile_{z,i,q}$. Scaling explanatory factors also has the advantage of controlling for outliers and time trends (Bhushan, 1994) and also accommodates for non-linearity with the dependent variable (Chan et al., 1996). β is the gradient for the earnings surprise variable and represents the average difference in PEAD between firms in the top and bottom ES quintiles. It can be interpreted as the magnitude of PEAD left unexplained by the model (Mendenhall, 2004). γ_z is the coefficient for the z^{th} interaction term and can be interpreted as the average difference in PEAD attributable to firms being in the top vis-à-vis the bottom decile of the explanatory factor. α is the average PEAD for firms defined by median characteristics across all factors and is expected to be statistically insignificant from zero.

This regression model with the set of multiplicative explanatory factors is a common test specification to test financial anomalies. The left hand variable is the *characterisation based abnormal returns* measure of Barber and Lyon (1997) which has been shown to be a robust measure for anomalous returns; and the explanatory factors are transformed through ordinate ranking based on the popular within-quarter sort (for example, see Bhushan, 1994; Mendenhall, 2004). This model produces a meaningful identification of the characteristics that explain financial anomalies (Chan et al., 1996; Kothari, 2001).

2.5.1.1. Results

While successive studies have attempted to explain PEAD, in Section 2.4 I find the anomaly statistically remains. Now I assess whether PEAD remains robust in a joint test that controls for all factors. The Fama-Macbeth regression results are in Panel B of Table 2.5 and show PEAD remains significant at 1.90% (significant at the 1% level). In other words, at the turn of the century the difference in PEAD effects between good news and bad news firms remains at almost 2%. The magnitude also point to economic significance; Jensen (1978) notes the importance of trading profitability in assessing market efficiency. The estimated coefficient of

$ES_{i,q}^{Scaled}$ of 0.0190 shows that, for a set of firms with median characteristics, firms in the highest ES quintile exhibit a 60-day abnormal return 1.90% higher than firms in the lowest ES quintile. Surprisingly, after controlling for all factors my tests show only arbitrage risk and institutional ownership are significant; the remaining coefficients are insignificant but exhibit signs almost entirely consistent with the literature. Higher arbitrage risk implies traders who seek to profit from PEAD must bear greater uncertainty regarding the outcome of any individual transaction, which is consistent with arguments that trading away PEAD requires holding large positions on relatively few stocks. The estimated coefficient for the interaction term $ES_{i,q}^{Scaled} * ArbRisk_{i,q}^{Scaled}$ is 0.0248 (significant at the 5% level) and shows that after controlling for other explanatory factors, the abnormal return for firms in the highest arbitrage-risk decile is 2.48% (significant at the 1% level) higher than firms in the lowest arbitrage-risk decile. This aligns with Mendenhall (2004, Table 3, p.887) who shows the abnormal return for firms in the highest arbitrage-risk decile is 6.81% higher than firms in the lowest arbitrage-risk decile for the period 1991 to 2000.[36] The coefficient for investor sophistication is negative at -0.0321 (significant at the 1% level) and suggests firms with the highest level of institutional ownership exhibit 3.21% less PEAD then firms with the lowest institutional ownership. This is consistent with both Campbell et al. (2009) and Chordia et al. (2009).

One interpretation of my result is the following: information may not always be fully impounded into stock price due to a portion of investors having low sophistication (and therefore interpret newly released accounting information poorly) and the mispricing may not be corrected for as trading away PEAD involves holding large positions that cannot be easily hedged. Assuming traders hedge their position using an index future or ETF my results suggest

[36] For comparison, for the sample period 1991 to 2000 Mendenhall (2004) finds 60-day PEAD to be 6.98%.

Table 2.5: Regressions of 60-day PEAD and 3-day Response against Scaled Multiplicative Factors

The table shows regression results for the specification $BHAR_{i,q} = a \quad + \beta\ ES_{i,q}^{Scaled} + \sum_{z=1}^{Z}\left[\gamma_z InteractionTerm_{z,i,q}^{Scaled}\right] + \ \varepsilon_{i,q}$ where the dependent variables are 60-day PEAD ($PEAD_{i,q}$); and 3-day response ($3DR_{i,q}$). All factor deciles are scaled to between -0.5 to +0.5. The variables are earnings surprise quintile ($ES_{i,q}^{Scaled}$); institutional ownership ($Insti_{i,q}^{Scaled}$); number of announcements released on same day ($Distract_{i,q}^{Scaled}$); number of analysts issuing forecasts within the 90 days prior to the earnings announcement ($Analyst_{i,q}^{Scaled}$); volatility of daily BHAR in the 40 trading days prior to earnings announcement ($Volatility_{i,q}^{Scaled}$); arbitrage risk ($ArbRisk_{i,q}^{Scaled}$); hedgeable risk ($ExpRisk_{i,q}^{Scaled}$); average of quoted spread at closing across 40 trading days prior to earnings announcement ($Spread_{i,q}^{Scaled}$); stock price at the end of quarter, q ($Price_{i,q}^{Scaled}$); average daily turnover (in millions of dollars) measured from 271 trading days to 22 trading days prior to earnings announcement ($Turn_{i,q}^{Scaled}$); market capitalisation ($Mcap_{i,q}^{Scaled}$); book-to-market ratio ($BM_{i,q}^{Scaled}$); BHAR across the past 40 trading days prior to earnings announcement ($Mom_{i,q}^{Scaled}$). Panel A shows pooled regressions while Panel B shows Fama and Macbeth (1973) regressions where values are the mean of estimated coefficients from quarterly regressions. Period: July 1995 to June 2011. ***. **, * represent t-test significance level at 0.01, 0.05 and 0.1 respectively.

	Panel A. Pooled Regression				Panel B. Fama and Macbeth Regression			
	3-day Response		60-day PEAD		3-day Response		60-day PEAD	
Intercept	0.00293	***	-0.00130	***	0.00300	***	2.53×10^{-5}	
$ES_{i,q}^{Scaled}$	0.0571	***	0.0210	***	0.0586	***	0.0190	***
$ES_{i,q}^{Scaled} * Insti_{i,q}^{Scaled}$	0.0216	***	-0.0310	***	0.0188	***	-0.0321	***
$ES_{i,q}^{Scaled} * Distract_{i,q}^{Scaled}$	-0.0108	***	0.0107	***	-0.0144	***	0.0128	
$ES_{i,q}^{Scaled} * Analyst_{i,q}^{Scaled}$	-0.00672	***	-0.0175	***	-0.00498		-0.0111	
$ES_{i,q}^{Scaled} * Volatility_{i,q}^{Scaled}$	0.00487	***	0.00525	***	-0.00489		0.00865	
$ES_{i,q}^{Scaled} * ArbRisk_{i,q}^{Scaled}$	0.0242	***	0.0261	**	0.0297	***	0.0248	**
$ES_{i,q}^{Scaled} * ExpRisk_{i,q}^{Scaled}$	0.0149	***	-0.0200	***	0.00811	**	-0.0154	
$ES_{i,q}^{Scaled} * Spread_{i,q}^{Scaled}$	-0.00238	***	-0.00233	**	-0.00954	*	0.00888	
$ES_{i,q}^{Scaled} * Price_{i,q}^{Scaled}$	0.00813	***	0.00889	**	0.00511		0.00765	
$ES_{i,q}^{Scaled} * Turn_{i,q}^{Scaled}$	-0.0209	***	-0.00551	**	-0.0200	**	-0.0110	
$ES_{i,q}^{Scaled} * Mcap_{i,q}^{Scaled}$	0.00076	***	-0.00413	**	-0.00267		0.00288	
$ES_{i,q}^{Scaled} * BM_{i,q}^{Scaled}$	-0.0213	***	0.00983	***	-0.0211	***	0.0174	
$ES_{i,q}^{Scaled} * Mom_{i,q}^{Scaled}$	-0.00744	***	0.00660	***	-0.00783	**	0.0101	

the greater the unexplained variance with respect to the market portfolio, the greater the PEAD.

Other than arbitrage risk and institutional ownership, the remaining explanatory variables are statistically insignificant, despite almost all signs of estimated coefficients showing consistency with the literature. For example, in the context of behavioural explanations, the estimated coefficient for investor distraction suggests PEAD effects during days with the most distractions are 1.28% higher, which aligns with Hirshleifer et al. (2009). Similarly, in the context of structural uncertainty explanations, the proxy for investor disagreement $Volatility_{i,q}^{Scaled}$ and information opacity $BM_{i,q}^{Scaled}$ are positively associated with PEAD, with the former contributing 0.865% to PEAD effects and the latter 1.74%. High analyst following, another proxy for low information opacity, suggests PEAD attenuates by 1.11%. High turnover, a proxy for indirect trading costs, is associated with PEAD attenuating by 1.10%. High spreads, proxying direct transaction costs, increase PEAD by 0.888%.

Table 2.5 also shows pooled regression results in contrast to Fama-Macbeth regressions to demonstrate the general over-finding of statistical significance in the estimated coefficients. The signs of the significant coefficients in Panel A are consistent with those in Panel B, however the coefficients that are insignificant in the Fama-Macbeth results increase in signficance in the pooled regression. In fact all variables are statistically significant. Consistent with Fama and French (2008) this suggests pooled regressions, relative to Fama-Macbeth regressions, over-find a relation between an independent and dependent variables.

Looking at the immediate price response results (left column of Panel B in Table 2.5) the estimate of the ES intercept suggests the average 3DR is 5.86%. The sign for the estimated coefficient for institutional ownership at 0.0188 is opposite to its counterpart in the PEAD results and suggests firms with high institutional ownership exhibit 1.88% (significant at the 1% level) higher 3DR. This is consistent with sophisticated investors being better at synthesising earnings news and therefore less likely to under-react. The estimate of -1.44% for investor distraction is consistent with Hirshleifer et al. (2009) that firms under-react during days with a large number of earnings announcements. Similarly the opposite signs between 3DR and PEAD results for spreads and turnover support Ng et al. (2008) that cost frictions manifest in a rational incomplete arbitrage of PEAD related mispricing. Interestingly, the coefficient for arbitrage risk and hedgeable risk are both significant and positive. Potentially these risk factors are proxies for the riskiness of earnings (see Collins and Kothari, 1989). The negative estimated coefficient for BM of -2.11% is also consistent with Collis and Kothari (1989) who show BM is a proxy for growth opportunities and a high BM implies poor future growth. I note that my estimates of analyst following and firm size are insignificant, however their negative signs are consistent with the results in Collins, Kothari and Rayburn (1987) who show these factors proxy the transparency of the information environment. Finally, my estimated coefficient for momentum suggests 3DR is inverse to momentum effects. This potentially captures the level of information leakage prior to earnings announcements.

Last, to explore why other factors lose their explanatory power when including arbitrage risk and institutional ownership as regression factors I consider the correlation matrix between arbitrage risk, institutional ownership and other factors. Mendenhall (2004) shows that arbitrage risk is negatively correlated with firm size, analyst following and stock price and its inclusion in regression specification removes the statistical significance of other control factors. In Section A.6 of the Appendix I compute the correlation matrix showing, consistent with Mendenhall (2004), $ArbRisk_{i,q}$ is correlated to the bid-ask spread ($\rho = 0.49$), turnover ($\rho = -0.28$), stock price ($\rho = -0.52$), volatility ($\rho = 0.68$) and size ($\rho = -0.48$); while $Insti_{i,q}$ is correlated to the bid-ask spread ($\rho = -0.21$), analyst following ($\rho = 0.24$) and stock price ($\rho = 0.22$). This suggests arbitrage risk and institutional ownership effects can potentially be considered catch-all terms for these other factors.

2.5.2. Allowing for Time-Trends in the Explanatory Variables

In this final section I allow for time-trends in the explanatory factors, to account for time-varying transaction costs. While scaled multiplicative factors is a common regression technique, the method removes trends in the control factors and hence ignores improvements in market liquidity across time. Chordia et al. (2009) note transaction costs were subject to significant decline at the turn of the century as a result of market structural changes including the decimalisation of tick size, the computerisation of financial markets and rising competition among equities exchanges. Bhardwah and Brooks (1992) proxy trading costs by stock price and stock turnover while Chordia et al. (2009) argue the direct measure of bid-ask spread is a superior proxy for transaction costs. To account for time-varying trends I include all 3 factors and follow the regression specification in Hirshleifer et al. (2009):

$$BHAR_{i,q} = \alpha_q + \beta\ ES_{i,q}^{Scaled} + \sum_{z=1}^{Z}\left[\gamma_z InteractionTerm_{z,i,q}^{non-scaled}\right] + \sum_{z=1}^{Z}\left[\delta_z Factors_{z,i,q}^{non-scaled}\right] + \varepsilon_{i,q} \tag{2.14}$$

Where $InteractionTerm_{z,i,q}^{non-scaled} = ES_{i,q}^{Scaled} * Factors_{z,i,q}^{non-scaled}$. Hence all explanations are unscaled. I winsorize each explanatory variable at the 1% and 99% level and use the log of $Spread_{i,q}$ to proxy for transaction costs.

The regression results are in Table 2.6 and show PEAD is positively associated with transaction costs.[38] I show two sets of results: 1) the left column controls for all explanatory factors; and 2) the right column follows Hirshleifer et al. (2009) includes additional dummy variables for each of the Fama-French ten industry classifications. Looking at the right column, the estimated

[38] Unpublished results show qualitatively the same results when using Amihud (2002) illiquidity as a regression factor.

coefficient for $ES_{i,q}^{Scaled}$ is significant at 6.49% (significant at the 1% level). This magnitude is substantially larger than the estimates in Table 2.5 and points to a far larger portion of PEAD left unexplained suggesting a linear relation between dependent and independent variables is a poor model assumption. The results lend support to Kothari (2001) and Chan et al. (1996) that scaling explanatory factors to control for non-linearity and outliers is a more suitable specification for explaining financial anomalies. Non-scaling also makes difficult a meaningful interpretation of the magnitude of estimated coefficients: with this in mind I assess only the sign and significance of the estimated coefficients without discussing the magnitude. The results show institutional ownership at -0.0379 (significant at the 5% level) has a significant inverse relationship with ES. While the log of bid-ask spreads is also significant at 0.006 (significant at the 5% level). Both factors are robust for the Fama-French ten industry classification dummies. Unpublished plots of the quarterly mean of each control variable show that for the period 1995 to 2011 the bid-ask spread had noticeably declined at the turn of the century. This suggests, controlling for all else, PEAD may have attenuated along with transaction costs. The results also show some evidence that high BM "value" stocks have higher PEAD than low BM "glamour" stocks (a proxy for information opacity). The remaining coefficients, although insignificant, have signs consistent with the literature, except for arbitrage risk. I note unscaled arbitrage risk at -0.3519 is not significant and this inconsistency must be interpreted in the context that arbitrage risk is highly non-linear with respect to PEAD (Mendenhall, 2004). My results therefore suggests transactions costs also explain PEAD.

Table 2.6: Fama and MacBeth Regressions of 60-day PEAD against Non-Scaled Multiplicative Factors

The table shows regression results for the specification $BHAR_{i,q} = \alpha + \beta\, ES_{i,q}^{Scaled} + \sum_{z=1}^{Z}\left[\gamma_z InteractionTerm_{z,i,q}^{non-scaled}\right] + \sum_{z=1}^{Z}\left[\delta_z Factors_{z,i,q}^{non-scaled}\right] + \varepsilon_{i,q}$ where the dependent variables are 60-day PEAD ($PEAD_{i,q}$); and 3-day response ($3DR_{i,q}$). The sample period is July 1995 to June 2011. The earnings surprise quintile $ES_{i,q}^{Scaled}$ is scaled to between -0.5 to +0.5. The remaining factors are not sorted into deciles and not scaled. The z^{th} variables ($Factors_{z,i,q}^{non-scaled}$) across firm *i* and in quarter *q* are institutional ownership ($Insti_{i,q}$); the decile rank based on number of announcements released on same day ($Distract_{i,q}$); number of analysts issuing forecasts within the 90 days prior to the earnings announcement ($Analyst_{i,q}$); volatility of daily BHAR in the 40 trading days prior to earnings announcement ($Volatility_{i,q}$); arbitrage risk ($ArbRisk_{i,q}$); hedgeable risk ($ExpRisk_{i,q}$); the logarithm of average of quoted spread at closing across 40 trading days prior to earnings announcement ($LogSpread_{i,q}$); stock price at the end of quarter, *q* ($Price_{i,q}$); average daily turnover (in millions of dollars) measured from 271 trading days to 22 trading days prior to earnings announcement ($Turn_{i,q}$); the market capitalisation ($Mcap_{i,q}$); book-to-market ratio ($BM_{i,q}$); BHAR across the past 40 trading days prior to earnings announcement ($Mom_{i,q}$); BHAR from the 2nd to the 61st trading day after earnings announcement ($PEAD_{i,q}$); and BHAR from the 1st trading day before earnings announcement to the 1st trading day after earnings announcement ($3DR_{i,q}$). FF10 represents Fama-French 10 industry classification dummies. ***. **, * represent t-test significance level at 0.01, 0.05 and 0.1 respectively.

Intercept	-0.0075		-0.0072	
$ES_{i,q}^{Scaled}$	0.0861	***	0.0649	**
$ES_{i,q}^{Scaled} * Insti_{i,q}$	-0.0365	**	-0.0379	**
$ES_{i,q}^{Scaled} * Distract_{i,q}$	0.0008		0.0005	
$ES_{i,q}^{Scaled} * Analyst_{i,q}$	-0.0004		-0.0003	
$ES_{i,q}^{Scaled} * Volatility_{i,q}$	0.4086		0.5602	
$ES_{i,q}^{Scaled} * ArbRisk_{i,q}$	-0.1445		-0.3519	
$ES_{i,q}^{Scaled} * ExpRisk_{i,q}$	-2.3512		-2.2923	
$ES_{i,q}^{Scaled} * LogSpread_{i,q}$	0.0092	***	0.006	**
$ES_{i,q}^{Scaled} * Price_{i,q}$	0.0001		-0.0001	
$ES_{i,q}^{Scaled} * Turn_{i,q}$	0.0009		-0.0056	
$ES_{i,q}^{Scaled} * Mcap_{i,q}$	1.40×10^{-7}		1.26×10^{-7}	
$ES_{i,q}^{Scaled} * BM_{i,q}$	0.0064		0.0080	*
$ES_{i,q}^{Scaled} * Mom_{i,q}$	0.0035		0.0026	
Additional Control Variables	$Factors_{z,i,q}^{non-scaled}$		$Factors_{z,i,q}^{non-scaled}$ and FF10	

2.6. Conclusion

In the anomalies literature PEAD has attracted numerous studies and explanations for the persistent under-reaction to earnings news and Fama (1998) has dubbed it the “granddaddy of under-reaction events” (p.286). I find that, controlling for a large set of explanatory variables, PEAD remains a significant anomaly at almost 2% across the 60 trading days after earnings announcement. This finding is both statistically and economically significant. I further find this under-reaction to earnings surprise is partially explained by low investor sophistication while the persistence of PEAD is associated with arbitrage risk and transaction costs. In other words, low investor sophistication causes the incomplete impounding of earnings news into the stock price, while the subsequent mispricing is not fully corrected for due to cost frictions and the arbitrage risk. Assuming traders hedge their position with the market index my results suggest the greater the idiosyncratic risk with respect to the market portfolio, the greater the PEAD.

To address concerns that findings of PEAD may be subject to an over-finding bias this paper controls for shifts in firm risks at earnings announcement and also addresses pooled-regression bias by employing Fama-Macbeth test procedures. Following Fama and French (2008) I demonstrate PEAD alpha is statistically and economically robust irrespective of model specification and that PEAD varies across firm characteristics almost entirely consistent with findings in the literature. However, individually or jointly considered these firm characteristics are insufficient to fully explain PEAD. Overall this paper supports the view that PEAD remains “a serious challenge … [and that] it has survived a battery of tests and the many attempts to explain it away” (Kothari, 2001, p.196). My sample period generally has no temporal overlap to PEAD studies published prior to the early-2000s and therefore my results can be viewed as an out-of-sample test supporting the existence of the PEAD anomaly.

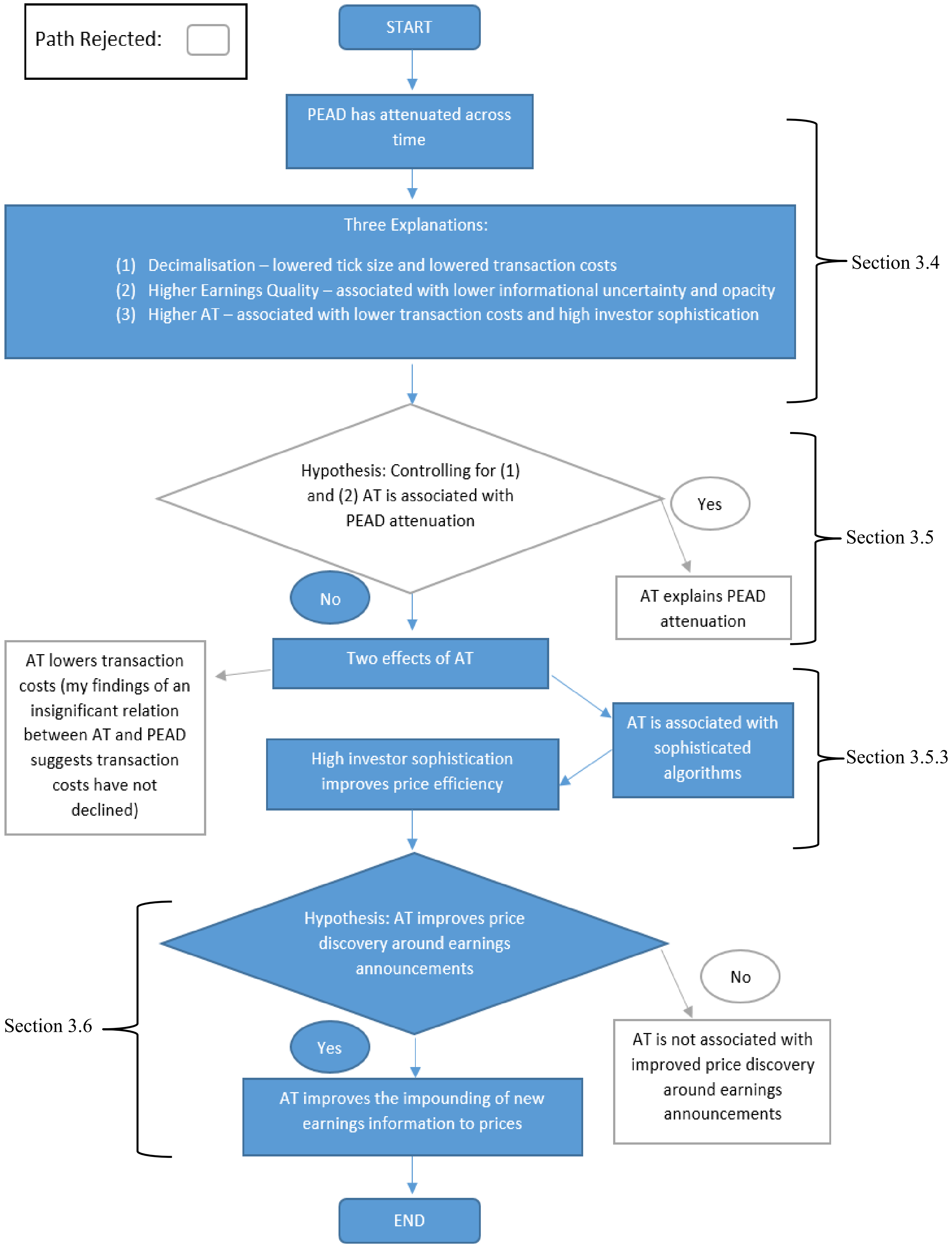
CHAPTER 3: DOES ALGORITHMIC TRADING ATTENUATE THE POST-EARNINGS ANNOUNCEMENT DRIFT?

3.1. Introduction

This chapter tests the relation between algorithmic trading (AT) and the post-earnings announcement drift (PEAD). "From a starting point of near zero in the mid-1990s" AT rose to 73% of trading volume in U.S. equity markets by 2009 (Hendershott, Jones and Menkveld, 2011, p.1) while over a similar sample period PEAD attenuated by more than 30% (see Section 3.4). Many studies suggest AT is associated with lower bid-ask spreads, improved price efficiency and sophisticated trading, which are also factors shown to lower PEAD effects. It therefore follows that AT and PEAD are potentially inversely related. Further, if sophisticated algorithmic traders are better at extracting trading signals from earnings information, price discovery is expected to improve. I therefore test the conjecture that the rise in AT may have attenuated PEAD, and that AT is associated with improvements in price discovery around earnings announcements.

My findings are summarised in the flow chart illustrated in Figure 3.1. A shaded box represents a statement or hypothesis consistent with my findings; a clear/non-shaded box represents a statement or hypothesis inconsistent with my findings. I begin my analysis by first documenting the attenuation of PEAD, which experienced significant structural decline in the early 2000s. I find the decline is concentrated among NYSE-listed firms and the attenuation exceeds 30%. I then present three explanations for the decline: 1) the phase-in of decimalisation (the reduction in minimum tick size completed in January 2001); 2) the structural improvement

Figure 3.1: Chapter 3 Flow Chart



in earnings quality in the early 2000s; and 3) the substantial increase in AT activity on the NYSE after May 2003. Decimalisation lowered transaction cost while a rise in earnings quality reduced informational uncertainty and opacity; a rise in AT is associated with declines in transaction costs and improvements in investor sophistication.

To formally test the relation between AT and PEAD controls are included for decimalisation and shifts in earnings quality. My method uses matched-sampling test procedures which remove the effects of decimalisation and time-trends in earnings quality; and I test whether differences in PEAD across matched pairs can be explained by differences in AT. My results find an insignificant relation (and therefore are inconsistent with studies suggesting AT lowers transaction costs).

In the second part of my analysis I suggest high investor sophistication and the use of sophisticated algorithms ought to improve price discovery. I suggest PEAD ought to be positively correlated to the proportion of price discovery left unrealised at earnings announcements and construct the Weighted Price Contribution (WPC) price discovery measure as a function of PEAD. I then test the impact of AT on the WPC measure and find price discovery improved by more than 12% after Autoquote was phased-in (referring to a change in the NYSE market microstructure completed in May 2003 that substantially increased the adoption of AT). My overall findings therefore suggest AT responds to earnings announcements not by way of attenuating PEAD effects but by improving the impounding of new trading signals to stock prices.

The rest of this chapter proceeds as follows. Section 3.2 presents the background to this study and Section 3.3 the data. Section 3.4 shows the structural decline in PEAD and Section 3.5 tests the relation between AT, PEAD and the immediate market response to earnings surprise.

Section 3.6 then tests the association between AT and price discovery around earnings announcements. Section 3.7 concludes this chapter.

3.2. Background

Studies generally find AT improves liquidity, lowers transaction costs[39] and improves price discovery. This can be explained by factors such as the associated increase in competition among sophisticated traders to supply liquidity and the reduction in price impact from order-splitting. A substantial proportion of AT originates with sophisticated institutional participants owing to the complexities and sophistication required for implementing AT. These participants process large quantities of order-flow information as well as execute high volume of orders (see Foucault, 1999; Foucault, Roell and Sandas, 2003; Rosu, 2009). Low transaction cost and high investor sophistication are also explanations for reduced PEAD effects as lower frictions encourage mispricing to be traded away while sophisticated investors are less prone to behavioural bias.

3.2.1. Algorithmic Trading

AT is defined as the "use of mathematical models, computers and telecommunication networks to automate the buying and selling of financial securities" (Kirilenko and Lo, 2013, p.52). Sophisticated market participants employ AT to improve order execution quality and lower price impact. A subset of AT is high frequency trading (HFT) which is typically associated with low latency and the fast execution of orders so as to profit from small market

[39] 'Transaction cost' can be defined as "all costs incurred in financial trading, including execution cost, commissions and rebates, information technology costs and other costs" (Brogaard, Hendershott, Hunt and Ysusi, 2014). However I do note a large proportion of transaction cost is "execution cost", or what Brogaard et al. (2014) define as "the market-adjusted execution shortfall, the volume-weighted percentage difference between the price available in the market when brokers receive institutional orders and the price at which the order is executed". The quoted bid-ask spread or the effective spread are, for example, measures of execution costs and often used as proxy for transaction costs.

discrepancies (Brogaard, 2010; Chlistalla, Speyer, Kaiser and Mayer, 2011).[40] Hirschey (2016) finds approximately 40% of trades on Nasdaq are HFT-driven.

In theory AT can narrow or widen the bid-ask spread.[41] For example, posting a resting order in a limit order book generates a "winner's curse" problem as orders can quickly become stale once new information arrives (Foucault, 1999; Hoffman, 2009; Boehmer and Kelly, 2009). Informed traders employing AT can therefore quickly pick off the stale orders and thus liquidity providers seeking to avoid adverse selection will quote a wider spread (see Bagehot, 1971; Barclay, Hendershott and McCormick 2003; Foucault, Roell and Sandas, 2003). Alternatively, liquidity providers may employ AT to effectively mitigate winners curse costs by swiftly cancelling stale orders; this conversely results in narrower spreads (assuming quote-based competition among liquidity providers).

Empirical evidence suggests higher levels of AT are associated with narrower spreads (Dutta and Madhavan, 1997; Bessimbinder, 2003a and 2003b; Hendershott and Riordan, 2013).[42] For example, Hendershott and Riordan (2013) examine the largest stocks on the Deutsche Bourse where AT is responsible for more than half of all market and limit orders. They show AT activity is inversely correlated to effective and quoted spreads. Menkveld (2013) also finds spreads declined by as much as 50% following new HFT entrants into a new Dutch equities exchange. Hirschey (2016) argues algorithmic liquidity provision has lower marginal costs and significant discount in trading commission relative to other market participants. Finally,

[40] Hasbrouck and Saar (2013) note AT can be partitioned into: 1) agency algorithms which intelligently split large orders; and 2) proprietary algorithms that scan for changes across the entire market's order book. The former represents the use of AT by portfolio managers and brokers to improve execution quality and reduce price impact (such as implementing order-splitting algorithms) while the latter represents HFT participants which profit from price inefficiencies. An additional characteristic of HFTs is they generally trade with their own capital, generate a large amount of message traffic and turnover, and are reluctant to hold inventory overnight (Hasbrouck and Saar, 2013).

[41] Jovanovic and Menkveld (2011) argue that theoretically HFT traders can exert both positive and negative welfare effects as a result of competition in informational and speed advantages.

[42] The evidence is that the relationship between quote-based competition and lower execution costs is weaker for Nasdaq relative to NYSE stocks. One reason is preferencing agreements on Nasdaq that do not enforce price-time priority (Dutta and Madhavan, 1997; Huang and Stoll; Bessimbinder, 2003a and 2003b).

Hendershott, Jones and Menkveld (2011) show the introduction of the Autoquote system to the NYSE also significantly improved spreads for large-cap stocks, but had insignificant impact on small-cap stocks (because AT is concentrated among large-cap stocks with high liquidity and high institutional participation).

The sophistication of AT in processing high quantities of market information efficiently is viewed to be beneficial to investors. AT has been shown to lower liquidity providers' monitoring costs; improve the management of capital and inventory constraints; reduce latency-sensitive execution risks as well as reduce the price impact of informed trades[43] (see Boehmer, 2005; Javanovic and Menkveld, 2011; Comerton-Forde, Hendershott, Jones, Moulton and Seasholes, 2010; Hendershott and Riordan, 2013; Menkveld, 2013; Brogaard and Hendershott, 2013; Hoffman, 2008; and Back and Baruch, 2007). Hirschey (2016) also note news agencies are increasingly providing machine-readable news specifically for algorithmic traders and therefore it is argued AT can remove the traditional trade-off between execution speed and execution cost/quality (Boehmer, 2005; Engle, Ferstenberg and Russell, 2006; Riordan and Stockenmaier, 2011). Algorithmic traders can also swiftly (sometimes in milliseconds) identify and respond to new market information and then update their strategies accordingly (Hendershott and Riordan, 2013; Hasbrouck and Saar, 2013). Given the associated combination of efficient and low-cost execution (Riordan and Stockenmaier, 2011) it is also

[43] The evidence suggests that technological advancement among financial market and trading participants has seen AT rise sharply on a global scale (Boehmer, Fong and Wu, 2015). The ability to craft varied and individualised algorithms that are both selective and specific in the search for and processing of information makes it a desirable tool for automating the trading process. Hendershott et al. (2011) explain that the precise motivation underlying electronic submission of orders is dependent on the type of market participant: "there are many different algorithms, used by many different types of market participants. Some hedge funds and broker-dealers supply liquidity using algorithms, competing with designated market makers and other liquidity suppliers…For assets that trade on multiple venues, liquidity demanders often use smart order routers to determine where to send an order…Statistical arbitrage funds use computers to quickly process large amounts of information contained in the order flow and price moves…Last but not least, algorithms are used by institutional investors to trade large quantities of stock gradually over time." (p. 2)

argued that trader sophistication and competitiveness increase considerably with the adoption of AT and the cost of *not* employing AT is significant. Therefore rational incentives exist for institutional traders to implement new AT technologies (McInish and Upson, 2012; Moallemi and Saglam, 2011).[44]

AT mostly originates from sophisticated institutional investors. The implementation of AT is complex, requiring significant resources, on-going development and know-how (see Sadoghi, Labrecque, Sing, Shum and Jacobsen, 2010; Hendershott et al., 2011). For example, one dominant feature of AT is the access to remote, rather than physical, execution venues (Chlistalla, 2011). Monitoring and executing across multiple venues dynamically requires the integration of computer hardware, software and network services along with the formulation of AT strategies. It is therefore common for AT to originate from participants that can effectively combine electronic order generation and routing with intelligent decision processing and quantitative analysis (Kirilenko and Lo, 2013). Hence, while AT can improve productivity, reduce human error and make possible fundamentally different trading strategies beyond the abilities of human traders, implementation of AT is concentrated among sophisticated institutional traders (see Kirilenko and Lo, 2013 Gsell and Gomber, 2006; Hoffman, 2014). In some cases, execution of AT also requires regulatory/exchange approvals which are generally issued to well-resourced and sophisticated financial institutions (Chlistalla, 2011).

Lastly, algorithmic traders generally improve price efficiency.[45] AT is associated with a

[44] I also note the critique that excessive adoption of AT by market participants can also potentially generate negative externalities (Gai et al, 2013).

[45] I do note some studies suggest improvements in liquidity associated with AT can periodically be illusory. For example, algorithmic traders' behaviour can be opportunistic if they do not have an obligation to constantly maintain provision of liquidity. For example, Kirilenko, Kyle, Samadi and Tuzun (2016) show for the E-mini S&P 500 futures during the Flash Crash of May 6th, 2010 HFTs either withdrew liquidity provision or became liquidity demanders. O'Hara and Easley et al. (2011) show high levels of price taking and adverse selection caused

reduction in average trade size but increased turnover (Hendershott and Riordan, 2009; Jovanovic and Menkveld, 2016) and this implies markets exhibit more price continuity in the sense that individual trades have less price impact (Black, 1971; Keim and Madhavan, 1996 and 1997). Brogaard, Hendershott and Riordan (2014) show using transaction level data from Nasdaq that in general HFT facilitates price discovery by trading towards permanent price changes and away from transitory pricing errors, while Hirschey (2016) finds HFTs are more skilled than other market participants in anticipating short term order-flow. Hendershott and Riordan (2013) also find algorithmic traders' order placements in the Deutsche Börse are a function of efficient liquidity demand and supply strategies. In other words, on a continual basis they tend to initiate more market orders when spreads are narrow but submit new limit orders when spreads widen, facilitating price efficiency and price discovery.

3.2.2. PEAD, Transaction Costs and Investor Sophistication

PEAD is one of the oldest financial anomalies and imply investors under-react to earnings news (Ball and Brown, 1968). The magnitude of under-reaction is positively correlated to standardized earnings surprise (Bernard and Thomas, 1989). Two factors that have robust explanatory power for reduced PEAD effects are low transaction costs and improvements in investor sophistication.

Liquidity providers impose transaction costs in the form of the bid-ask spread on market participants as they face time-varying liquidity and asymmetric information (O'Hara, 2003). In the context of PEAD Ng et al., (2008) show the presence of the bid-ask spread implies both existence and persistence of investor under-reaction. To illustrate using a standard market

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the withdrawal of HFT liquidity provision in the hours preceding the Flash Crash. Nevertheless Hasbrouck and Saar (2010) find despite fleeting liquidity by HFT and high cancellation rates of limit orders, low-latency trading is on average correlated with improved market quality. Chaboud, Chiquoine, Hjalmarsson and Vega (2014) also show, using data from the foreign exchange market, that despite withdrawing activity prior to expected macroeconomic news announcements algorithmic traders re-enter the market and increase the supply of liquidity in the hours immediately following news release.

microstructure framework where one rational arbitrageur interacts with one market maker, assume a stock's fundamental value increases from \$50 to \$55 per share (due to positive earnings news) and the expected transaction cost is the bid-ask spread of \$2 (i.e., the pre-announcement bid and ask are \$49 and \$51, respectively). The rational arbitrageur will then place bids with the market maker up to \$53 per share; any bid orders above this price have negative expected return because of the \$2 transaction cost. It therefore follows a cost-induced upper bound impedes the full impounding of earnings news to the stock price.

Transaction costs can also explain the persistence of PEAD. Applying the same example above, consider firm news arriving to the arbitrageur during the post-announcement period. For simplicity assume 50% of the time the arbitrageur receives good news (reflecting an increase of \$2 per share in the stock's fundamental value) and 50% of the time the information received is bad news (reflecting a decrease of \$2 per share). The expected value of the post-announcement news therefore continues to be zero. With good news, the stock's fundamental value rises from \$55 to \$57 and it is therefore profitable for the arbitrageur to trade up to \$55. With bad news the arbitrageur refrains from trading and the stock price remains at \$53. On average the stock price will therefore drift towards 50% × \$55 + 50% × \$53 = \$54. It follows, iteratively, as more news arrives the price converges towards the fundamental value.

Transaction cost may have a relatively small effect on equilibrium risk premiums but lower transaction cost enables more efficient asset allocation among heterogeneous investors and facilitates the sharing of risk (Amihud and Mendelson, 1986 and 1988; Brennan and Subrahmanyam, 1996; Brennan, Chordia and Subrahmanyam, 1998; Chordia, Roll and Subrahmanyam, 2001; Pastor and Stambaugh, 2001; Hasbrouck, 2009; O'Hara, 2003, Constantinides, 1986; Heaton and Lucas, 1996; Vayanos, 1998). Many studies argue a substantial decline in transaction cost therefore ought to encourage the trading away of market mispricing (see Jensen, 1978; Bhardwaj and Brooks, 1992; Lesmond, Schill and Zhou, 2004;

Shleifer and Vishny, 1997) and Chordia, Subrahmanyam and Tong (2014) find the general decline in transaction costs over the past two decades has contributed to the attenuation of numerous financial anomalies.

The second factor that explains PEAD is that unsophisticated investors tend to under-react to earnings news. Consistent with research in behavioural economic studies show investors are prone to behavioural bias in the form of naive expectations of future earnings (Bernard and Thomas, 1989 and 1990) and conservatism (over-confidence) towards public news (private news) (Barberis, Shleifer and Vishny, 1998; Daniel, Hirshleifer and Subrahmanyam, 1998). For example, Kaniel, Liu, Saar and Titman (2012) show individual/retail traders are 'news-contrarian' and hence slow down price adjustments to earnings surprise. In contrast, institutional participants are on average sophisticated participants (Bartov et al., 2000; Campbell et al., 2009) and the empirical evidence finds overall institutional investors correctly predict the direction of earnings surprise (Ke and Ramalingegowda, 2005; Campbell, et al., 2009). Another proxy for increased sophistication is analyst coverage. First, analysts are incentivised by both career advancement and reputation to provide accurate information to both current as well as prospective shareholders. Second, they are informed participants due to their analytical ability and personal access to company managers (see Lim, 2001). Brown and Han (2000) also demonstrate empirically that the number of analysts following a stock is inversely correlated to the magnitude of PEAD. I note analysts often occupy positions in sophisticated investment banks (which give incentives in the form of betterremuneration, reputation and career advancement) (Hong and Kubik, 2003; Clement, 1999) and such institutions are generally major generators of AT. Hence AT may also proxy high sophistication due to its association with sophisticated analysts.

3.3. Data

My sample data obtains for each firm-quarter earnings announcement the associated PEAD, level of AT activity and other firm-quarter characteristics. To compute PEAD I follow Hirshleifer et al. (2009) and use the CRSP-Compustat merged database and the I/B/E/S database.[46] CRSP provides daily stock price data, the Compustat data provides quarterly accounting filings, and I/B/E/S data contains quarterly analyst forecast and earnings announcement information[47].

My sample covers the period 1st July 1995 to 30th June 2011. I select only data after 1994 as it has shown to be robust for event studies (Hirshleifer et al., 2009; DellaVigna and Pollett, 2009). I select from the CRSP-Compustat merged data all firms with primary stock listing on the NYSE, AMEX and Nasdaq. Closed-end funds, Real Estate Investment Trusts, American Depository Receipts and foreign stocks are excluded.[48] The sample data is then matched to the I/B/E/S dataset via a CRSP-Compustat-I/B/E/S matching procedure provided by the Wharton Research Data Service. Berkman and Truong (2009) show a substantial number of earnings announcements are made after trading hours and therefore immediate price response may only be impounded to stock price on the next trading day. To control for this forward-looking bias, all announcements made after 4:00pm are assumed to be made the following trading day.[50] I then remove the following observations: 1) firm-quarter observations with less than \$5 million in market capitalisation (Mendenhall, 2004); 2) firms with stock prices less than \$1 before stock-split adjustment (Hirshleifer et al., 2009); and 3) firm-quarter observations whereby the

[46] Obtained from the Wharton Research Data Service.
[47] I/B/E/S contains data collected every third Thursday of the calendar month from analysts giving forecasts to the next quarter's corporate earnings.
[48] I select for CRSP stock codes 10 and 11.
[50] If there is a discrepancy of announcement time between Compustat and I/B/E/S I select the earlier of the two dates (DellaVigna and Pollet, 2009).

actual or median earnings per share forecast is higher than the stock price (Hirshleifer et al., 2009).

It should be noted that many studies of PEAD restrict sample selection to only NYSE- and AMEX-listed firms (see Bernard and Thomas, 1989 and 1990; Bhushan, 1994; Bartov et al., 2000; and Ng et al., 2008) however I retain stocks listed on the Nasdaq (in contrast to Chapter 2) as I use Nasdaq firms as a control group for my statistical tests.

For data on AT I obtain the Autoquote phase-in schedule and construct proxies for AT activity. Each NYSE stock has a specific date for the phasing-in of Autoquote and I obtain this list from Hendershott's website.[51] The list includes the NYSE listing codes which I use to obtain U.S. intraday trade and quote data from Thomson Reuters Tick History (TRTH).[52] I use the TRTH data to infer AT activity at the firm-level. The data is organised by Reuters Instrument Code (RIC) and each RIC is associated with an equity or derivative instrument. For each NYSE-listed common stock, I obtain from SIRCA the RIC codes, the NYSE listing codes and consolidated time-stamped trade and quote data. The data records every order placed at the inside quote which updates the National Best Bid and Offer (NBBO). I then apply the following filters:

1. Remove irregular trades based on some technical conditions in the TRTH "qualifiers" data field following Boehmer, Fong and Wu (2015) (see Section C.2 in the Appendix).
2. Require all traded price, traded volume, bid price, bid volume, ask price and ask volume data fields to be greater than zero.
3. The ask price must be greater than the bid price.
4. All intraday trade and quote observations must be between 9:35am and 3:55pm.

[51] http://faculty.haas.berkeley.edu/hender/.
[52] Provided by the Securities Industry Research Centre of Asia-Pacific (SIRCA).

To compute the level of AT activity I then follow Hendershott et al. (2011) and Boehmer et al. (2014) and take the negative of volume divided by the total number of messages. Hence for each stock *i* and trading day *t*:

$$AT_{i,t} = \frac{Turnover_{i,t}}{-100 * (NoTrades_{i,t} + NoQuote_{i,t})} \tag{3.1}$$

Where $Turnover_{i,t}$ is the daily dollar volume, $NoTrades_{i,t}$ is the number of trades and $NoQuote_{i,t}$ is the number of quote updates at the NBBO.

To measure earnings surprise (ES), following Chapter 2 I calculate ES by the standardized analyst forecast-error: $ES_{i,q} = \frac{Actual_{i,q} - MedForecast_{i,q}}{Price_{i,q}}$ where for firm *i* in quarter q, $ES_{i,q}$ is earnings surprise, $Actual_{i,q}$ is the announced earnings per share[53], $MedForecast_{i,q}$ is the median of analyst forecasts[54] and $Price_{i,q}$ is the price per share reported at the end of the quarter (I note $q \in \{1,2,\ldots,64\}$).[55] I also create quarterly ES quintiles $ES_{i,q}^{quintile} \in \{1,2,3,4,5\}$ based on break points in the previous calendar quarter and then scale the variable based on the following: $ES_{i,q}^{Scaled} = \left(\frac{ES_{i,q}^{quintile} - 1}{4} - 0.5\right)$. In other words the scaled ES has a min-max range of one unit (between -0.5 and $+0.5$).

I then measure PEAD by buy-and-hold abnormal returns (BHAR): $BHAR_{i,q,t} = \prod_n^N (1 + r_{i,q,t+n}) - \prod_n^N (1 + r_{i,t+n}^{MM})$ where for announcement date *t*, $r_{i,q,t}$ is the daily stock return (including dividends), $r_{i,t+n}^{MM}$ is the daily return of a market-adjustment portfolio, and *n* represents the holding period from the *n*th trading day after the date of announcement to the *N*th

[53] For $Actual_{i,q}$ I use the actual earnings data (primary earnings per share, excluding extraordinary items, adjusted for stock splits and dividends) from I/B/E/S. It should be noted that despite being in both Compustat and I/B/E/S the common practice is to take earnings data from I/B/E/S. The reason being that for some Compustat data earnings are restated after an announcement while in contrast I/B/E/S includes the originally stated reported earnings (see Livnat and Mendenhall, 2006; Bradshaw and Sloan, 2002).

[54] Using only the latest forecast for each analyst issued within the 90 days prior to the earnings announcement.

[55] Prices are adjusted for stock-splits.

trading day. In line with common practice I take n equal to 2 and N equal to 61. I also proxy the immediate market response to earnings news by the 3-days response (3DR) which is the BHAR from one trading day prior to earnings announcement to one trading day after (hence n equals -1 and N equals 1). For the market-adjustment portfolio in Section 3.4 I use the return on the S&P 500 index (including dividends); for the rest of this study I use a matched size and book-to-market portfolio.[56] The distribution of BHAR is assumed to have a mean of zero 3DR to fully reflect announcement surprise.

Following Chapter 2 I also include 13 factors as control variables (the construction of each factor is discussed in Section A.2 of the Appendix). Briefly, for firm i and quarter q the factors are:

1) $Insti_{i,q}$ the percentage of shares owned by institutional investors, proxying investor sophistication (Campbell et al., 2009)[57];

2) $Distract\_U_{i,q}$ the number of earnings announcements per trading day, proxying investor distraction (Hirshleifer et al., 2009);

3) $Analyst_{i,q}$ the number of analyst forecasts, proxying information diffusion (Brown and Han, 2000);

4) $Volatility_{i,q}$ the volatility of abnormal returns, proxying uncertainty (Gerard, 2012);

5) $ArbRisk_{i,q}$ the residual variance from the stock's one-factor market model regression,[58] proxying unhedgeable risk (Mendenhall, 2004);

6) $ExpRisk_{i,q}$ the explained variance from the stock's market model regression, proxying hedgeable risk (Mendenhall, 2004);

[56] Following Chapter 2 I use 5x5 size and BM matched portfolios and the data is obtained from Professor Kenneth French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data library.html.
[57] I obtain institutional ownership data from CDA Spectrum which contains Form 13F filings.
[58] The market model is the returns of the S&P 500 index (inclusive of dividends) adjusted for the risk-free rate.

7) $Illiq_{i,q}$ the Amihud (2002) illiquidity factor, proxying stock illiquidity (Sadka, 2006);

8) $Spread_{i,q}$ the average bid-ask spread at close, proxying direct transaction cost (Ng et al., 2008);

9) $Price_{i,q}$ the end-of-quarter stock prices, proxying trading commissions (Blume and Goldstein, 1992);

10) $Turn_{i,q}$ the average daily dollar volume of shares traded, proxying indirect trading costs and order processing costs (Bhushan, 1994);

11) $Mcap_{i,q}$ the market capitalisation, proxying size effects (Foster, et al., 1984; Bernard and Thomas, 1989);

12) $BM_{i,q}$ the book-to-market ratio, proxying informational opacity (Yan and Zhao, 2011); and

13) $Mom_{i,q}$ the cumulative abnormal return for the 40 days prior to earnings announcement, proxying momentum effects (Vega, 2006).

3.3.1. Summary Statistics

The summary statistics are presented in Table 3.1. For the sample period 1st July 1995 to 30th June 2011 the number of firm-quarter observations is 130,494. Due to the inclusion of Nasdaq earnings announcements this is approximately double the number of observations in Chapter 2. The mean and median of market capitalisation is \$5.066 billion and \$0.723 billion, respectively (the 25th percentile is \$227 million and the 75th percentile is \$2.689 billion). Mean of daily stock turnover is \$8.71 million and the 25th and 75th percentiles are \$10,000 and \$7.00 million respectively. The 25th and 75th percentiles of stock price are \$11.25 and \$35.37. These values are generally smaller compared with Chapter 2 and are consistent with the literature.

The summary statistics imply Nasdaq stocks tend to have on average lower liquidity, lower analyst coverage, higher book-to-market ratio and higher volatility.

I also break down the summary statistics by before and after the completion of Autoquote on 27 May 2003. Table 3.2 shows that across both good and bad news the most noticeable shift following Autoquote is the decline in the bid-ask spread. Average spreads for good (bad) news declined from 230 (254) basis points to 50 (63) basis points. This reflects the reduction in tick-size (the NYSE reduced tick-size in 1997 from one-eighth of a dollar to one-sixteenth; and then a further reduction to 1 cent via decimalisation in 2001). Improvements in the Amihud (2001) liquidity measure accompanied the reduction in spreads.

I note across both high and low ES quintiles PEAD attenuated. While PEAD averaged 1.78% (-2.81%) before May 2003, after the phase-in of Autoquote PEAD declined to 1.55% (-1.75%). Thus the difference between good and bad news PEAD declined by a third (from 4.59% to 3.30%). Noticeably, the immediate earnings response as proxied by 3DR grew from 2.92% (-2.41%) for good (bad) news before Autoquote to 4.01% (-3.78%), a rise of nearly 50% in the range between good and bad news (from 5.38% to 7.79%). The attenuation of PEAD and accentuation of 3DR is consistent with the effects of lower transaction costs and higher investor sophistication. It is also noticeable that these changes are accompanied by an increase in ES (as shown in the first row of Table 3.2) which suggests the quality of earnings information may have improved (potentially, earnings information became more informative or firms disclosed a larger proportion of news during announcement periods).

Table 3.1: Summary Statistics

The below values are computed summary statistics across NYSE, AMEX and Nasdaq firms in the period July 1995 to June 2011. For firm i in quarter q the variables are: earnings surprise ($ES_{i,q}$); institutional ownership ($Insti_{i,q}$); number of announcements released on the same day ($Distract\_U_{i,q}$); number of analysts issuing forecasts within the 90 days prior to earnings announcement ($Analyst_{i,q}$); volatility of daily BHAR in the 40 trading days prior to earnings announcement ($Volatility_{i,q}$); arbitrage risk ($ArbRisk_{i,q}$); hedgeable risk ($ExpRisk_{i,q}$); average of Amihud illiquidity measured across 40 trading days prior to earnings announcement ($Illiq_{i,q}$); average of quoted spread at closing across 40 trading days prior to earnings announcement ($Spread_{i,q}$); stock price at the end of the quarter q ($Price_{i,q}$); average daily turnover (in millions of dollars) measured from 271 trading days to 22 trading days prior to earnings announcement ($Turn_{i,q}$); market capitalisation ($Mcap_{i,q}$); book-to-market ratio ($BM_{i,q}$); BHAR across 40 trading days prior to earnings announcement ($Mom_{i,q}$); BHAR from the 2nd to the 61st trading day after earnings announcement ($PEAD_{i,q}$); and BHAR from the 1st trading day before earnings announcement to the 1st trading day after earnings announcement ($3DR_{i,q}$).

	mean	std	1st	25th	median	75th	99th
$ES_{i,q}$	-0.0027	0.0811	-0.07494	-0.00054	0.000366	0.00186	0.0321
$Insti_{i,q}$	0.57	0.25	0.04	0.39	0.60	0.77	0.98
$Distract\_U_{i,q}$	114.62	118.34	4	22	62	150	316
$Analyst_{i,q}$	5.21	5.06	1	2	3	7	24
$Volatility_{i,q}$	0.025	0.017	0.0065	0.014	0.021	0.032	0.086
$ArbRisk_{i,q}$	0.020	0.044	0.00135	0.0055	0.011	0.023	0.127
$ExpRisk_{i,q}$	0.00341	0.00625	1.44×10^{-6}	0.00042	0.00132	0.00362	0.0312
$Illiq_{i,q}$	0.278	2.43554	2.79×10^{-5}	0.000917	0.005616	0.039624	5.2755
$Spread_{i,q}$	0.0109	0.016032	0.000216	0.001432	0.005167	0.014312	0.07073
$Price_{i,q}$	25.91	19.78	1.68	11.25	21.5	35.37	92.62
$Turn_{i,q}$	8.71	24.35	0.00031	0.01	0.92	7.00	447.66
$Mcap_{i,q}$	5,066	19,389	24.96	227	723	2,689	83,090
$BM_{i,q}$	0.65	0.93	0.049	0.30	0.49	0.78	3.44
$Mom_{i,q}$	-0.00388	0.183	-0.429	-0.0894	-0.0105	0.0688	0.537
$PEAD_{i,q}$	-0.00466	0.218	-0.504	-0.110	-0.0140	0.0839	0.661
$3DR_{i,q}$	0.00231	0.0835	-0.233	-0.0341	0.00068	0.0381	0.244
Number of Observations	130,494						

Table 3.2: Pre- vs Post-Autoquote: Mean Values across Earnings Surprise Quintiles before and after 27 May 2003

The below values are computed summary statistics across NYSE, AMEX and Nasdaq firms in the period July 1995 to June 2011. The values are presented across ES quintiles for before and after 27th May 2003. For firm *i* in quarter *q* the variables are: earnings surprise ($ES_{i,q}$); institutional ownership ($Insti_{i,q}$); number of announcements released on the same day ($Distract\_U_{i,q}$); number of analysts issuing forecasts within the 90 days prior to earnings announcement ($Analyst_{i,q}$); volatility of daily BHAR in the 40 trading days prior to earnings announcement ($Volatility_{i,q}$); arbitrage risk ($ArbRisk_{i,q}$); hedgeable risk ($ExpRisk_{i,q}$); average of Amihud illiquidity measured across 40 trading days prior to earnings announcement ($Illiq_{i,q}$); average of quoted spread at closing across 40 trading days prior to earnings announcement ($Spread_{i,q}$); stock price at the end of the quarter *q* ($Price_{i,q}$); average daily turnover (in millions of dollars) measured from 271 trading days to 22 trading days prior to earnings announcement ($Turn_{i,q}$); market capitalisation ($Mcap_{i,q}$); book-to-market ratio ($BM_{i,q}$); BHAR across 40 trading days prior to earnings announcement ($Mom_{i,q}$); BHAR from the 2nd to the 61st trading day after earnings announcement ($PEAD_{i,q}$); and BHAR from the 1st trading day before earnings announcement to the 1st trading day after earnings announcement ($3DR_{i,q}$).

	Before 27th May 2003					After 27th May 2003				
ES Quintile	Bad News	2	3	4	Good News	Bad News	2	3	4	Good News
$ES_{i,q}$	-0.0145	-0.00017	0.00037	0.00118	0.00843	-0.03693	-0.00056	0.000587	0.001952	0.0131
$Insti_{i,q}$	0.43	0.52	0.60	0.54	0.45	0.56	0.65	0.71	0.68	0.61
$Distract\_U_{i,q}$	98.60	113.13	119.82	116.61	109.90	114.19	114.04	117.35	122.27	121.21
$Analyst_{i,q}$	3.50	5.20	6.20	4.84	3.56	4.20	6.20	7.43	6.41	4.78
$Volatility_{i,q}$	0.033	0.0267	0.0245	0.0268	0.0322	0.0280	0.0195	0.0174	0.0197	0.0257
$ArbRisk_{i,q}$	0.026	0.0166	0.0150	0.0192	0.0277	0.0260	0.0149	0.0113	0.0161	0.0263
$ExpRisk_{i,q}$	0.0025	0.0020	0.0021	0.0021	0.00262	0.0052	0.0036	0.003	0.0042	0.0060
$Illiq_{i,q}$	0.694	0.205	0.0392	0.141	0.578	0.509	0.089	0.046	0.103	0.348
$Spread_{i,q}$	0.0254	0.016094	0.01066	0.0153	0.0230	0.0063	0.0029	0.0019	0.0026	0.0050
$Price_{i,q}$	17.40	28.67	40.19	28.47	18.87	16.59	28.43	36.53	28.41	18.80
$Turn_{i,q}$	0.091	0.274	0.485	0.211	0.087	0.212	0.488	0.700	0.544	0.282
$Mcap_{i,q}$	1,645	6,324	9,947	3,611	1,463	2,019	6,943	10,313	6,555	2,819
$BM_{i,q}$	0.78	0.53	0.43	0.58	0.80	0.88	0.55	0.50	0.60	0.85
$Mom_{i,q}$	-0.049	-0.017	0.0106	0.0126	0.018	-0.020	-0.013	0.0012	0.0069	0.0197
$PEAD_{i,q}$	-0.0281	-0.0141	-0.0003	0.00106	0.0178	-0.0175	-0.0098	-0.0075	-5.20×10^{-5}	0.0155
$3DR_{i,q}$	-0.0241	-0.0066	0.0061	0.0155	0.0292	-0.0378	-0.0179	0.0034	0.0198	0.0401
Number of observations	13,023	15,536	9,868	12,797	12,663	13,183	14,403	12,257	13,407	13,357

3.4. The Attenuation of PEAD

I now demonstrate that PEAD has attenuated across time and identify three market features that can explain the decline: 1) the introduction of decimalisation (completed in April 2001); 2) the phase-in of Autoquote on the NYSE (completed in May 2003); and 3) a substantial rise in earnings quality in the early 2000s.

Decimalisation refers to the reduction of minimum trade tick-size on both the NYSE and the Nasdaq from fractional pricing to one cent.[61] Bessimbinder (2003b) finds decimalisation resulted in a significant improvement in liquidity via the reduction in quoted and effective spreads for large cap, high liquidity and NYSE stocks (however results were mixed for small cap, medium cap and Nasdaq stocks). Autoquote refers to the NYSE implementing the electronic dissemination of order-book updates (which significantly increased the advantage and use of AT);[62] and Hendershott et al. (2011) find Autoquote resulted in a significant decline in effective spreads. Boehmer (2005) states both decimalisation and Autoquote are "structural changes [that] could have substantial effects on relative execution costs" (p.556).

The early 2000s also saw substantial improvements in earnings quality which Ball and Shivakumar (2008) represents as a "sharp increase" (p.978) in the proportion of total annual firm-news released around earnings announcements. The authors suggest this is largely attributable to the increased monitoring of financial reporting by auditors, internal auditors,

[61] NYSE stocks were phased in from 28th August 2000 to 29th January 2001; Nasdaq stocks were phased in from 12th March 2001 to 9th April 2001.

[62] The phase-in of the NYSE Autoquote began on 29th January 2003 for six large-cap stocks. Over 200 additional stocks were phased in over the next two months and the remaining stocks phased in on 27th May, 2003. Autoquote refers to the NYSE updating the limit order book in real-time and disseminating the inside quote electronically. This gave algorithmic traders an advantage as the improvement gave immediate feedback about the potential terms of trade and was unlikely to directly affect the trading behaviour of slower-reacting humans. Prior to its introduction NYSE specialists also manually disseminated the inside quote for the equities market. However, market depth declined sharply following decimalisation while tick-size narrowed. This greatly increased the number of order book updates and hence made excessively onerous the specialist's role of manually managing the order book.

boards as well as the financial media, improving the detection of low-quality financial reporting. It is also associated with increased financial reporting quality due to "changed manager and auditor incentives after Enron/Sarbanes-Oxley" (p. 978). In a separate study Anilowski, Feng and Skinner (2007) find the early 2000s saw listed U.S. firms increasingly release management's forward earnings guidance concurrently with earnings announcements.

Studies find PEAD attenuates with lower transaction cost, lower structural uncertainty and higher investor sophistication (Vega, 2006; Ng et al., 2008; Campbell et al., 2009) and therefore the above factors indicate PEAD may have attenuated; and 3DR may have grown (or *accentuated*). To formally test this hypothesis I conduct a time-dummy test and assess whether the returns of a PEAD-based investment strategy significantly declined after July 2003. Consistent with Chapter 2 I measure PEAD following Barber and Lyons (1998): $BHAR_{i,q,t} = \prod_{n=2}^{61}(1 + r_{i,q,t+n}) - \prod_{n=2}^{61}(1 + r_{i,t+n}^{MM})$ and for the adjustment-portfolio $r_{i,t+n}^{MM}$ I use the daily returns of the S&P 500 Index (inclusive of dividends). This follows Berkman and Koch (2015) and implicitly assumes traders hedge with the market portfolio. I proxy quarterly returns of the investment strategy $PEAD_q$ by the difference in mean $BHAR_{i,q,t}$ between the highest and lowest ES (which simulates taking a long position on good news and a short position on bad news):

$$PEAD_q = \left(\sum_{g=1}^{G(q)} BHAR_{g,q,t}^{good} / G_q\right) - \left(\sum_{b=1}^{B(q)} BHAR_{b,q,t}^{bad} / B_q\right) \qquad (3.2)$$

Where for quarter q, $G_{(q)}$ is the number of stocks in the highest ES quintile and $B_{(q)}$ is the number of stocks in the lowest ES quintile. Following Berkman and Koch (2015) I run the following regression specification:

$$PEAD_q = \beta_0 + \beta_1 TimeDummy_q + \beta_2 AggLiq_q + \beta_3 VIX_q$$
$$+\beta_4 RecessionDummy_q + \varepsilon_q \qquad (3.3)$$

Where $TimeDummy_q$ is a time dummy variable equal to 1 for all quarters after 30th June 2003 and zero otherwise; $AggLiq_q$ is the quarterly average of the aggregate market liquidity factor in quarter q following Pastor and Stambaugh (2003);[63] VIX_q is the quarterly average of the CBOE VIX Index and proxies for market-wide uncertainty; and $RecessionDummy_q$ is equal to 1 if the quarter is in a recession (defined by NBER) and zero otherwise.[64] The specification therefore tests for whether average returns of a long-short PEAD strategy changed after controlling for general shifts in market condition as proxied by market liquidity and market uncertainty. A decline in PEAD suggests β_1, which measures the shift in PEAD after July 2003, ought to be negative. And under tests where the dependent variable is quarterly 3DR, β_1 ought to be positive if earnings quality improved.

3.4.1. Results

I first conduct separate regressions for NYSE and non-NYSE firms as Autoquote was NYSE-specific and Bessimbinder (2003b) finds the effects on liquidity due to decimalisation were substantially weaker for Nasdaq stocks. Consistent with this cross-exchange variation my results show a significant reduction in PEAD for NYSE but not for non-NYSE firms. In Panel A of Table 3.3 the right column displays the estimated coefficient for the intercept and time dummy to be 0.0679 and -0.0272 respectively (excluding the aggregate liquidity factor $AggLiq_q$ as control variable), which suggests PEAD for NYSE stocks declined from an average of 6.79% (significant at the 1% level) by 2.72% (significant at the 5% level). Looking at the estimated coefficient of the control variables, the proxy for market uncertainty VIX_q is -0.00031 (insignificant at the 10% level) and suggests a rise in market uncertainty is inversely

[63] Data on Pastor and Stambaugh (2003) liquidity factors are obtained from Lubos Pastor's website: http://faculty.chicagobooth.edu/lubos.pastor/research.

[64] Recession data obtained from the National Bureau of Economic Research (NBER): http://www.nber.org/cycles/cyclesmain.html.

correlated to PEAD. This is inconsistent with the view that structural uncertainty increases PEAD however I note the results must be interpreted in light of the recession dummy $Recessiondummy_q$ (which also proxies for elevated uncertainty) and suggests PEAD is 2.47% larger in recession periods. I also note the estimated coefficient for the control variables are all statistically insignificant. Next, the results show that including $AggLiq_q$ as a control does not change my main finding: the magnitude of $\hat{\beta}_1$ remains almost unchanged, although the significance of $\hat{\beta}_1$ declines from the 5% to 10% level. (However in robustness tests reported in Sections B.1, B.2 and B.3 in the Appendix I find improved statistical significance). Further, the estimated coefficient of $AggLiq_q$ is negative which is consistent with the expected inverse relationship between PEAD and liquidity (Sadka, 2006). One interpretation of these results is therefore that PEAD has declined but a large proportion of the attenuation remains unexplained by improvements in aggregate market liquidity.

Panel B of Table 3.3 then shows results for non-NYSE listed firms and shows PEAD returns are 4.50% before July 2003 and declined by one-sixth after July 2003 (but are statistically insignificant at the 10% level); and similar to Panel A the estimated coefficients for all other control variables are insignificant. The sign of the estimated coefficient for VIX_q is 0.00038 and suggests higher market uncertainty is correlated to higher PEAD; and the estimated coefficient for $RecessionDummy_q$ suggests PEAD is 1.75% higher during periods of recession. My overall findings for NYSE and non-NYSE firms is therefore consistent with the literature as Autoquote is specific to NYSE stocks and Bessimbinder (2003b) shows that, unlike the NYSE, decimalisation was overall weak or insignificant on the improvement in liquidity for non-NYSE firms (other than large and high liquidity stocks). While my results cannot imply AT did not increase for non-NYSE stocks, the results are consistent with NYSE

Table 3.3: Regression of Quarterly Hedge Portfolio Returns – Autoquote Structural Break

I test the change in PEAD and 3DR after 30th June 2003. The table show regression results for the following specification $PEAD_q = \beta_0 + \beta_1 TimeDummy_q + \beta_2 AggLiq_q + \beta_3 VIX_q + \beta_4 RecessionDummy_q + \varepsilon_q$ where for quarter q $PEAD_q$ is the difference in mean of $BHAR_{i,q}$ between the highest and lowest ES quintiles (and therefore proxies a PEAD-based strategy that takes a long position on good news and a short position on bad news). The adjustment portfolio for computing BHAR is the S&P 500 index (including dividends). $TimeDummy_q$ is a time dummy variable equal to 1 for all quarters after 30th June 2003 and zero otherwise; $AggLiq_q$ is the quarterly average of the aggregate market liquidity factor in quarter q, following Pastor and Stambaugh (2003); VIX_q is the quarterly average of the CBOE VIX Index and proxies for market-wide uncertainty; and $RecessionDummy_q$ is equal to 1 if the quarter is in a recession (defined by NBER) and zero otherwise. The left column also shows regression results for 3DR (i.e. the dependent variable is the difference in mean 3DR between the highest and lowest ES quintiles). T-statistics are computed based on Newey-West robust standard errors. ***, **, * represent significance at 0.01, 0.05, 0.1, respectively. Sample period: July 1995 to June 2011. Number of observations: 64.

Dependent Variable:	3-day Response				60-day PEAD			
Panel A: NYSE Firms								
Intercept	0.0224	**	0.020	**	0.0679	***	0.0706	***
$TimeDummy_q$	0.034	***	0.0329	***	-0.0272	**	-0.0259	*
$AggLiq_q$			0.106				-0.119	
VIX_q	0.00168	***	0.00193	***	-0.00031		-0.0006	
$RecessionDummy_q$	0.00433		0.00935		0.0247		0.0191	
R-Square	0.528		0.545		0.060		0.0678	
Panel B: Non-NYSE Firms								
Intercept	0.0637	***	0.0623	***	0.0450	**	0.0417	**
$TimeDummy_q$	0.0117	***	0.0111	***	-0.00748		-0.00907	
$AggLiq_q$			0.0591				0.147	
VIX_q	0.00056	**	0.00071	**	0.00038		0.00074	
$RecessionDummy_q$	0.0030		0.00581		0.0175		0.0244	
R-Square	0.208		0.224		0.029		0.044	

firms having stronger attenuation as vis-à-vis to non-NYSE firms because of the additional structural change embedded in Autoquote.

To examine the robustness of my results I also conduct four robustness tests (in Sections B.1, B.2 and B.3 in the Appendix I discuss in detail the test specifications and results). First, I assess time-varying PEAD in a factor-based asset pricing model and test whether the estimated alpha significantly changed after July 2003 based on the Carhart (1997) four-factor model. The results (Section B.1) show PEAD significantly attenuated by 2.47% (significant at the 1% level). Second, I show using Fama-Macbeth regressions that quarterly PEAD, as proxied by the estimated coefficient to the scaled earnings surprise variable, almost halved (Section B.2). The estimated coefficients are computed following a multivariate procedure (with Fama-Macbeth regressions) outlined in Section 2.5.1 of Chapter 2. Third, given my findings in Chapter 2 that arbitrage risk and institutional ownership are robust explanatory variables for PEAD, I show across portfolios sorted by arbitrage risk and institutional ownership the cross-sectional means of PEAD have declined. For 25 portfolios based on 5×5 arbitrage risk quintile and institutional ownership quintile, PEAD declined in 17 portfolios while the remaining eight are mostly portfolios with low institutional ownership or high arbitrage risk, which proxy for small firms. Finally, I also test for an unknown structural break in time-varying PEAD. Following Andrews (1993) the test maximizes the F-statistic across a set of Chow tests and consistently finds July 2003 as the structural break. I also visually represent this decline in PEAD across time in Figure B.1 of the Appendix.

3.4.2. The Rise in Earnings Quality

As discussed above, the early 2000s also experienced a structural increase in earnings quality which potentially increased 3DR. I therefore replace the dependent variable in Equation 3.3 with 3DR (which proxies for the immediate response to ES). The results are in the left column of Panel A and Panel B of Table 3.3. For NYSE stocks, controlling for other factors, 3DR increased 3.40% (significant at the 1% level) from 2.24% (significant at the 1% level). In other words, the magnitude of earnings response to ES increased substantially after June 2003. The R-squared exceeds 50% suggesting a large proportion of the variation of 3DR is explained by the model. The opposite signs of the estimated coefficients for $TimeDummy_q$ between the PEAD and 3DR results are consistent with lower transaction cost and higher investor sophistication attenuating PEAD and also suggest the level of under-reaction to ES has declined. For example, the estimated coefficient of $AggLiq_q$ is positive (although insignificant), consistent with the predictions of Ng et al. (2008) that lower transaction cost improves price response to ES. VIX_q at 0.00193 is significant (at the 1% level) suggesting that a significant proportion of 3DR can also be explained by expectations of higher market uncertainty: which is consistent with Cready and Gurun (2010) who find strong correlation between firm-level ES and aggregate market returns. The authors note "earnings information directly impacts aggregate market return…specifically…this impact moves market values in a direction opposite earnings surprise" (p.330). The authors find positive ES (i.e., good news) tends to increase market discount factor; while negative ES (i.e., bad news) tends to reduce market discount factor.

Looking at the non-NYSE results I note the intercept, which is interpreted as the average 3DR before July 2003, is 6.37% and approximately three times larger than NYSE stocks. This suggests returns for non-NYSE stocks are more dependent on earnings information. But similar to NYSE results the time dummy is positive and significant, showing 3DR increased by 1.11% (significant at the 1% level) after July 2003. The estimated coefficient of VIX is also positive and significant.

I note PEAD for non-NYSE stocks experienced insignificant decline while 3DR saw a significant increase. This is consistent with the general rise in earnings quality but a weak improvement in liquidity (from decimalisation). Further I note the increase in 3DR is approximately 1½ times that of the decline in PEAD for both NYSE and non-NYSE (in other word total BHAR across the 63 trading days covering 3DR and PEAD has risen). This cannot be explained by the decline in transaction costs but is consistent with Ball and Shivakumar (2008) who argue the proportion of information firms release at earnings information has substantially increased. My overall results therefore suggest 3DR has accentuated while PEAD has attenauted and the explanations are a reduction in transaction cost and/or a rise in AT and/or a rise in earnings quality.

3.5. Algorithmic Trading and PEAD

I now control for decimalisation and the rise in earnings quality. My hypothesis is that if AT attenuates PEAD then, controlling for these two factors, firms with higher AT should exhibit smaller PEAD because AT improves market liquidity and is less prone to under-reaction. To control for decimalisation I exclude all firm-quarter observations before July 2001 and to control for earnings quality I employ a matched sampling procedure and assess whether variations in PEAD across matched pairs can be explained by differences in AT. My results show very weak evidence of AT attenuating PEAD and overall I do not find an inverse relation between AT and PEAD. I also test the relation between AT and 3DR and find strong evidence in favour of AT accentuating 3DR.

3.5.1. Controlling for Decimalisation

To remove the effects of decimalisation I constrain my test period and assess the change in PEAD across two samples: one representing pre-Autoquote period and the other representing post-Autoquote period. To construct my sample data: 1) I filter only NYSE-listed firms and for each firm I select earnings announcements within 14 months before and after the firm's date of Autoquote phase-in. I therefore only consider announcements between 1st October 2001 and 27th September 2004, which does not overlap with decimalisation or with quarters subject to economic recession.[68] 2) Following Bessimbinder (2003b) all firms that were de-listed or had a change in ticker sign are removed. I also exclude firms with share prices below \$5 and above \$150 as of 31st March 2001. 3) I remove all firm-quarter observations where the date of earnings announcement is within 65 trading days before or after the firm's date of Autoquote phase-in. This filters out observations where the associated PEAD overlaps with the firm's date of Autoquote phase-in and also addresses concerns about endogeneity between variations in earnings information immediately after Autoquote. 4) All firm-quarter earnings announcements before the respective firms' date of Autoquote phase-in are assigned the dummy variable $DummyPreAQ_{i,q}$ equal to 1 and all remaining announcements are assigned $DummyPreAQ_{i,q}$ equal to 0. Implicitly I am therefore assuming the Autoquote phase-in schedule is a valid dummy variable for testing the effects of AT.[69] I then run the below

[68] The U.S. economy was subject to recession in the 2nd and 3rd quarters of 2001 (from NBER-based recession indicators).

[69] For this I rely on the findings in Hendershott et al. (2011) who demonstrate that the date of Autoquote implementation can be considered a valid instrument to test the market impact of AT. A concern is that its staggered introduction could potentially bias regression estimates if the time-dummy variable is correlated to the error term of the dependent variable. However Hendershott et al. (2011) argue the Autoquote rollout schedule was fixed months in advance and "it seems highly unlikely that the phase-in schedule could be correlated with the idiosyncratic liquidity months in the future" (p.15). This argument also applies to the correlation between future earnings surprise and the Autoquote schedule. I also note ES is a function of actual earnings, analyst forecast and stock price. It is highly unlikely the phase-in schedule correlates to the shifts in the macro economy or affects the decision of firm managers; nor the process by which analysts produce forecasts or forecast error. Staggered scheduling of Autoquote, however, has the potential to cause biased estimates if firms are strategic in terms of periods they choose to make announcements (Anilowski, Feng and Skinner, 2007). Bad news tends to be announced later in the quarter relative to good news (Anilowski, Feng and Skinner, 2007) and as the Autoquote schedule is a staggered phase-in across the first two quarters of 2003 there is potentially an issue of endogeneity between news and the Autoquote schedule. I avoid this concern by testing good news and bad news separately in my matched-sampling method.

regression specification following Hirshleifer et al. (2009):

$$
\begin{aligned}
BHAR_{i,q} \quad = \quad & \alpha \\
& + \beta_1 ES_{i,q}^{Scaled} \\
& + \beta_2 \left[ES_{i,q}^{Scaled} * DummyPreAQ_{i,q} \right] \\
& + \textstyle\sum_{z=1}^{Z} \left[\delta_z Factors_{z,i,q}^{non-scaled} \right] \\
& + \textstyle\sum_{z=1}^{Z} \left[\gamma_z ES_{i,q}^{Scaled} * Factors_{z,i,q}^{non-scaled} \right] + \varepsilon_{i,q} \qquad (3.4)
\end{aligned}
$$

Where $Factors_{z,i,q}^{non-scaled}$ represent control factors. β_1 can be interpreted as the average PEAD *after* Autoquote has been phased in; and β_2 can be interpreted as the change in PEAD between pre-Autoquote to post-Autoquote. α represents any remaining portion of PEAD left unexplained. I also follow Mendenhall (2004) and remove the top and bottom 1% outliers for each control factor. The regression control factors are institutional ownership ($Insti_{i,q}$); investor distraction ($Distract_{i,q}$);

analyst coverage ($Analyst_{i,q}$); volatility ($Volatility_{i,q}$); arbitrage risk ($ArbRisk_{i,q}$); hedgeable risk ($ExpRisk_{i,q}$); stock price ($Price_{i,q}$); turnover ($Turn_{i,q}$); market capitalisation ($Mcap_{i,q}$); book-to-market ratio ($BM_{i,q}$); and momentum ($Mom_{i,q}$). Standard errors are adjusted for heteroskedasticity and autocorrelation by clustering across both firm and date of earnings announcement following Thompson (2011).

For robustness I also augment the above test to adjust for a firm's *relative* improvement in AT. This is because a relatively large improvement in AT is expected to exert stronger downward pressure on PEAD. To do so I consider whether a relatively higher (lower) increase in AT attenuates PEAD relatively more (less). The test involves creating two more test samples: one with firms characterised by low improvements in AT (*LowATChange*) and the other by high improvements in AT (*HighATChange*). For the *HighATChange* sample I expect a significant and positive estimate of β_2 and for the *LowATChange* sample I expect a smaller or insignificant estimate of β_2. I include control variables to account for other explanations for cross-sample variations.

To classify firms into *HighATChange* or *LowATChange* I employ the measure for AT by Hendershott et al. (2011) where, for each firm (as identified by its unique PERMNO identifier) I compute the improvement in AT activity based on the following ratio:

$$ATChangeRatio_i = {M \sum_{n=1}^{N} \left[ATproxy_{i,q,n}^{PostAQ}\right]} \Big/ {N \sum_{m=1}^{M} \left[ATproxy_{i,q,m}^{PreAQ}\right]} \tag{3.5}$$

Where for firm *i*, *N* is the number of earnings announcements in the post-Autoquote sample and M is the number of earnings announcements in the pre-Autoquote sample. Hence $ATChangeRatio_i$ is the improvement in AT relative to pre-Autoquote levels averaged across the number of earnings announcements. AT activity per earnings announcement is defined by the following:

$$ATProxy_{i,q} = \frac{1}{N} \sum_{n}^{N} AT_{i,t-n} \tag{3.6}$$

Where again *t* is the date of earnings announcement. In other words $ATProxy_{i,q}$ is the average daily AT activity from 41 trading days to 2 trading days prior to the earnings announcement. To exclude firms that in general have very little AT activity I remove firm-quarter observations with zero turnover or zero updates (at the inside quote) for more than 10 of the 40 trading days. Firms are then ranked by $ATChangeRatio_i$: those above the 50th percentile are assigned to the *HighATChange* sample and those below the 50th percentile are assigned to the *LowATChange* sample.

3.5.1.1. Results

The results show that despite an overall low level of PEAD for the specific sample period there is significant variation in PEAD across firms with high improvement in AT in contrast to low improvement in AT. Noticeably, high AT improvement corresponds to significant PEAD attenuation. I first discuss the full sample results in Panel A of Table 3.4 which shows, without adjusting for control factors, post-Autoquote PEAD significantly declined. The left column shows on average PEAD declined by 2.54% (significant at the 5% level) to 1.54% (significant at the 10% level) in the 14 months after Autoquote. However including control factors the decline is not significant. The estimated coefficient of 0.00974 (insignificant at the 10% level) for $ES_{i,q}^{Scaled} * DummyPreAQ_{i,q}$ and -0.0043 (insignificant at the 10%) for $ES_{i,q}^{Scaled}$ suggest PEAD declined by 0.97% following Autoquote to -0.43%. The results therefore shows, after controls, Autoquote had an insignificant effect on PEAD. Further, including control variables, the estimated intercept loses its significance indicating the proportion of PEAD that cannot be accounted for by earnings surprise is explained by the other regression variables. I note this finding that PEAD was not a significant market anomaly between October 2001 and September 2004 is consistent with Hirshleifer et al. (2009) who observes that PEAD effects were especially small for this sample period.

I then assess whether there are cross-sectional differences between firms subject to high AT improvement as vis-à-vis low AT improvement. Estimating Equation 3.4, but separately for *LowATChange* and *HighATChange* samples, the left column of panel B shows on average PEAD for high improvement in AT declined by 4.71% (significant at the 1% level) to -0.767% (insignificant at the 10% level)l and the right column shows, controlling for other factors, this decline is statistically significant. Again, the intercept loses its significance after the inclusion of the control variables which suggests for firms subject to high improvements in AT PEAD

Table 3.4: The Effects of AT on PEAD

The table show the effects of Autoquote on PEAD for NYSE-listed firms based on the regression specification: $BHAR_{i,q} = \alpha + \beta_1 ES_{i,q}^{Scaled} + \beta_2\left[ES_{i,q}^{Scaled} * DummyPreAQ_{i,q}\right] + \sum_{z=1}^{Z}\left[\delta_z Factors_{z,i,q}^{non-scaled}\right] + \sum_{z=1}^{Z}\left[\gamma_z ES_{i,q}^{Scaled} * Factors_{z,i,q}^{non-scaled}\right] + \varepsilon_{i,q}$ where $DummyPreAQ_{i,q}$ is equal to 1 for all observations before the date of Autoquote phase-in, and equal to 0 otherwise. The control factors $Factors_{z,i,q}^{non-scaled}$ are: institutional ownership ($Insti_{i,q}$); investor distraction ($Distract_{i,q}$); analyst coverage ($Analyst_{i,q}$); volatility ($Volatility_{i,q}$); arbitrage risk ($ArbRisk_{i,q}$); hedgeable risk ($ExpRisk_{i,q}$); stock price ($Price_{i,q}$); turnover ($Turn_{i,q}$); market capitalisation ($Mcap_{i,q}$); book-to-market ratio ($BM_{i,q}$); and momentum ($Mom_{i,q}$). The top and bottom 1% outliers for each control factor are removed. Panel A shows the regression results for the entire sample. Panel B and Panel C then classify sample observations into a *HighATChange* sample and a *LowATChange* sample respectively. The classification is based on the level of improvement in AT and each firm is assigned an $ATChangeRatio_i$ representing the average improvement in its level of AT relative to pre-Autoquote AT levels. Firms are then ranked by $ATChangeRatio_i$ and those above the 50th percentile are assigned to the *HighATChange* sample; while those below the 50th percentile are assigned to the *LowATChange* sample. The sample period is 1st October 2001 and 27th September 2004. Standard errors are adjusted for heteroskedasticity and autocorrelation by clustering across both firm and date of earnings announcement following Thompson (2011). ***, **, * represent significance level at 0.01, 0.05 and 0.1 respectively.

Panel A: Full Sample				
			Including Control Factors	
Intercept	0.00902	***	0.0029	
$ES_{i,q}^{Scaled}$	0.0154	*	-0.0043	
$ES_{i,q}^{Scaled} * DummyPreAQ_{i,q}$	0.0254	**	0.0097	
Panel B: *HighATChange* (High Improvement in AT)				
			Including Control Factors	
Intercept	0.0086	***		
$ES_{i,q}^{Scaled}$	-0.0077		-0.0844	
$ES_{i,q}^{Scaled} * DummyPreAQ_{i,q}$	0.0471	***	0.0470	**
Panel C: *LowAtChange* (Low Improvement in AT)				
			Including Control Factors	
Intercept	0.0198	***	-0.0690	
$ES_{i,q}^{Scaled}$	0.0297	**	0.1143	
$ES_{i,q}^{Scaled} * DummyPreAQ_{i,q}$	-0.0103		-0.0378	

was completely removed after the phase-in of Autoquote. In contrast, Panel C shows firms with low improvement in AT experienced insignificant change following the phase-in of Autoquote. The signs of the estimated coefficient for $ES_{i,q}^{Scaled} * DummyPreAQ_{i,q}$ indicate that, unlike firms with high improvements, AT may have in fact *increased* PEAD. Hence while Panel A results show the overall market experienced low levels of PEAD, my findings suggest in the cross-section firms with high improvements in AT are associated with attenuated PEAD.

3.5.2. Controlling for Earnings Quality

In addition to controlling for decimalisation I now also adjust for changes in earnings quality. Studies show factors that reduce structural uncertainty or alleviate informational opacity tend to attenuate PEAD (see Sadka, 2006; Vega, 2006; Han and Brown, 2011) and one determinant of uncertainty and opacity is the quality of earnings information. Ball and Shivakumar (2008) show the quality of earnings information increased substantially in the early 2000s due to changes in corporate disclosure standards and firm management issuing forward earnings guidance during announcements. Hence this general upward trend in earnings quality may also explain the structural decline in PEAD. To control for both decimalisation and earnings quality I employ a matched-sample procedure and assess whether the difference in PEAD across matched pairs can be explained by differences in AT. Further, I conjecture that given AT is associated with sophisticated investors, who on average are likely better at extracting signals from market information, AT is potentially concentrated among firms expected to release relatively higher quality information.

My test method follows Davies and Kim (2009) and matches without replacement via a one-to-one nearest neighbour matching criteria. My matching procedure is as follows: 1) I take all NYSE-listed firms and filter for earnings announcements between the 1st January 2004 and 31st

December 2007. This removes any overlap with decimalisation, the phase-in of Autoquote or the 2008 economic recession. 2) I retain only observations in the top or bottom ES quintiles (i.e., ES quintile equal to 1 or 5). 3) I match a firm-quarter earnings announcement by random selection[70] with another firm-quarter observation (without replacement) by minimising the matching error (defined as the linear combination of the absolute size and price ratios):

$$\left| {}^{Mcap_u}\!\big/_{Mcap_v} - 1 \right| + \left| {}^{Price_u}\!\big/_{Price_v} - 1 \right| \qquad (3.7)$$

Where *u* and *v* identify the matched observations, *Mcap* is market capitalisation, and *Price* is the stock price. To control for time-trends in earnings quality I only match firms if the earnings announcement dates share the same calendar year. This also controls for time trends in other factors such as the level of AT and size of spreads. 4) Fourth, I conduct the matching procedure separately for good news and bad news and hence only match observations if they are assigned the same ES quintile. 5) Fifth, for each matched pair the observation with the higher $ATProxy_{i,q,t}$ is assigned to a *HighAT* bin while the remainder is assigned to a *LowAT* bin. Matched pairs with equal levels of AT are removed. 6) Finally, for every firm-quarter observation I also match to an earnings announcement in the pre-Autoquote period.[71] The matching criterion minimises the earnings surprise ratio: $\left| {}^{ES_u}\!\big/_{ES_v} - 1 \right|$ and I impose the restriction that matched pairs must be of the same market capitalisation quintile.[72] If a firm-quarter *ES* is equal to zero I assign it a value of 0.0001. Hence each post-Autoquote matched pair also has a corresponding pre-Autoquote matched pair.

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[70] I randomise through ranking firms alphabetically.

[71] I choose the pre-Autoquote period 1st July 1995 to 31st December 2002. My results do not qualitatively change if I choose the period 1st July 1995 to 31st December 2000.

[72] Matching with or without replacement does not alter my main findings. Market capitalisation breakpoints are selected based on the sorting of NYSE firms in the most recent calendar month of July.

A set of results which would be consistent with AT attenuating PEAD are summarised in Table 3.5 and the underlying intuition is the following. First, if relatively high levels of AT attenuate PEAD I expect PEAD to vary across *LowAT* and *HighAT* bins given, *ceteris paribus,* high AT should exert greater downward pressure on PEAD. Second, AT increased substantially after Autoquote and I therefore expect PEAD in the post-Autoquote period to attenuate (after controlling for decimalisation and earnings quality) given AT is associated with improved liquidity. My matched sampling procedure therefore aims to test the difference in PEAD across high/low AT bins and pre/post Autoquote samples. To illustrate my argument, the top row of Panel A in Table 3.5 shows, for good news firms, post-Autoquote PEAD is expected to be positive in both *HighAT* and *LowAT* bins but the difference is expected to be negative:

$$0 < E\left[Diff_{i,Good\ News,Post}^{PEAD}\right]$$

$$= 1/P \sum_{p=1}^{P}\left[BHAR_{i,p,Good\ News,Post}^{HighAT} - BHAR_{i,p,Good\ News,Post}^{LowAT}\right] \qquad (3.8)$$

Where in the post-Autoquote period $E\left[Diff_{i,Good\ News,Post}\right]$ is the expected difference in mean across matched pairs; and p indexes the number of matched pairs. The second row in Table 3.5 shows pre-Autoquote PEAD is also expected to be positive. Finally, the third row shows the expected difference in PEAD between post-Autoquote and pre-Autoquote firms. Again, given the positive relation between PEAD and transaction cost *ceteris paribus* PEAD is expected to decline after Autoquote, and this attenuation is expected to be larger for firms with high AT. Panel B also shows the expected sign for computed PEAD for firms announcing bad news.

Table 3.5: Expected Signs for PEAD

The table shows the expected signs for computed statistics of PEAD that is consistent with AT attenuating PEAD. For each matched pair the observation with the higher AT (measured by $ATProxy_{i,q,t}$) is assigned to a $HighAT$ bin while the other is assigned to a $LowAT$ bin. It is expected that higher levels of AT exert a greater downward pressure on PEAD. The right column states the expected sign for the PEAD of $HighAT$ firms minus the PEAD of $LowAT$ firms. The 3rd row for each panel states the expected sign for the PEAD of post-Autoquote firms minus the PEAD of pre-Autoquote firms. Panel A shows the expected signs for firms announcing good news; and Panel B shows the expected sign for firms announcing bad news.

Panel A: Good News			
	HighAT	*LowAT*	*HighAT minus LowAT*
Post-Autoquote	Positive	Positive	Negative
Pre-Autoquote	Positive	Positive	
Post-Autoquote minus Pre-Autoquote	Negative	Negative or zero	Negative
Panel B: Bad News			
	HighAT	*LowAT*	*HighAT minus LowAT*
Post-Autoquote	Negative	Negative	Positive
Pre-Autoquote	Negative	Negative	
Post-Autoquote minus Pre-Autoquote	Positive	Positive or zero	Positive

3.5.2.1. Results

The matched sampling results across NYSE firms are presented in Table 3.6. Overall, the findings are inconsistent with higher AT attenuating PEAD (after controlling for both decimalisation and shifts in earnings quality). I first discuss the results for good news (Panel A). If AT lowers transaction costs and therefore attenuates PEAD my first hypothesis is that on average PEAD for high AT firms ought to be smaller than PEAD for low AT firms. In other words, following Equation 3.8 the average $Diff^{PEAD}_{i,Good\ News,Post}$ should be negative. Looking at the top row of Table 3.6 the mean PEAD for *HighAT* and *LowAT* bins are both positive and significant with *HighAT* at 1.68% (significant at the 1% level) and *LowAT* at 0.97% (significant at the 1% level). This suggests investors under-react to good news irrespective of the level of AT. However, average PEAD for *HighAT* firms is higher than for *LowAT* firms which is inconsistent with higher levels of AT attenuating PEAD. To test whether this difference in PEAD is statistically significant I conduct a Wilcoxon signed rank test (Wilcoxon, 1945; Woolson, 1998)[77] and find the difference of 0.70% is insignificant at the 10% level. In other words, there is no significant difference in attnation across high AT and low AT samples. Similarly, looking at the top row of Panel B for bad news, the results suggest higher AT does not attenuate PEAD. *HighAT* firms have an average PEAD of -2.94% (significant at the 1% level) and *LowAT* firms have an average of -1.35% (significant at the 1% level). This difference in mean of 1.6% (significant at the 1% level) suggests that rather than attenuating PEAD, higher AT is potentially *accentuating* PEAD.

[77] This follows Davies and Kim (2009) who find that for the above class of matched sampling procedures the Wilcoxon test is superior to a two-sample t-test.

I note one critique of my matched sampling procedure is that firms in the *HighAT* and *LowAT* buckets may vary across ES and this could bias my results (for example, *LowAT* firms may systematically have lower ES compared with *HighAT* firms). As a remedy I use the PEAD of pre-Autoquote period matched samples as a control (shown in the second row of Panel A and Panel B). The third row in Panel A and Panel B show that after this adjustment is made the results nevertheless are inconsistent with high AT attenuating PEAD. For good news, *HighAT* firms exhibit an increase of PEAD by 1.69% (significant at the 5% level) while *LowAT* firms see a decline of 2.74% (significant at the 1% level). This suggests firms with relatively low AT experienced more PEAD attenuation. Looking at bad news, both *HighAT* and *LowAT* firms experienced attenuation in PEAD from pre- to post-Autoquote (as shown in the third row of Panel B). *HighAT* saw an attenuation of 2.00% while *LowAT* saw an attenuation of 1.21%. I test the difference between the two and the difference of 0.78% is however insignificant. Therefore, while there are some initial evidence that Autoquote attenuated PEAD for firms announcing bad news, the test results show the difference is insignificant across high and low AT firms.

I now discuss robustness tests. First, I exclude matched pairs with a relatively small difference in AT activity by sorting matched pairs by the difference in $ATProxy_{i,q,t}$ and removing pairs in the smallest 25th percentile. The results are shown in the right column of Panel A of Table 3.7 and find the difference in PEAD across high and low AT continues to be insignificant. The average difference in PEAD between *HighAT* and *LowAT* firms are, for good news at 0.713% (insignificant at the 10% level), and bad news at -0.514% (insignificant at the 10% level).[78]

[78] I note my tests do not impose a caliper/distance restriction on my matched sampling. This is because Davies and Kim (2009) argue that for sufficiently large samples matching without restriction produce more efficient test statistics. For robustness, in unreported results I find removing poor matches with large matching errors does not change my main findings.

Table 3.6: Matched Sampling and Difference-in-Difference Tests for PEAD across AT

The table shows matched sampling test results of PEAD for NYSE-listed firms. Post-Autoquote firm-quarter observations are matched by price and market capitalisation via a one-to-one nearest neighbour matching (without replacement) and matched pairs must both belong to the same calendar year. The matching procedure is conducted separately for good news and bad news (i.e., ES quintile rank of 1 and 5). For each matched pair the observation with the higher AT (as measured by $ATProxy_{i,q,t}$) is assigned to a $HighAT$ bin while the other is assigned to a $LowAT$ bin. Matched pairs with equal levels of AT are removed. Every firm-quarter observation in the post-Autoquote period is also matched by ES and size quintile to an earnings announcement in the pre-Autoquote period. The right column shows the difference in PEAD of $HighAT$ firms minus the PEAD of $LowAT$ firms; and the 3rd row for each panel shows the difference in PEAD of post-Autoquote firms minus the PEAD of pre-Autoquote firms. Post-Autoquote sample period is from 1st January 2004 to 31st December 2007. Pre-Autoquote sample period is from 1st July 1995 to 31st December 2002. ***, **, * represent 0.01, 0.05, 0.1 significance level for t-statistic respectively. ###, ##, # represent 0.01, 0.05, 0.1 significance level for Wilcoxon signed rank statistic respectively.

	Panel A: Good News					
	HighAT		*LowAT*		*HighAT minus LowAT*	
Post-Autoquote	0.0168	***	0.0097	***	0.007	
Pre- Autoquote	-0.0001		0.0371	***		
Post-Autoquote minus Pre-Autoquote	0.0169	##	-0.0274	###	0.0442	###
	Panel B: Bad News					
	HighAT		*LowAT*		*HighAT minus LowAT*	
Post- Autoquote	-0.0294	***	-0.0135	***	-0.016	###
Pre- Autoquote	-0.0494	***	-0.0256	***		
Post-Autoquote minus Pre-Autoquote	0.02	#	0.0121	#	0.0078	

The results also remain poor after controlling for pre-Autoquote PEAD; for good news PEAD accentuated by 2.35% (significant at the 5% level) and for bad news the difference of 1.18% is insignificant at the 10% level.

As an additional robustness test which controls for earnings quality I also match by size, price and total BHAR across the 63 days announcement period (from one trading day before earnings announcement to 61 trading days after). This BHAR measure proxies for the total amount of unexpected news that is released at earnings announcement. Again the results suggest an insignificant relation with AT. Panel B of Table 3.7 shows *HighAT* firms have accentuated PEAD with the average difference in PEAD between *HighAT* and *LowAT* firms for good news at 0.105% (significant at the 10% level) and bad news at -0.687% (significant at the 1% level). Controlling for pre-Autoquote PEAD, good news PEAD saw accentuation by 3.55% (significant at the 5% level) and for bad news PEAD attenuated by 3.11% (significant at the 1% level). Hence, only bad news show some consistency with high AT attenuating PEAD.

Finally I restrict the matched sampling procedure only to NYSE firms that are components of the S&P 500. This ensures the matched pairs have significant levels of AT activity. The results continue to show an insignificant relation with AT. Panel C of Table 3.7 shows *HighAT* firms have accentuated PEAD with the average difference in PEAD between *HighAT* and *LowAT* firms for good news at 0.121% (insignificant at the 10% level) and bad news at -0.233% (insignificant at the 10% level). Controlling for pre-Autoquote, good news PEAD accentuated by 2.27% (significant at the 10% level) and bad news PEAD accentuated by 1.71 % (significant at the 10% level).

Table 3.7: Matched Sampling Tests – Robustness Tests

The table shows matched sampling test results of 3DR and PEAD for NYSE-listed firms. Post-Autoquote firm-quarter observations are matched via a one-to-one nearest neighbour matching (without replacement) and matched pairs must both belong to the same calendar year. The matching procedure is conducted separately for good news and bad news. For each matched pair the observation with the higher AT (as measured by $ATProxy_{i,q,t}$) is assigned to a $HighAT$ bin while the other is assigned to a $LowAT$ bin. Matched pairs with equal levels of AT are removed. Every firm-quarter observation in the post-Autoquote period is also matched by ES and size quintile to an earnings announcement in the pre-Autoquote period. Each panel shows the difference in PEAD of $HighAT$ firms minus the PEAD of $LowAT$ firms; and the difference in PEAD of post-Autoquote firms minus the PEAD of pre-Autoquote firms. Panel A shows results for firm-quarter observations matched by price and market capitalisation; the 25% of matched pairs with the smallest difference in AT activity are removed. Panel B shows results for matched firm-quarter observation matched by market capitalisation, price and the BHAR measured from 1 trading day prior to earnings announcement to 61 trading days after. Panel C shows results where the matching procedure is only implemented for stocks of the S&P 500 index that are listed on the NYSE (firm-quarter observations are matched by price and market capitalisation). Post-Autoquote sample period is from 1st January 2004 to 31st December 2007. Pre-Autoquote sample period is from 1st July 1995 to 31st December 2002. ###, ##, # represent 0.01, 0.05, 0.1 significance level for Wilcoxon signed rank statistic respectively.

		3 Day Response		PEAD	
		Mean	Wilcox SR Test	Mean	Wilcox SR Test
Panel A: HighAT minus LowAT (removing low differences in AT)					
Good News	*Post-Autoquote*	0.0115	##	0.00713	
	Post-Autoquote minus Pre-Autoquote	0.00692	#	0.0235	##
Bad News	*Post-Autoquote*	-0.0100	##	-0.00514	
	Post-Autoquote minus Pre-Autoquote	-0.011	##	0.0118	
Panel B: HighAT minus LowAT (matched by Size, Price and 63-day BHAR)					
Good News	*Post-Autoquote*	0.00134	#	0.00105	#
	Post-Autoquote minus Pre-Autoquote	0.00157	#	0.0355	##
Bad News	*Post-Autoquote*	-0.00932	#	-0.00687	###
	Post-Autoquote minus Pre-Autoquote	-0.00798	#	0.0311	###
Panel C: HighAT minus LowAT (Only NYSE components of S&P 500)					
Good News	*Post-Autoquote*	0.00934	#	0.0121	
	Post-Autoquote minus Pre-Autoquote	0.00236		0.0227	#
Bad News	*Post-Autoquote*	-0.0135	#	-0.00233	
	Post-Autoquote minus Pre-Autoquote	-0.0234	##	-0.0171	#

3.5.3. Algorithmic Trading and Earnings Response

If AT has no relation to the attenuation of PEAD does it still affect returns around earnings announcements? In addition to lowering transaction costs, AT is associated with sophisticated algorithms; and news agencies increasingly provide machine-readable announcement information specifically for algorithmic traders (Hirschey, 2013). Further, the findings by Ball and Shivakumar (2008) suggest the shift in earnings quality is in part due to regulatory changes and if sophisticated algorithmic traders have a superior understanding of the regulatory environment – such as disclosure rules[79] – they may prefer dealing in stocks with more informative announcements. If sophisticated traders are better at analysing market news and extracting trading signals they presumably prefer to deal in stocks which release higher quality information.[80] I therefore conjecture if AT proxies for investor sophistication firms which are expected to release high quality information attract relatively more AT.

To test this hypothesis I examine whether AT is positively correlated to 3DR. If there is no relation between AT and earnings quality, these variations across AT should have insignificant explanatory power on the variation of 3DR. On the other hand, if the level of AT is associated with the preference for higher earnings quality then on average higher AT should be positively correlated to higher 3DR. Using the same matched pairs selected in Section 3.5.2 I test the difference in the pair's 3DR across *LowAT* and *HighAT* bins; and across pre- and post-Autoquote samples. A set of results which are consistent with AT accentuating 3DR are

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[79] Ball and Shivakumar (2008) write "one explanation for the sharp increase is an increased relative informativeness of earnings…it could arise from changes in accounting standards such as Statement of Financial Accounting (SFAS) 142 and SFAS 144, which set new rules for the impairment of intangible and tangible long-term assets, effective 2002, or from the Financial Accounting Standards Board's increased emphasis on "fair value" accounting generally. It could [also] be due to changes in managers' and auditors' incentives, in response to the Enron era scandals or the enactment of the Sarbanes-Oxley Act of 2002…these events most likely increased the expected legal and political costs of being discovered to have engaged in low-quality reporting." (p.993).

[80] Investors sophisticated in extracting signals from public information, such as earnings news, can be highly informed traders (Vega, 2004).

summarised in Table 3.8 and show that the signs of the expected difference in 3DR across *HighAT* and *LowAT* firms are opposite to that for the PEAD analysis. The top row for Panel A of Table 3.8 shows that for good news, post-Autoquote 3DR is expected to be positive for both *HighAT* and *LowAT* bins and the difference in mean is expected to be positive:

$$0 > E\left[Diff_{p,Good\ News,Post}^{3DR}\right] = 1/\sum_{p=1}^{P}\left[3DR_{u,p,Good\ News,Post}^{HighAT} - 3DR_{v,p,Good\ News,Post}^{LowAT}\right] \quad (3.9)$$

This is because if AT traders prefer firms that release more information, market response to earnings news should be on average larger for *HighAT* than *LowAT* firms. The second row shows pre-Autoquote 3DR is expected to be positive and, like Table 3.5, this row represents matched firms that control for variation in ES across *HighAT* and *LowAT* bins. Finally, if AT is associated with the sophisticated analysis of earnings information then 3DR is expected to increase relatively more under high AT after controlling for ES. Hence the third row shows the expected difference in 3DR between post-Autoquote and pre-Autoquote firms ought to be positive for the *HighAT* bin. Panel B shows the expected signs for bad news firms.

3.5.3.1. Results

Table 3.9 presents the results and my findings show a significant and positive relation between AT and 3DR (after controlling for both decimalisation and shifts in earnings quality). Panel A shows good news firms with *HighAT* have an average 3DR of 3.91% (significant at the 1% level) and *LowAT* firms 3.53% (significant at the 1% level). The difference in mean of 0.38% is significant at the 10% level and suggests high AT firms are associated with a larger earnings response. I note the changes in 3DR from pre- to post-Autoquote are also positive for both high and low AT firms, with the change larger for *HighAT* firms at 0.28% (but insignificant at the

Table 3.8: Expected Sign of 3DR

The table shows the expected signs for computed statistics of 3DRthat is conssieth with AT accentuating 3DR. For each matched pair the observation with the higher AT (measured by $ATProxy_{i,q,t}$) is assigned to a $HighAT$ bin while the other is assigned to a $LowAT$ bin. It is expected that higher levels of AT exert a greater upward pressure on 3DR. The right column states the expected sign for the 3DR of *HighAT* firms minus the 3DR of $LowAT$ firms. The 3rd row for each panel states the expected sign for the 3DR of post-Autoquote firms minus the 3DR of pre-Autoquote firms. Panel A shows the expected sign for firms announcing good news; and Panel B shows the expected sign for firms announcing bad news.

Panel A: Good News			
	$HighAT$	$LowAT$	$HighAT$ *minus* $LowAT$
Post-Autoquote	Positive	Positive	Positive
Pre-Autoquote	Positive	Positive	
Post-Autoquote minus Pre-Autoquote	Positive	Positive or zero	Positive
Panel B: Bad News			
	$HighAT$	$LowAT$	$HighAT$ *minus* $LowAT$
Post-Autoquote	Negative	Negative	Negative
Pre-Autoquote	Negative	Negative	
Post-Autoquote minus Pre-Autoquote	Negative	Negative or zero	Negative

10% level). I find a similarly consistent result for bad news (Panel B of Table 3.9): *HighAT* firms have a larger 3DR of -3.79% (significant at the 1% level) and *LowAT* firms have -3.75% (significant at the 1% level); though small the difference in mean of 0.03% is significant at the 10% level. I also again note the change in 3DR from pre- to post-Autoquote is consistent with high AT accentuating 3DR and is larger for *HighAT* firms at -0.63% (but insignificant at the 10% level) versus -0.33% for *LowAT* firms. Finally, for robustness I conduct a two-sample pooled t-test between $Diff^{3DR}_{i,Good\ News,Post}$ and $Diff^{3DR}_{i,Bad\ News,Post}$ and find the difference of 0.42% to be significant at the 1% level.

In Table 3.7 I present robustness test results. The left column of Panel A shows, after removing matched pairs with a relatively small differences in AT, the results increase in significance. For good news, *HighAT* 3DR increased by 1.15% (significant at the 5% level) and bad news declined by 1.00% (significant at the 5% level). After controlling for pre-Autoquote 3DR the results remain consistent: for good news 3DR accentuated by 0.692% (significant at the 10% level) and for bad news 3DR accentuated by 1.11% (significant at the 5% level).

Matching by size, price and 63-days BHAR the results in Panel B show *HighAT* firms again saw accentuated earnings response with the average difference in 3DR between *HighAT and LowAT* for good news accentuating by 0.134% (significant at the 10% level) and bad news accentuating by -0.932% (significant at the 10% level). Controlling for pre-Autoquote 3DR, good news accentuated by 0.157% (significant at the 10% level) and bad news accentuated by -0.798% (significant at the 10% level).

Finally, matching only NYSE firms that are components of the S&P 500 index, the results in Panel C show *HighAT* firms have accentuated 3DR with the average difference for good news at 0.934% (significant at the 10% level) and bad news at -1.35% (significant at the 10% level). Controlling for pre-Autoquote 3DR: good news accentuated by 0.236% (but insignificant at the 10% level) and bad news accentuated by 2.34% (significant at the 5% level). Hence my overall results suggest a positive relation between AT and accentuated 3DR. I also note in unpublished results that the BHAR across the 63 days announcement period[81] is overall higher for *HighAT* firms. This is consistent for *HighAT* firms announcing disproportionately more news than *LowAT* firms.

3.6. Algorithmic Trading and Price Discovery

I now examine whether AT is associated with improved price discovery. The association between high AT and high 3DR may suggest algorithmic traders are skilled in predicting abnormal returns at earnings announcement, however it is reasonable to expect such anticipated mispricing to be traded/arbitraged away immediately. My findings may also suggest algorithmic traders are more efficient in responding to ES, however this implies AT reduces investor under-reaction which is inconsistent with my results that AT does not attenuate PEAD. One potential explanation that is consistent with my overall findings is that high earnings quality can produce new or higher quality trading signals. Ball and Shivakumar (2008) argue larger 3DR is attributable to higher earnings quality and it follows that an increase in the quality of earnings information gives rise to more opportunities for sophisticated traders to improve the quality of their trading signals. A specific example which can accentuate 3DR but may not attenuate PEAD is if earnings information aids algorithmic traders in extracting improved signals for forecasting earnings momentum (see Bernard and Thomas, 1989).[82] I therefore conjecture if algorithmic traders prefer trading in stocks with high earnings quality they are expected to contribute to price discovery for this set of firms. My explanation also reconciles the findings by Hendershott et al. (2011) and Ball and Shivakumar (2008) whereby the former

[81] From one trading day before earnings announcement to 61 trading days after.
[82] Earnigns momemtum refers to the autocorrelation of quarterly firm ES.

Table 3.9: Matched sampling and difference-in-difference tests for 3DR across AT

The table shows matched sampling test results of 3DR for NYSE-listed firms. Post-Autoquote firm-quarter observations are matched by price and market capitalisation via a one-to-one nearest neighbour matching (without replacement) and matched pairs must both belong to the same calendar year. The matching procedure is conducted separately for good news and bad news (i.e., ES quintile rank of 1 and 5). For each matched pair the observation with the higher AT (as measured by $ATProxy_{i,q,t}$) is assigned to a *HighAT* bin while the other is assigned to a *LowAT* bin. Matched pairs with equal levels of AT are removed. Every firm-quarter observation in the post-Autoquote period is also matched by ES and size quintile to an earnings announcement in the pre-Autoquote period. The right column shows the difference in 3DR of *HighAT* firms minus the 3DR of *LowAT* firms; and the 3rd row for each panel shows the difference in 3DR of post-Autoquote firms minus the 3DR of pre-Autoquote firms. Post-Autoquote sample period is from 1 January 2004 to 31 December 2007. Pre-Autoquote sample period is from 1 July 1995 to 31 December 2002. ***, **, * represent 0.01, 0.05, 0.1 significance level for t-statistic respectively. ###, ##, # represent 0.01, 0.05, 0.1 significance level for Wilcoxon signed rank statistic respectively.

Panel A: Good News						
	HighAT		*LowAT*		*High AT minus Low AT*	
Post-Autoquote	0.0391	***	0.0353	***	0.0038	#
Pre- Autoquote	0.0363	***	0.034	***		
Post-Autoquote minus Pre-Autoquote	0.0028		0.0013		0.002	###
Panel B: Bad News						
	HighAT		*LowAT*		*High AT minus Low AT*	
Post- Autoquote	-0.0379	***	-0.0375	***	-0.0003	###
Pre- Autoquote	-0.0316	***	-0.0342	***		
Post-Autoquote minus Pre-Autoquote	-0.0063		-0.0033		-0.0022	

show large-cap stocks are subject to the most improvement in price discovery by AT while the latter show large-cap firms exhibit the highest earnings quality. I now test whether AT improves price discovery around earnings announcements and whether the improvement is concentrated among large-cap firms. My method assumes 3DR realised during the earnings period is a function of a price discovery process, where PEAD represents the portion of price discovery still to be realised. To quantify the level of price discovery around announcements[85] I use the Weighted Price Contribution (WPC) measure:

$$WPC_q \ \sum_{i=1}^{I}\left[{}^{3DR_{i,q}}\big/_{BHAR[-1,61]_{i,q}}\left({}^{\left|BHAR[-1,61]_{i,q}\right|}\big/_{\sum_{i=1}^{I}\left|BHAR[-1,61]_{i,q}\right|}\right)\right] \tag{3.10}$$

Where for firm *i,* in quarter *q,* $BHAR[-1,61]_{i,q}$ represents the BHAR from one trading day prior to earnings announcement to 61 trading days after. WPC_q is therefore a weighted-average of the proportion of returns realised across the first three trading days relative to the whole 63 days announcement period. To test whether price discovery improves with AT I assess the change in WPC_q for the NYSE around the time of the Autoquote-phase in. To control for shifts in earnings quality I match each NYSE-listed stock to a Nasdaq-listed stock (given Autoquote is NYSE-specific). My use of Nasdaq firms is motivated by Ball and Shivakumar's (2008) finding that the general rise in earnings quality was not affected by the sample composition of listed firms and that earnings quality increased irrespective of firm characteristics, book-to-market ratio, firm leverage or industry classification.

For my matching procedure I follow Bessimbinder (2003b) and separate my sample across size.[86] Given NYSE firms are in general larger than Nasdaq firms I control for size by implementing the following: 1) I exclude stocks that have changed ticker symbol and exclude

[85] This price discovery measure has been employed in Barclay and Warner (1993), Cao et al. (2000), Huang (2002), and Barclay and Hendershott (2003 and 2008).
[86] This matched pair method was used to study the effects of decimalisation between NYSE and Nasdaq stocks in Bessimbinder (2003b).

all stocks with share prices below \$5 and higher than \$150 as of 31st March 2001. 2) For each calendar quarter I create three matched groups of *Large*, *Medium* and *Small*. 2a) For the *Large* group I sort, within-quarter, Nasdaq firms by market capitalisation and select the largest 100 firms. I then match to a NYSE firm within the same calendar quarter (matched without replacement) by minimising the following matching error:

$$\left| {Mcap_u^{NASDAQ}}\Big/{Mcap_v^{NYSE}} - 1 \right| + \left| {ES_u^{NASDAQ}}\Big/{ES_v^{NYSE}} - 1 \right| \tag{3.11}$$

Where u and v identify the matched observations, *Mcap* is market capitalisation and *ES* is earnings surprise. Hence firms are matched by size and unexpected earnings news. If a firm-quarter *ES* is equal to zero I assign it a value of 0.0001.[87] 2b) For the *Small* group, for each quarter I randomly select 100 firms from the smallest NYSE quintile and then match to a Nasdaq firm within the same quarter (matched without replacement) using the matching error of Equation 3.11. 2c) For the *Medium* group, for each quarter I exclude the largest 100 NYSE firms as well as all NYSE firms in the smallest quintile. I then randomly select a firm in the remaining sample and match to a Nasdaq firm from the same quarter (matched without replacement) by the matching error of Equation 3.11). 3) I then assign all matched pairs between 1st July 2002 and 30th June 2003 to the pre-Autoquote sample and all matched pairs between 1st October 2003 and 30th September 2004 to the post-Autoquote sample. 4) Finally, I sort into quintile, within each quarter, the matched pairs based on the market capitalisation of the NYSE stock. Therefore for both pre- and post-Autoquote samples I have 20 groups across 4 calendar quarters (with 5 size quintiles in each quarter). The WPC is then computed for each

[87] I note in Bessimbinder (2003b) the matching criterion is for size only but I have included the second matching criterion of earnings surprise. This is because I cannot rely on large-sample properties due to my relatively small sample size.

group following Equation 3.10 and statistical inference is made based on two-sample pooled t-tests, following Bessimbinder, 2003b).

A set of findings which will be consistent with AT improving price discovery is presented in Table 3.10 and the underlying intuition is that I expect WPC_q to increase for large NYSE firms following Autoquote, controlling for the WPC of Nasdaq firms. Hence the left column of the first row in Table 3.12 shows, for large NYSE firms, that the expected difference in WPC between pre- and post-Autoquote ought to be positive:

$$0 > E[Diff_{NYSE}^{WPC}] = \overline{WPC_{q,NYSE}^{PostAutoquote}} - \overline{WPC_{q,NYSE}^{PreAutoquote}} \qquad (3.12)$$

Where $E[Diff_{NYSE}^{WPC}]$ is the expected difference between the mean of WPC_q in the pre- and post-Autoquote sample for NYSE firms. The middle column shows that in contrast the difference for Nasdaq firms is expected to be either positive or zero. This is because the rise in earnings quality may potentially increase price discovery for Nasdaq firms; however Nasdaq was not subject to a structural increase in AT. Finally the right column shows that the expected sign of the difference in WPC across the two exchanges ought to be positive: $0 > E\left[DiffinDiff_{q,g}\right] = \overline{WPC_{q,g}^{NYSE}} - \overline{WPC_{q,g}^{Nasdaq}}$ where q is for calendar quarter and g represents the within-calendar quintiles. Hence, controlling for changes in price discovery of large Nasdaq firms, large NYSE firms are expected to have improved price discovery. I note this difference in WPC could be either positive or insignificant for *Medium* and *Small* firms (second and third row of Table 3.10 respectively) given Hendershott et al. (2011) find Autoquote improved liquidity and price discovery overwhelmingly for large-cap stocks; and Ball and Shivakumar (2008) find high earnings quality is concentrated among the largest firms.

Table 3.10: Expected Sign of Change in Price Discovery

The table shows the expected signs for computed statistics of WPC (that is consistent with AT improving price discovery. WPC is a proxy for price discovery around earnings announcements and for firm *i,* in quarter *q,* $WPC_q = \sum_{i=1}^{I}\left[{3DR_{q,i}}/{BHAR[-1,61]_{i,q}}\left({\left|BHAR[-1,61]_{i,q}\right|}/{\sum_{i=1}^{I}\left|BHAR[-1,61]_{i,q}\right|}\right)\right]$ and the measure represents a weighted-average of the proportion of returns realised across the first three trading days relative to the whole 63 day announcement period. To assess WPC across both NYSE and Nasdaq each NYSE firm is matched to a Nasdaq firm. For each calendar quarter three matched groups are created: *Large*, *Medium* and *Small*. The right column shows the expected difference in NYSE WPC minus Nasdaq WPC; and the left column shows the expected difference in post-Autoquote WPC minus pre-Autoquote WPC. Post-Autoquote sample period is from 1st October 2003 to 30st September 2004. Pre-Autoquote sample period is from 1st July 2002 to 30th June 2003.

	Post-Autoquote WPC minus Pre-Autoquote WPC		*NYSE minus Nasdaq*
	NYSE	Nasdaq	
Large	Positive	Positive or zero	Positive
Medium	Positive or zero	Positive or zero	Positive or zero
Small	Positive or zero	Positive or zero	Positive or zero

3.6.1. Results

Consistent with my conjecture, I find for large NYSE stocks price discovery improved; mid-size stocks have insignificant change, and small stocks experienced an improvement due to significant deterioration in price discovery for Nasdaq stocks. Looking at the first row of Panel A in Table 3.11, price discovery for the *Large* sample on average increased by 9.00% (significant at the 1% level) after Autoquote was phased in. In contrast, the control group (Nasdaq firms) experienced a decline of 3.42% (insignificant at the 10% level). This suggests that a structural increase in AT improves price discovery. Computing the difference in WPC across the two exchanges price discovery increased by 12.4% (significant at the 1% level) following the phase-in of Autoquote. This suggests the results are robust for shifts in earnings quality.

Now looking at *Medium* firms (second row of Panel A), price discovery saw insignificant change. For NYSE firms, WPC decreased by 2.16% (insignificant at the 10% level) after Autoquote phased-in compared to an increase of 2.93% (insignificant at the 10% level) for the control group. The change in WPC across the two exchanges is -5.09% (insignificant at the 10% level). Finally, for the *Low* sample the difference in WPC across NYSE and Nasdaq is significant and positive at 14.5%. This suggests price discovery also increased for small-caps. However, looking at the results this is mostly attributable to a decline in price discovery of Nasdaq stocks which saw a deterioration of 9.31% (significant at the 1% level). The change for NYSE stocks was also insignificant at 5.20% (insignificant at the 10% level).

For robustness I then repeat the above matching procedure but match by size and price (following Davies and Kim, 2009). The results are shown in Panel B of Table 3.11 and reinforce my main findings. The results for the *Large* sample remain unchanged, with price discovery increasing 9.19% (significant at the 1% level) for NYSE stocks and decreasing by

Table 3.11: Difference in Difference – Autoquote

The table shows the results for computed statistics of WPC (for both NYSE and Nasdaq firms). WPC is a proxy for price discovery around earnings announcements and for firm i, in quarter q, $WPC_q = \sum_{i=1}^{I}\left[\frac{3DR_{i,q}}{BHAR[-1,61]_{i,q}}\left(\frac{|BHAR[-1,61]_{i,q}|}{\sum_{i=1}^{I}|BHAR[-1,61]_{i,q}|}\right)\right]$ and the measure represents a weighted-average of the proportion of returns realised across the first three trading days relative to the whole 63 day announcement period. To assess WPC across both NYSE and Nasdaq each NYSE firm is matched to a Nasdaq firm. For each calendar quarter three matched groups are created: *Large*, *Medium* and *Small*. For the *Large* group Nasdaq firms are sorted, within-quarter, by market capitalisation. The largest 100 firms are then matched to NYSE firms within the same calendar quarter (via one-to-one matching without replacement). If a firm-quarter *ES* is equal to zero it is assigned a value of 0.0001. For the *Small* group, for each quarter 100 firms are randomly selected from the smallest NYSE quintile and then matched to a Nasdaq firm within the same quarter (one-to-one matching without replacement). For the *Medium* group, for each quarter the largest 100 NYSE firms and smallest NYSE quintile are excluded. A firm is then randomly selected in the remaining sample and matched to a Nasdaq firm from the same quarter (one-to-one matching without replacement). The right column shows the expected difference in NYSE WPC minus Nasdaq WPC; and the left column shows the expected difference in post-Autoquote WPC minus pre-Autoquote WPC. Panel A shows results for firms matched by market capitalisation and earnings surprise. Panel B shows results for firms matched by market capitalisation and price. Panel C implements an alternative matching procedure where, for each quarter, NYSE firms are sorted alphabetically and every 10th stock is selected and matched (without replacement) to a Nasdaq firm by market capitalisation and earnings surprise. To compute standard errors, within each quarter the matched pairs are sorted into quintiles based on the market capitalisation of the NYSE stock. Hence the pre-Autoquote and post-Autoquote samples have 20 groups across 4 calendar quarters (with 5 size quintiles in each quarter). The WPC is then computed for each group and statistical inferences are based on two-sample pooled t-tests. Post-Autoquote sample period is from 1st October 2003 to 30th September 2004. Pre-Autoquote sample period is from 1st July 2002 to 30th June 2003. ***, **, * represent 0.01, 0.05, 0.1 significance level for t-statistic respectively.

	Post-Autoquote WPC minus Pre-Autoquote WPC				*NYSE minus Nasdaq*	
Panel A: Matched only by Market Cap and Surprise						
	NYSE firms		Nasdaq firms			
Large	0.09	***	-0.0342		0.124	***
Medium	-0.0216		0.0293		-0.0509	
Small	0.052		-0.0931	***	0.145	***
Panel B: Matched only by Market Cap and Price						
	NYSE firms		Nasdaq firms			
Large	0.0919	***	-0.0358		0.128	***
Medium	-0.0317		0.0220		-0.0538	
Small	0.0281		-0.0381		0.0662	
Panel C: O'Hara and Ye (2011) Matching Procedure						
	NYSE firms		Nasdaq firms			
NYSE-matched firms	0.0836	**	-0.0605		0.144	***

3.58% (insignificant at the 10% level) for the control group. The difference in WPC is therefore 12.8% (significant at the 1% level). The results for the *Medium* sample are also essentially unchanged with price discovery decreasing by 3.17% (insignificant at the 10% level) for NYSE stocks and increasing by 2.20% (insignificant at the 10% level) for the control group. The difference in WPC is -5.38% (insignificant at the 10% level). Last, for the *Small* sample I note that the deterioration of price discovery at -3.81% (insignificant at the 10% level) in the control group is no longer significant. The change in price discovery for NYSE firms remains largely unchanged at 2.81% (insignificant at the 10% level) and the difference in WPC across the two exchanges is also now insignificant at 6.62% (insignificant at the 10% level). Hence, my overall finding shows a structural increase in AT improves price discovery for large-cap NYSE stocks while having insignificant effects on the remaining sizes.

Finally, to rule out my results are driven by outliers or biased firm composition I conduct an alternative matching procedure following O'Hara and Ye (2011). I again match, for each calendar quarter, NYSE-listed stocks to Nasdaq-listed stocks by the following: 1) I exclude stocks that have changed ticker symbol and exclude all stocks with share prices below \$5 and above \$150 as of 31st March 2001. 2) I then, for each quarter, sort NYSE firms by name alphabetically and select every 10th stock and match (without replacement) to the Nasdaq sample by minimising the following matching error:

$$\left| {Mcap_u^{NASDAQ}}\Big/{Mcap_v^{NYSE}} - 1 \right| + \left| {ES_u^{NASDAQ}}\Big/{ES_v^{NYSE}} - 1 \right| \qquad (3.13)$$

I sort based on NYSE firms given NYSE firms are in general larger than Nasdaq firms. 3) I then assign all matched pairs between 1st July 2002 and 30th June 2003 to the pre-Autoquote sample and assign all matched pairs between 1st October 2003 and 30th September 2004 to the post-Autoquote sample. 4) To compute standard errors I again sort into quintile, within each quarter, the matched pairs based on the market capitalisation of NYSE stock.[90] WPC is then computed for each group following Equation 3.10.[91] The results are in Panel C of Table 3.11 and show price discovery for NYSE firms improved by 8.36% (significant at the 5% level) while control firms saw an insignificant decline of 6.05% (insignificant at the 10% level). Overall the difference in WPC across the two exchanges suggests large firms subject to Autoquote experienced a 14.4% (significant at the 1% level) improvement in price discovery compared with the control group.

3.7. Conclusion

Overall my findings show AT may not be associated with improved liquidity around announcement periods but AT nevertheless improves price discovery. While this is inconsistent with the general view that AT improves liquidity it does align with studies finding AT contributes to price efficiency.

My analysis begins by testing for a structural decline in PEAD and my results show declines are concentrated among NYSE-listed firms (and attenuation exceeds 30% from 1995 to 2011). The structural break is located around the early 2000s which corresponds to the structural increase in AT for NYSE firms (as a result of Autoquote). However I argue PEAD attenuation may also be attributed to decimalisation and an upward trend in earnings quality. I then formally test the relation between AT and PEAD but remove the bias associated with decimalisation and earnings quality. To control for decimalisation I assess the effects of AT by restricting my sample test period and instrumenting the phase-in schedule of Autoquote. To control for the variation in earnings quality I then employ matched sampling techniques to

[90] Therefore for both the pre- and post-Autoquote samples I have 20 groups consisting of 4 calendar quarters with 5 size quintiles in each quarter.

[91] Following Bessimbinder (2003b), statistical inferences are computed from two-sample pooled t-tests.

bucket-paired stocks in high and low AT bins. I then examine whether high AT firms have significantly lower PEAD relative to low AT firms. My findings show the rise in AT and decline in PEAD are not statistically related.

To test the conjecture that AT contributes to price discovery I then consider whether AT is associated with a larger response to earnings news. Proxying earnings response by 3DR I find AT is concentrated among stocks that exhibit relatively high 3DR. I suggest this is because algorithmic traders prefer to trade stocks that have high quality trading signals and therefore AT is potentially concentrated among firms that release disproportionally more information at announcements. This also implies AT is concentrated among firms with high earnings quality. I then test the conjecture that AT improves price discovery for firms associated with high earnings quality and find price discovery as proxied by Weighted Price Contribution (WPC) improved by more than 12% after Autoquote was phased in. Overall my study therefore suggests AT responds to earnings announcement not by way of attenuating PEAD effects but by improving the impounding of trading signals to stock prices.

CHAPTER 4: DOES ALGORITHMIC TRADING IMPROVE LIQUIDITY AFTER ADJUSTMENT FOR ORDER-SPLITTING?

4.1. Introduction

This chapter tests whether AT significantly improves market liquidity once an adjustment is made for the potential under-estimation of effective spreads. While AT has been shown to improve market liquidity – the commonly-cited Hendershott, Jones and Menkveld (2011) shows high AT significantly reduces effective spread – recent studies argue the benefits of AT are over-estimated (see Gai, Yao and Ye, 2013; Kim and Murphy, 2013; Lyle and Naughton, 2016). One particular critique is that AT encourages order-splitting and large orders are therefore increasingly camouflaged into sequences of small transactions (see Kim and Murphy, 2013; Easley, Prado and O'Hara, 2014). Kim and Murphy (2013) argue this causes effective spread to be under-estimated but can be corrected for by treating sequences of consecutive buy or sell orders as a single transaction.

I apply an adjustment to order-book data following Kim and Murphy (2013) and revisit the study by Hendershott et al. (2011) on the relation between AT and liquidity measures. Hendershott et al. (2011) find improvements in liquidity are associated with the phasing-in of Autoquote [92] and I follow the study by using the Autoquote phase-in schedule as an instrumental variable for testing the effects of a structural increase in AT on liquidity measures.

[92] Referring to the NYSE implementing the electronic real-time dissemination of updates for the inside quote which significantly increased the benefits of adopting AT and increased AT order flow. Autoquote was phased in between 29th January 2003 and 27th of May, 2003

After applying the adjustment my findings show AT contributes significantly less to market quality than previously documented. Effective spreads do not decline significantly and tests on the components of effective spreads suggest the level of revenue generated from liquidity provision is completely offset by losses due to adverse selection. My results are consistent with studies showing order-splitting causes under-estimation of price impact. Consistent with Hendershott et al. (2011) I do find the phase-in of Autoquote is associated with overall lower adverse selection but higher realised spreads and this aligns with algorithmic traders being opportunistic, taking advantage of their speed to mitigate price impact while imposing higher adverse selection costs on slower traders.

To adjust for bias in the measure of effective spreads I follow Kim and Murphy (2013) and collapse consecutive sequences of buy and sell orders. However, while previous methods collapse consecutive sequences irrespective of the time interval between orders I only collapse "fast" trades and therefore treat clusters of orders traded in a short time interval as a single transaction.

To begin my analysis I apply the method of Hendershott et al. (2011) but without adjustment to order-splitting and show consistent findings with previous published results. I find an improvement in AT is associated with a significant decline in effective spreads and that the improvement in liquidity is concentrated among large market capitalisation stocks. However I show Hendershott et al.'s (2011) main findings are only significant for relatively fast trades. I also separate effective spreads into constituent components of adverse selection and realised spreads and find, consistent with Hendershott et al. (2011), that adverse selection decline significantly more than increases in realised spreads and therefore improvements in liquidity are attributable to a relative decline in adverse selection.

I then show after adjustment for order-splitting, shifts in effective spreads are insignificant. For each stock I collapse eligible trades that are among the 5% fastest of all trades into a single transaction – typically this means for the largest (smallest) firms two consecutive trades are collapsed together only if the time interval between trades is less than 20 seconds (2.88 minutes).[93] I find that although high AT continues to be associated with a decline in adverse selection costs and an increase in realised spreads, the estimated coefficients indicate a smaller reduction in adverse selection compared to results from uncollapsed trades. Further, the reduction in adverse selection is completely offset by increases in realised spreads, and changes in effective spreads are insignificant.

My results also provide empirical evidence on the implications of transacting against fast and slow traders. I find that with high AT 1) fast (slow) trades are associated with a smaller (larger) decline in adverse selection, and 2) fast (slow) trades are associated with a smaller (larger) increase in realised spreads. Hence, although higher AT corresponds with lower overall adverse selection, fast liquidity providers are relatively better at avoiding adverse selection from slow traders. And although higher AT corresponds with overall higher realised spreads, slow traders generate relatively higher revenues for liquidity providers employing AT. Hence with higher levels of AT, the cost of liquidity (relative to fast traders) increases for slow traders.

The rest of the chapter proceeds as follows: Section 4.2 discusses the background to this study; Section 4.3 presents the data; Section 4.4 introduces the method for the analysis of uncollapsed data; Section 4.5 presents empirical results across different trading speeds; Section 4.6 presents empirical results after trades are collapsed; Section 4.7 concludes this chapter.

[93] While Kim and Murphy (2013) shows the adjustment to order-splitting via collapsing trade sequences reduces estimation bias of liquidity measures, the assumption (implicitly relied upon in this chapter) that collapsed trades reasonably proxy actual pre-split large orders remains untested.

4.2. Background

AT now plays a dominant role in securities exchange order-flow. From a starting point of near zero in the mid-1990s, AT has risen so that in 2009 it accounts for 73% of the trading volume in U.S. equity markets (Hendershott et al., 2011, p.1). Carrion (2013) notes that market structure developments such as decimalisation, Reg NMS and automated electronic order books have encouraged AT.[94] There is further high competition among brokers, investment banks and exchanges to promote low latency order matching systems, co-location infrastructure and direct market access (DMA) services to support AT (see Jain, 2005; Boehmer, 2005; Hendershott and Riordan, 2011; Gai et al., 2013; and Hasbrouck and Saar, 2013; O'Hara, 2015).

However AT also enables high-frequency arbitrage which generates a "winner's curse" cost upon slow traders. This form of high-frequency trading (HFT) is a subset of AT and refers to proprietary algorithms that scan for changes across the entire market's order book and then quickly execute orders to profit from price inefficiencies (Hasbrouck and Saar, 2013).[95] Studies find that AT tends to provide liquidity when liquidity is expensive and removes liquidity when liquidity is cheap (Hendershott and Riordan, 2014). However the empirical evidence also shows that fast traders can quickly transition from liquidity-making to liquidity-taking strategies and liquidity provision can therefore occasionally be illusory (Brogaard, Hendershott and Riordan, 2014). Gai et al. (2013) show the fastest of all orders provide a "trivial

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[94] Decimalisation refers to the reduction in minimum tick-size adopted by US exchanges in the early 2000s. Reg NMS refers to the Regulation National Market System of 2007 which encouraged market fragmentation and competition among technologically sophisticated brokers, exchanges and alternative trading venues.

[95] HFT is a subset of AT. Hasbrouck and Saar (2013) notes AT can be partitioned into: 1) agency algorithms which intelligently split large orders, and 2) proprietary algorithms that scan for changes across the entire market's order book. The former represents the use of AT by portfolio managers and brokers to improve execution quality and reduce price impact (such as implementing order-splitting algorithms) while the latter represents HFT participants which profit from price inefficiencies. An additional characteristic of HFTs is they generally trade with their own capital, generate a large amount of message traffic and turnover and are reluctant to hold inventory overnight (Hasbrouck and Saar, 2013).

contribution" (p.26) to liquidity and price efficiency and find that technological improvements in 2010 on Nasdaq increased the speed of trading from microseconds to nanoseconds but are associated with insignificant improvement in liquidity (despite a large rise in message traffic). The authors argue greater speed merely shifts a greater portion of liquidity costs from fast to slow traders and "trading speed above some threshold should be a zero-sum game". Lyle and Naughton (2016) observe that after controlling for the improved quality of market monitoring by liquidity providers, high AT is associated with an *increase* in spreads for the period 2002 to 2007. The authors argue AT plays a role in lowering a liquidity provider's monitoring costs, however this component of AT is subject to diminishing returns. Lyle and Naughton (2016) therefore claim their results explain why, despite the increase in AT, spreads on the US equity market have not significantly declined since 2007.

A debate continues as to whether the benefits of AT are overstated. Some studies show traders employing liquidity provision strategies using AT are opportunistic and can quickly withdraw liquidity followed by swift insertion of liquidity-taking orders, creating fleeting and unreliable liquidity (Cvitanic and Kirilenko, 2010; Kirilenko, Kyle, Samadi and Tuzun, 2016; Easley, Prado and O'Hara, 2012). In this sense fast traders are unlike the traditional NYSE specialists who are subject to the Price Continuity Rule and stand ready and able to provide bid-ask quotes throughout the trading day (Panayides, 2007). Regulators have also raised concerns of potential market destabilisation by high-frequency trading (HFT) liquidity provision. In particular, U.S. Securities and Exchange Commission Chairwoman Mary Shapiro raised the issue of whether "the most sophisticated and active trading firms that ordinarily act as liquidity providers be allowed to suddenly become aggressive liquidity takers during a price move in a way that exacerbates the price move."[96] Regulatory proposals to combat fleeting liquidity have included

[96] "Strengthening Our Equity Market Structure" by Mary L. Schapiro, Speech at the Economic Club of New York, September 7, 2010.

imposing a minimum time-in-force on AT liquidity provision[97] and fees for high rates of order cancellation.[98]

Kim and Murphy (2013) contribute to this debate by considering whether measures of liquidity have been subject to estimation bias because of AT-facilitated order-splitting. They find it is increasingly common to see large sequences of consecutive buy or sell orders in high-frequency order-book data, and the size of the individual orders is inversely related to the length of the sequences.[99] Institutional traders also increasingly attempt to obtain better price execution by splitting large orders into smaller and smaller transactions to reduce price impact and mitigate against detection by the rest of the market (see Bertsimas and Lo, 1998).[100] The authors argue this autocorrelation in trade data, as well as the loss in size-variation, causes estimates of a large order's effective spreads to be biased downwards and therefore AT may not be associated with improved liquidity. In other words, the true price impact of a single small trade is now correlated to the cumulative price impact of many other small trades; and the variation in transaction costs with respect to size is difficult to quantify if there are few large orders being transacted. Empirical market microstructure models that relate price changes to individual trade size, negate this cumulative effect of smaller orders (see Glosten and Harris, 1988) and

[97] European Commission Public Consultation: Review of the Markets in Financial Instruments Directive (MiFID), February, 2011, p.7.
[98] Recommendations Regarding Regulatory Responses to the Market Events of May 6, 2010: Summary Report of the Joint CFTC-SEC Advisory Committee on Emerging Regulatory Issues, p.11.
[99] Kim and Murphy (2013) considered the S&P500 Exchange Traded Fund SPY from 1997 to 2009 and found that the average string of consecutive buy or sell orders increased from two to twelve; the average size of individual trades decreased from 5,600 shares in to 400 shares; the standard deviation of individual trade size declined from 22,000 shares to 5,100 shares; and the average time between trades decreased from 67.5 seconds to 0.1 seconds. In other words, small buy orders are more often immediately followed by small buy orders, and small sell orders are more often immediately followed by small sell orders.
[100] Hendershott et al. (2011) writes "before AT took hold, a pension fund management who wanted to buy 30,000 shares of IBM might hire a broker-dealer to search for a counter party to execute…Alternatively, (he) might have hired a NYSE floor broker to go stand at the IBM post and quietly "work the order"…Now virtually every large broker-dealer offers a suite of algorithms to its institutional customers to help them execute orders…Algorithms typically determine the timing, price, quantity and routing orders, dynamically monitoring market conditions across different securities and trading venues, reducing market impact by optimally and sometimes randomly breaking large orders into smaller pieces" (p. 2).

therefore the splitting of large orders can be indistinguishable from small orders (Kim and Murphy, 2013). Nevertheless, *ceteris paribus*, larger order imbalance generates higher adverse-selection costs (see Kyle, 1985) and forces market-makers to deviate from their optimal inventory position (Stoll, 1978). This additional inventory risk causes market-makers to widen their quoted spreads and hence charge more for liquidity (Comerton-Forde, Hendershott, Jones, Moulton and Seasholes, 2010).

Last, anticipatory trades by AT can increase price impact. Brogaard, Hendershott and Riordan (2014) show HFTs compete aggressively to profit from short-run price changes via liquidity-taking orders while Foucault, Hombert and Rosu (2016) argue speed, news anticipation and order-flow anticipation are defining traits of HFT's aggressive liquidity-taking. Electronic algorithms employed in anticipation of order-splitting (Easley, Prado and O'Hara, 2012) and aggressive HFT orders trading in response to order imbalance, account for more than a quarter of overall market turnover (Brogaard et al., 2014). Traders increasingly employ the same technological advantages of AT to detect and trade in the same direction as the order flow subject to order-splitting[101] and therefore small trades conditioned on order-splitting are more likely to attract aggressive HFT orders.

4.3. Data

My sample period is from 1st January 2003 to 31st July 2003 and my sample data utilise trade-tick data, quarterly corporate disclosures and the Autoquote phase-in schedule. For comparison, Hendershott et al.'s (2011) sample period is from 1st December 2002 to 31st July 2003. I note I was unable to obtain pre-2003 data however I will show my summary statistics in Table 4.1

[101] To protect traders from being picked off by ultra fast algorithms the Wall Street Journal reports one trading venue is slowing down the speed of orders (http://www.wsj.com/articles/iexs-next-challenge-delivering-on-its-promises-1466330401, accessed 9th, October 2016).

resemble that of Hendershott et al. (2011). I also note I use an alternative source of intraday trade and quote data compared to Hendershott et al. (2011) who use Trades and Quotes (TAQ) data, a dataset which provides historical tick by tick data for all securities listed on the NYSE, AMEX and Nasdaq National Market System (NMS). However I note both my data and TAQ show all order-book changes at the inside quote and therefore the choice of dataset should not affect my result.

I obtain U.S. intraday trade and quote data from Thomson Reuters Tick History (TRTH).[102] The TRTH data are organised by Reuters Instrument Code (RIC) and each RIC is associated with an equity or derivative instrument. For each NYSE-listed common stock, I obtain from SIRCA the RIC codes, the NYSE listing codes and consolidated time-stamped trade and quote data. The data therefore records every order placed at the inside quote as represented by the National Best Bid and Offer (NBBO). I then apply the following filters: 1) I remove irregular trades based on some technical conditions in the TRTH "qualifiers" data field following Boehmer, Fong and Wu (2015) (see Section C.2 in the Appendix) ; 2) I require all traded price, traded volume, bid price, bid volume, ask price and ask volume data fields to be greater than zero; 3) the ask price must be greater than the bid price; 4) all intraday trade and quote observations must be between 9:35am and 3.55pm. I obtain market capitalisation data from Compustat,[103] based on quarterly accounting filings and match to the TRTH data based on the NYSE listing code. Finally, each stock has a unique date for the phasing-in of Autoquote and I obtain this list from Hendershott's website.[104] The list includes the NYSE listing codes which I use to match to TRTH data.

[102] Provided by the Securities Industry Research Centre of Asia-Pacific (SIRCA).
[103] The data is provided by Wharton Research Data Services (WRDS).
[104] http://faculty.haas.berkeley.edu/hender/.

To arrive at my final sample data the following stocks are removed: 1) stocks with a closing share price below $5 or above $1000 on the first day of trading in January 2003; 2) any newly listed stock in the sample period or any stock which changed listing symbols; 3) stocks with less than 100 trading days of data; 4) stocks which have less than 21 trades on any trading day. My sample contains 913 eligible stocks compared with 1082 in Hendershott et al. (2011).

Table 4.1 presents the summary statistics across market capitalisation sorted into quintiles. Following Hendershott et al. (2011) I winsorize all variables in this study at the 0.05% and 99.95% level. Detailed description and construction of the variables are discussed in Section C.1 of the Appendix. The values are consistent with the summary statistics in Hendershott et al. (2011, p.17). The measures of liquidity I consider throughout this study are effective spreads, adverse selection and realised spreads. Effective spreads is the difference between the traded price by a liquidity taker and the bid-ask midpoint price at the time of the transaction; it represents the cost borne for immediate liquidity. Adverse selection is the degree by which the midpoint price moves against the liquidity provider's position five minutes after a trade; it proxies the gross losses borne by the liquidity provider to the liquidity taker. And realised spreads is the degree to which the bid-ask midpoint price moves in favour of the liquidity provider after a trade; it assumes the liquidity provider can on average close out a trade in five minutes at the midpoint and therefore proxies the gross revenues generated by liquidity provision. Section 4.4.1 discusses these measures in more detail. Looking at Table 4.1, effective and realised spreads all decrease with respect to firm size and adverse selection also decrease with respect to firm size. For example, the effective spread is 3.37 basis points for firms in the largest quintile and 9.61 basis points for firms in the smallest quintile. Adverse selection at the five minute level averages 2.08 basis points for the largest quintile and 5.78 basis points for the smallest. Realised spreads at the five minute level average 1.29 basis points for the largest quintile and 3.84 for the smallest quintile. These measures are computed without collapsing trade sequences. My values closely resemble the summary statistics of Hendershott et al. (2011, Table 1, p.17) for the largest quintiles (which are the focus of Hendershott et al.'s (2011) main findings) while my values for the smallest quintile tend to be smaller. In Hendershott et al. (2011) the mean effective spreads, adverse selection and realised spreads are 3.63 (14.50), 2.42 (10.16) and 1.21 (4.34) basis points respectively for the largest (smallest) quintiles.

One substantial difference between my data and Hendershott et al.'s (2011) is the number of order book messages. I show the average number of order book messages at the inside quote increases with respect to firm size (from 823 messages per common stock per day for the smallest quintile to 5,476 messages per common stock per day for the largest). Hendershott et al. (2011) use data from the NYSE System Order Data which contains all order submissions, cancellations and trade reports handled by the NYSE's SuperDOT system. They show that by excluding orders from exchanges specialists, floor brokers and manual entries, the number of messages for the largest (smallest) quintile firm is approximately 50,000 (4,400) messages per common stock per day. This variable however does not influence my results and consistent with Hendershott et al. (2011) I do not use this variable in my tests.

Table 4.1: Summary Statistics by Size Quintile

This table presents summary statistics on daily data from the period 1st January 2003 to 31st July 2003. Mean values are based on 913 NYSE-listed stocks sorted into market capitalisation quintiles where 1 is the smallest firms and 5 is the largest firms. Quintile break points are computed based on market capitalisation at the end of June 2003. For each stock *j* and day *t*: $qspread_{j,t}$ is the turnover-weighted quoted half-spread (bps), $espread_{j,t}$ is the turnover-weighted effective half-spread (bps), $rspread_{j,t}$ is the turnover-weighted realised half-spread (bps) at 5 minutes, $adv\_selection_{j,t}$ is the turnover-weighted adverse selection half-spread (bps) at 5 minutes, $messages_{j,t}$ is the number of order book changes (/day), $turnover_{j,t}$ is the share turnover ($million), $volatility_{j,t}$ is the daily price range standardized by the daily close price (%), $price_{j,t}$ is the daily closing price ($), $market\_cap_{j,t}$ is the number of shares outstanding times price as of June 2003 ($billion), $trade\_count_{j,t}$ is the number of trades, $trade\_size_{j,t}$ is the mean trade size ($1,000), $volume_{j,t}$ is the number of shares transacted (1,000s). All variables are 99.9% winsorized.

	1 (smallest cap)		2		3		4		5 (largest cap)	
Variables	mean	stdev	mean	stdev	mean	stdev	mean	stdev	mean	stdev
$qspread_{j,t}$	13.51	12.94	9.06	10.40	5.17	7.03	4.38	5.89	4.42	8.40
$espread_{j,t}$	9.61	9.28	6.59	7.73	4.05	5.36	3.39	4.14	3.37	5.81
$adv\_selection_{j,t}$	5.78	9.11	4.70	7.83	2.88	4.25	2.26	3.74	2.08	4.57
$rspread_{j,t}$	3.84	9.37	1.89	5.92	1.18	4.13	1.13	3.74	1.29	4.94
$messages_{j,t}$	823	637	1,437	951	2,228	1,272	3,357	1,895	5,476	3,456
$turnover_{j,t}$	1.28	3.51	3.24	5.77	8.00	12.94	18.26	24.25	62.00	86.06
$volatility_{j,t}$	2.50	1.96	2.75	2.17	2.59	1.87	2.55	1.75	2.66	1.82
$price_{j,t}$	19.39	11.95	22.15	12.68	31.09	33.10	30.53	17.15	33.10	18.74
$market\_cap_{j,t}$	0.36	0.27	0.75	0.47	1.76	1.85	3.63	2.75	22.56	40.08
$trade\_count_{j,t}$	130	173	296	255	518	364	868	579	1,606	1,166
$trade\_size_{j,t}$	8.92	18.12	10.25	46.67	14.59	36.62	18.39	21.98	30.38	62.31
$volume_{j,t}$	537	1,135	598	3,741	603	1,554	748	1,529	1,163	3,543
Number of Observations	23,373		25,836		27,275		26,383		28,845	

Table 4.2: Summary Statistics Before and After Autoquote

This table presents summary statistics on daily data for before and after the phase-in of Autoquote. The sample period is 1st January 2003 to 31st July 2003. Mean values are based on 913 NYSE-listed stocks sorted into market capitalisation quintiles where 1 is the smallest firms and 5 is the largest firms. Quintile break points are computed based on market capitalisation at the end of June 2003. For each stock *j* and day *t*: $qspread_{j,t}$ is the turnover-weighted quoted half-spread (bps), $espread_{j,t}$ is the turnover-weighted effective half-spread (bps), $rspread_{j,t}$ is the turnover-weighted realised half-spread (bps) at 5 minutes, $adv\_selection_{j,t}$ is the turnover-weighted adverse selection half-spread (bps) at 5 minutes, $messages_{j,t}$ is the number of order book changes (/day), $turnover_{j,t}$ is the share turnover ($million), $volatility_{j,t}$ is the daily price range standardized by the daily close price (%), $price_{j,t}$ is the daily closing price ($), $market\_cap_{j,t}$ is the number of shares outstanding times price as of June 2003 ($billion), $trade\_count_{j,t}$ is the number of trades, $trade\_size_{j,t}$ is the mean trade size ($1,000), $volume_{j,t}$ is the number of shares transacted (1,000s). t-stat refers to two-sample pooled t-test. ***, **, * represent 1%, 5% and 10% significance level respectively. All variables are 99.9% winsorized.

	1(smallest cap)			2			3			4			5 (largest cap)		
Variables	Before	After	t-stat	Before	After	t- stat	Before	After	t- stat	Before	After	t- stat	Before	After	t- stat
$qspread_{j,t}$	13.46	13.6		9.62	8.17	***	5.49	4.68	***	4.86	3.64	***	5.41	3.28	***
$espread_{j,t}$	9.81	9.29	***	7.17	5.66	***	4.3	3.67	***	3.73	2.86	***	4.05	2.59	***
$adv\_selection_{j,t}$	6.42	4.76	***	5.39	3.6	***	3.39	2.1	***	2.68	1.61	***	2.68	1.49	***
$rspread_{j,t}$	3.4	4.54	***	1.79	2.06	***	0.92	1.57	***	1.05	1.26	***	1.38	1.19	***
$messages_{j,t}$	738	959		1,235	1,759	***	1,916	2,715	***	2,905	4,054	***	4,097	7,055	***
$turnover_{j,t}$	1.11	1.54	***	2.77	3.99	***	7.11	9.39	***	17.33	19.69	***	46.31	79.96	***
$volatility_{j,t}$	2.48	2.52		2.84	2.61	***	2.67	2.46	***	2.65	2.4	***	2.77	2.54	***
$price_{j,t}$	18.48	20.84	***	21.1	23.84	***	29.71	33.25	***	29.71	31.8	***	30.74	35.79	***
$market\_cap_{j,t}$	0.34	0.39	***	0.7	0.82	***	1.62	1.98	***	3.49	3.86	***	25.96	30.12	***
$trade\_count_{j,t}$	119	148	***	269	339	***	491	560	***	835	920	***	1,340	1,910	***
$trade\_size_{j,t}$	8.41	9.74	***	10.2	10.31		13.68	16.03	***	17.72	19.42	***	27.37	33.82	***
$volume_{j,t}$	524	557	**	645	523	**	607	598		745	753		1,142	1,187	

Table 4.2 contains average values of summary data for before and after the Autoquote phase-in. The results are shown across market capitalisation quintiles and the pooled two-sample t-test supports the view by Kim and Murphy (2013) that higher AT is associated with improved liquidity measures (when unadjusted for order-splitting), increased order traffic and higher turnover. There is noticeable variation between pre- and post-Autoquote figures. For example, for the largest firms (where Hendershott et al. (2011) observed the biggest improvements in liquidity) average effective and realised spreads declined by 36% (from 4.05bps to 2.59bps) and 14% (from 1.38 to 1.19 basis points) respectively after the phasing-in of Autoquote (both declines are significant at the 1% level). Adverse selection declined the most, by 48% (from 2.68 to 1.49 basis points) and the decline is significant at the 1% level. As expected, these declines are less pronounced for smaller firms. The number of order book messages and trades increased for all size quintiles. The largest firms saw the average number of order book messages increase by 72%, from 4,097 per day to 7,055, while the average number of trades per day rose 43%, from 1,340 to 1,910. For the smallest firms the average number of order book messages increased by 29% and the average number of trades per day increased by 26%. Across all size quintiles turnover also increased but trade size remained more or less constant. For example, the largest firms saw annualised turnover almost doubled from an average of $46 million to $80 million while average trade size increased just 4% from 1,142 shares to 1,188 shares. Hence, although turnover is growing trade size has not.

4.3.1. Autoquote

Autoquote refers to the event in 2003 in which the NYSE began updating the limit order book in real-time and disseminating the inside quote electronically. This gave algorithmic traders an advantage as Autoquote gives immediate feedback about the potential terms of trade but was unlikely to directly affect the trading behaviour of slower-reacting humans. Prior to its introduction NYSE specialists manually disseminated the inside quote for the equities market. However after the introduction of decimalisation tick-size narrowed and this greatly increased the number of order book updates and made excessively onerous the specialist's role of manually managing the order book. Further, NYSE specialists were required to manage an additional "liquidity quote" in order to efficiently transact with investors who wanted to match for significant size (typically at least 15,000 shares). Autoquote alleviated some of the burdens for specialists and added new capability and efficiency for both liquidity demanders and suppliers and its phase-in is considered an exogenous event by Hendershott et al. (2011).

The Autoquote phase-in schedule provided by Hendershott's website shows the first stage of Autoquote phase-in began on 29th January 2003 for six large-cap stocks. Over the next two months, over 200 additional stocks across all size quintiles were then gradually phased in. The remaining stocks were phased in on 27th May, 2003. Hendershott et al. (2011) argue Autoquote affects liquidity only via its impact on AT and therefore the dates of Autoquote phase-in constitute a valid dummy-variable instrument to test the relation between liquidity and AT. They also note the Autoquote phase-in schedule was fixed months in advance and therefore "it seems highly unlikely that the phase-in schedule could be correlated to idiosyncratic liquidity months into the future" (p.15).

4.4. Method

4.4.1. Test Method of Hendershott et al. (2011)

There are many theoretical frameworks for measuring liquidity (see Glosten and Milgrom 1985; Kyle 1985; Easley and O'Hara, 1987). I follow Glosten (1987) and Hendershott et al. (2011) and measure market liquidity by a stock's effective spread which represent the immediate cost borne by the liquidity taker with respect to the midpoint price. For the n^{th}transaction in stock j:

$$espread_{j,n} = q_{j,t}(p_{j,n} - m_{j,t})/m_{j,n} \qquad (4.1)$$

Where $espread_{j,n}$ is effective spread, $p_{j,n}$ is traded price, $q_{j,n}$ is buyer-seller indicator (i.e. +1 for a buy and -1 for a sell) and $m_{j,n}$ is the bid-ask midpoint. To compute $q_{j,n}$ I follow the trade classification algorithm of Lee and Ready (1991) and use contemporaneous quotes to sign trades (see Bessimbinder, 2003). I classify a transaction as a buy if the traded price is above the midpoint of the bid-ask quote, and a sell otherwise. For trades with the price equal to the midpoint I classify a transaction as a buy if the most recent price change was positive and as a sell if the most recent price change was negative.

I further break down effective spread into adverse selection and realised spread:

$$adv\_selection_{j,n} = q_{j,n}(m_{j,n+5minute} - m_{j,n})/m_{j,n} \qquad (4.2)$$

$$rspread_{j,n} = q_{j,n}(p_{j,n} - m_{j,n+5minutes})/m_{j,n} \qquad (4.3)$$

Where $adv\_selection_{j,n}$ is adverse selection, $rspread_{j,n}$ is realized spread, and $m_{j,n+5minute}$ is the bid-ask midpoint five minutes after the n^{th}transaction. Following Hendershott et al. (2011), I interpret $adv\_selection_{j,n}$ as the gross losses incurred by liquidity providers due to price impact and $rspread_{j,n}$ as liquidity providers' estimated revenue. The three variables have the following relation:

$$espread_{j,n} = adv\_selection_{j,n} + rspread_{j,n} \qquad (4.4)$$

Hence I implicitly assume liquidity providers can close their positions at the quoted midpoint after five minutes.

To test the relation between liquidity and AT, I apply the model in Hendershott et al. (2011). The dependent variables are either the daily turnover-weighted measures of effective spreads, adverse selection or realised spreads. The independent variable is the Autoquote dummy variable. To remain consistent with Hendershott et al. (2011) my dependent variables are divided by two and therefore represent half-spreads. I control for day and firm fixed effects and test the following specification:

$$L_{j,t} = \alpha_j + \gamma_t + \beta_1 AQ_{j,t} + \gamma_1 turnover_{j,t} + \gamma_2 volatility_{j,t} + \gamma_3 ticksize_{j,t}$$

$$+\gamma_4 logmcap_{j,t} + \varepsilon_{j,t} \qquad (4.5)$$

Where $L_{j,t}$ is the daily turnover-weighted liquidity measure, α_j represents firm fixed effects, γ_t represents day dummy variables for day t, and $AQ_{j,t}$ is the Hendershott et al. (2011) dummy variable equal to +1 for periods with Autoquote phased-in and zero otherwise. I also include the following control variables: share turnover, tick size, the log of market capitalisation and volatility based on daily price range standardized by the daily stock price $(P_{j,t}^{High} - P_{j,t}^{Low})/P_{j,t}$ (see Parkinson, 1980). The estimated standard errors are robust to general cross-sectional and time-series heteroscedasticity and within-group autocorrelation (see Arellano and Bond, 1991).

4.4.1.1. Results

Regression results to Equation 4.5 are presented in Table 4.3 and are consistent with estimates reported in Hendershott et al. (2011, Table III, p.20). Effective spreads declined significantly following Autoquote and the reduction in adverse selection exceeded the increase in realised spreads. Panel A shows market capitalisation-weighted effective spreads declined by 9.72 basis points (significant at the 1% level) after stocks were subject to Autoquote. Further, with the exception of turnover, the sign and magnitude of the control variables' coefficients are consistent with Hendershott et al. (2011) and suggest high effective spreads are associated with high volatility, high tick-size and low market capitalisation. An estimated coefficient of volatility at 0.139 (significant at the 1% level) suggests a 1% increase in the daily high-low price range increases effective spreads by 0.139 basis points. An estimated coefficient of relative tick-size at 1.07 (significant at the 1% level) suggests a 100 basis point increase in relative tick-size increases effective spreads by 1.07 basis points. An estimated coefficient of the log of market capitalisation at -1.29 (significant at the 1% level) suggests a 1% increase in market capitalisation decreases effective spreads by 1.29 basis points.

My coefficient estimate for turnover is inconsistent to the findings in Hendershott et al. (2011) and suggests on average higher turnover is associated with higher spreads. However the magnitude of 0.000147 is very small and suggests on average for every $100 million increase in daily turnover effective spreads increase by 1.47 basis points. Given the mean of daily turnover for firms in the largest quintile is $62 million, the effect of the variable is therefore small. In contrast to all other control variables, the coefficient for turnover is also not robust across size quintiles.

Panel B shows the regression results across market capitalisation quintiles. Consistent with Hendershott et al. (2011) the largest and second largest quintiles exhibit significant decline in effective spreads post-Autoquote of 14.8 and 16.4 basis points respectively. The smallest firms experienced an increase in effective spreads of 60.42 basis points.

Table 4.3: Regression Results following Hendershott et al. (2011)

The table regresses measures of liquidity on the Hendershott et al. (2011) Autoquote dummy variable. Sample period is from 1st January 2003 to 31st July 2003. The specification is: $L_{j,t} = \alpha_j + \gamma_t + \beta_1 AQ_{j,t} + \gamma_1 turnover_{j,t} + \gamma_2 volatility_{j,t} + \gamma_3 ticksize_{j,t} + \gamma_4 logmcap_{j,t} + \varepsilon_{j,t}$ where the dependent variable $L_{j,t}$ is measures of daily turnover-weighted liquidity in basis points: 1) half quoted-spreads; 2) half effective spreads; 3) half adverse selection; and 4) half realised spreads, α_j represents firm fixed effects, γ_t represents day dummy variables and $AQ_{j,t}$ is a dummy variable equal to +1 for periods with Autoquote phased-in and zero otherwise. The remaining factors are control variables: share turnover, volatility, tick size and the log of market capitalisation. Panel A shows market capitalisation-weighted results. Panel B presents results across quintiles based on market capitalisation. Break points are computed using market capitalisation at the end of June 2003. Panel C presents results across quintiles based on the time interval (TI) between trades. For each stock the 20th, 40th, 60th, and 80th break points are computed based on TI in the sample period. Standard errors are robust to general cross-sectional and time-series heteroscedasticity and within-group autocorrelation (see Arellano and Bond, 1991). ***, **, * represent 1%, 5% and 10% significance level respectively.

Panel A: Market Capitalisation Weighted										
	$AQ_{j,t}$		$turnover_{j,t}$		$volatility_{j,t}$		$ticksize_{j,t}$		$logmcap_{j,t}$	
Dependent Variable: effective spreads (bps)										
	-0.0972	***	0.000147	***	0.139	***	1.070	***	-1.29	***
Panel B: Quintile by Market Capitalisation										
Dependent Variable: effective spreads (bps)										
1 (smallest)	0.604	***	-0.0462	***	1.164	***	1.517	***	0.837	
2	-0.183		0.006		0.808	***	-0.113	***	-8.992	***
3	-0.035		-0.002		0.272	***	0.232	***	-4.948	***
4	-0.164	***	-0.001		0.288	***	0.171	***	-4.233	***
5 (largest)	-0.148	**	0.000472		0.176	***	0.382	***	-2.259	***
Panel C: Quintile sorted by Time Between Trades										
Dependent Variable: effective spreads (bps)										
1 (fastest)	-0.088	***	0.000234	**	0.188	***	2.157	***	-1.703	***
2	-0.223	***	-0.0029	***	0.418	***	0.182	***	-3.311	***
3	-0.330	***	-0.0205	***	0.634	***	2.659	***	0.392	**
4	-0.122		-0.0473	***	1.020	***	1.340	***	-2.606	***
5 (slowest)	0.693	***	-0.1697	**	0.563	***	-0.053	***	-6.933	***
Dependent Variable: quoted spreads (bps)										
1 (fastest)	-0.234	***	0.000	***	0.337	***	2.921	***	-2.220	***
2	-0.263	***	-1×10^{-8}	***	0.746	***	0.074		-4.604	***
3	-0.257	***	-3×10^{-8}	***	1.309	***	3.123	***	-0.287	*
4	-0.147		-9×10^{-8}	***	1.800	***	1.726	***	-4.591	***
5 (slowest)	2.890	***	-6.7×10^{-7}	***	1.562	***	0.161	***	-16.514	***

Panel C: (Continued)										
	$AQ_{j,t}$		$turnover_{j,t}$		$volatility_{j,t}$		$ticksize_{j,t}$		$logmcap_{j,t}$	
Dependent Variable: adverse selection (bps)										
1 (fastest)	-0.228	***	0.000983	***	0.307	***	3.039	***	-0.869	***
2	-0.643	***	0.00160		0.605	***	0.632	***	-1.533	***
3	-0.922	***	-0.020	***	0.965	***	1.971	***	0.783	***
4	-1.173	***	-0.029	**	1.390	***	0.907	***	-0.870	**
5 (slowest)	-1.068	***	-0.102		0.885	***	-0.155	***	-4.773	***
Dependent Variable: realised spreads (bps)										
1 (fastest)	0.140	***	-0.00075	***	-0.117	***	-0.877	***	-0.843	***
2	0.435	***	-0.00465	***	-0.191	***	-0.436	***	-1.765	***
3	0.595	***	-3.5×10^{-5}		-0.339	***	0.691	***	-0.370	
4	1.055	***	-0.018		-0.382	***	0.429	***	-1.789	***
5 (slowest)	1.760	***	-0.069		-0.322	**	0.101	***	-2.190	***

Hendershott et al. (2011)note AT are less common in small stocks and this may serve as a partial explanation. The sign of the Autoquote Dummy is also negative for all quintiles except the smallest firms.

Estimated coefficient for turnover is insignificant for all other quintiles except the smallest quintile; estimated coefficients for volatility are positive and significant for all quintiles and range between 0.176 and 1.164; estimated coefficients for tick size are positive and significant for all quintiles except for the second smallest quintile, and range between -0.11 and 1.52; estimated coefficients for the log of market capitalisation are negative and significant for all quintiles except the smallest quintile and range between -8.99 and 0.83. Again, other than turnover, my results are consistent with Hendershott et al. (2011, Table II, p.20) who show market capitalization-weighted estimated coefficients of -1.01 (insignificant at the 5% level), 0.69 (significant at the 1% level), 0.73 (significant at the 1% level) and -1.30 (significant at the 1% level) for turnover, volatility, tick size and the log of market capitalisation respectively.

In Section C.3 of the Appendix I also show results for adverse selection and realised spreads across size quintiles. Estimated coefficients of $AQ_{j,t}$ for adverse selection range between -0.51 basis points for the largest firms and -1.00 for the smallest firms (all significant at the 1% level). Estimated coefficients of $AQ_{j,t}$ for realised spreads range between 0.36 basis points for the largest firms and 1.60 for the smallest firms (all significant at the 1% level). In other words overall asymmetric information declined after Autoquote and realised spreads increased after Autoquote. My results for the three largest quintiles resemble those in Hendershott et al. (2011), however results for the two smallest quintiles diverge as they are found to be insignificant in Hendershott et al. (2011) but significant in mine.

Overall my estimates suggest a smaller reduction in effective spreads than in Hendershott et al. (2011). Estimated coefficients for the largest and second largest quintiles are -0.09 and -0.22 respectively, compared to -0.18 and -0.32 respectively in Hendershott et al. (2011). I attribute a portion of this to excluding data for the entire month of December 2002[108] as the effective spread was near its highest in December 2002 for Hendershott et al.'s (2011) sample test period[109].

4.5. Fast vs Slow Trades

I now discuss whether the improvement in liquidity as found in Hendershott et al. (2011) is more attributable to fast or slow trades. Kim and Murphy (2013) argue fast trades rather than slow trades are better proxies for speed-sensitive algorithms, which trade upon order book changes. The underlying intuition is that the combination of AT speed advantage and the incentive to trade on new information quickly imply traders employing AT are more likely to react swiftly to order book imbalance. It is argued this speed advantage imposes higher adverse selection costs on slower traders while algorithmic traders themselves are better positioned to avoid adverse selection (Biais, Foucault and Moinas, 2011). Further, because HFTs generate high turnover and are a substantial source of liquidity provision their cost base is lowered by large exchange fee rebates and therefore HFTs potentially quote tighter spreads (Carrion, 2013). I consider these arguments by testing the model specification in Hendershott et al. (2011) on fast and slow trades.

I take the time interval (TI) between two consecutive trades as the metric for trading speed. This is computed by taking, for each stock, a trade's timestamp minus the timestamp of the

[108] I was unable to obtain complete NYSE trade and quote data for pre-2003 period.
[109] See Figure 2 in Hendershott, et al. (2011, p.9).

immediate previous trade. TI is only measured if both trades are computed on the same day and therefore, across all stocks, the first trade of each day is removed. For each stock I further assign trades into a TI quintile. A high quintile proxies slow trades and a low quintile proxies fast trades. The break points are computed based on each stock's TI computed across the entire sample period. To account for the large variation in TI across firms I compute break-points within-firm rather than at the aggregated level.

I present summary statistics on firm TI in Table 4.4 and show the median TI for the largest firms is 0.125 minutes (7.53 seconds) before Autoquote and 0.109 minutes (6.53 seconds) after Autoquote. The median TI for the smallest firms is 2.08 minutes (125 seconds) before Autoquote and 1.76 minutes (106 seconds) after Autoquote. Even the fastest trades are subject to large variance across stocks. For example for large firms the TI at the 1st percentile is 0.0003 minutes (0.02 seconds) before Autoquote and 0.0002 minutes (0.01 seconds) after Autoquote, while for small firms the TI is 0.018 minutes (1.08 seconds) before Autoquote and 0.014 minutes (0.85) seconds after Autoquote. This suggests the speed of AT is potentially firm-specific (for example, the speed of order insertion and cancellation can depend on a stock's correlation to activity in equities indices, commodity prices, futures or listed ETFs).

4.5.1. Results

I re-test Equation 4.5 but on the cross-section of trading speed quintiles. My results show improvements in liquidity are concentrated among faster trades, but the fastest trades contribute relatively less improvement to liquidity. I also show adverse selection declined the least for the fastest trades while realised spreads increased the most for the slowest trades. This supports findings that higher AT is effective in reducing adverse selection costs but also

Table 4.4. Summary Statistic of Time Between Trades by Size Quintile

The table shows the mean and percentile breakpoints of time interval ($TI_{j,n}$) between two trades (minutes) for before and after Autoquote. $TI_{j,n}$ is computed by taking, for each stock j, the n^{th} trade's timestamp minus the timestamp of the immediate previous trade. $TI_{j,n}$ is computed only if both trades occurred on the same day. Values are computed based on 913 NYSE-listed stocks sorted into market capitalisation quintiles where 1 is the smallest firms and 5 is the largest firms. The sample period is 1st January 2003 to 31st July 2003.

	1 (smallest cap)		2		3		4		5 (largest cap)	
	Before	After	Before	After	Before	After	Before	After	Before	After
Mean of $TI_{j,n}$	4.877	3.819	1.574	1.285	0.866	0.752	0.486	0.427	0.261	0.234
1st	0.018	0.014	0.017	0.009	0.007	0.007	0.001	0.006	0.00003	0.00002
5th	0.037	0.030	0.024	0.022	0.019	0.021	0.018	0.015	0.017	0.014
25th	0.460	0.388	0.177	0.135	0.106	0.085	0.070	0.057	0.046	0.041
median	2.083	1.760	0.723	0.613	0.414	0.355	0.230	0.197	0.125	0.109
75th	5.967	4.866	2.006	1.656	1.109	0.976	0.637	0.562	0.336	0.301
95th	18.413	14.024	5.888	4.807	3.234	2.821	1.792	1.586	0.942	0.859
99th	33.094	24.067	10.435	8.338	5.605	4.903	3.179	2.821	1.662	1.529

suggests the fastest trades are not associated with the *greatest* reduction in adverse selection costs. My results are consistent with liquidity providers generating higher revenues from the slowest traders.

Results in Panel C of Table 4.3 show the decline in effective spreads is concentrated in the three fastest TI quintiles. The fastest trades experienced a decline in spreads by 8.8 basis points (significant at the 1% level); the second and third quintile experienced larger declines of 22.3 (significant at the 1% level) and 33.0 (significant at the 1% level) basis points respectively. These results are evidence the fastest trades are not associated with the most improvement in liquidity. The fourth quintile shows insignificant change and the fifth quintile show a significant increase in spreads. These results suggest slower trades did not experience an improvement in liquidity. The sign of the coefficient for turnover is positive for the fastest trades but is increasingly negative for slower trades. This suggests, *ceteris paribus*, during days with high turnover the fastest trades are not associated with improvement in liquidity. The signs of the coefficients for volatility, tick-size and size remain largely unchanged with my findings in Section 4.4.

Adverse-selection significantly declined across all speed quintiles and tended to decline further for slower trades. The fastest trades declined by 22.8 basis points (significant at the 1% level) and the slowest trades declined by 106.8 basis points (significant at the 1% level). This suggests algorithmic traders are better at avoiding adverse selection from slow traders. Realised spreads significantly increased across all quintiles, and tended to increase more for slower trades. The fastest trades increased by 14.0 basis points (significant at the 1% level) and the slowest trades by 176.0 basis points (significant at the 1% level). This suggests slow traders pay relatively more for liquidity after the Autoquote phase-in. A higher realised spread potentially suggests liquidity providers are better at anticipating mispricing and interpreting signals from order-book imbalance.

My finding of a simultaneous reduction in adverse selection and increase in realised spreads is consistent with the results in Hendershott et al. (2011). Lower adverse selection cost is consistent with theories that AT gives rise to more efficient quoting and a reduction in the probability of liquidity providers being "picked off" by slow quotes. This reduction is concentrated among fast trades which are more associated with AT. Hendershott et al. (2011) attribute the higher realised spreads to a one-off competitive advantage enjoyed by algorithmic traders as a result of the Autoquote phase-in and this advantage ought to decline as new entrants introduce competing algorithms. I show this advantage is highest when transacting against slow trades. The dual finding that slower trades have less price impact and pay more for liquidity also suggests such behaviour is more likely uninformed liquidity trades or random noise trades (see Kyle, 1985; Easley, Engle, O'Hara and Wu, 2008).

Last, irrespective of trade speed, the estimated coefficient for volatility is positive with respect to adverse selection and negative with respect to realised spreads. In other words, during periods of high volatility market-makers in aggregate are subject to greater adverse selection costs and generate less market-making revenue. This provides empirical evidence for why liquidity provision may be fleeting during high volatility and suggests switching from liquidity provision to liquidity taking strategies can be potentially more profitable in such periods.

4.6. Collapsing Trade Sequences

I now discuss my method of collapsing trade sequences. Kim and Murphy (2013) argue high-frequency order book data have high instances of order-splitting and exhibit serial correlation in returns. They argue collapsing sequences of consecutive buy or sell trades into one transaction corrects for a downward bias in the estimation of effective spreads and show intraday returns more closely resemble a white noise distribution (a standard assumption in market microstructure models). I follow their adjustment method.

Let s index the s-th string of consecutive buys or sells in the series of trades n. I then define the price and volume of a post-adjustment trade (KM trade) by:

$$V_s = \sum_{n \in s} V_n \tag{4.6}$$

$$p_s = \sum_{n \in s} \frac{V_n p_n}{V_s} \tag{4.7}$$

Where V_n is the size of an individual trade at time n, V_s is the total size within a sequence of consecutive buy or sell trades, p_n is the price of an individual trade and p_s is the average price paid within a sequence of consecutive buy or sell trades. The timestamp of a KM trade is equal to the timestamp of the last individual trade in the sequence. Hence a sequence can be constituted by trades at different prices. This is reasonable given a trader who is fragmenting his orders will potentially execute small orders at multiple price levels in the limit order book (Kim and Murphy, 2013).

Further, I only collapse a trade if its TI is less than an upper bound. This is to exclude collapsed trades containing long periods of market idleness. Kim and Murphy (2013) did not impose an upper bound as their object of study is the highly liquid and active S&P500 exchange traded fund (SPY). I impose a TI upper-bound at the 5th percentile level of each stock and Table C.2 in Section C.4 of the Appendix presents the summary statistics.[110] For the largest quintile at

[110] In Tables C.4 and C.5 of Section C.4 in the Appendix I also show results at the 25th percentile as well as not imposing an upper bound on TI at all. The results show as the upper bound is relaxed Autoquote is associated with *insignificant* improvements in liquidity. However at the 1st percentile unreported results show Autoquote remains significantly associated with improved liquidity.

the 5th percentile (last row in Table C.2) the median ranked firm has an upper bound TI of 0.055 minutes (3.32 seconds). In other words, for half of all large firms a trade is eligible to be collapsed only if its TI is less than 3.32 seconds. In comparison, the first row of Table C.2 shows the median ranked firm for the smallest quintile has an upper bound of 0.333 minutes (20 seconds). Table C.2 also shows 95% of large firms have a TI upper bound of less than 20 seconds (hence for 95% of large firms a trade is eligible to be collapsed only if the associated TI is less than 20 seconds) and in comparison 95% of small firms have a TI upper bound of less than 2.876 minutes. I note it is reasonable for large firms to have smaller TI upper bounds as the expected execution cost of order-splitting is inversely related to market liquidity (Bertsimas and Lo, 1998).

4.6.1. Results

It is argued that the increasingly common practice of splitting orders causes the measure for effective spreads to be biased downwards and this can be corrected for by collapsing sequences of consecutive buy or sell orders. Table 4.5 presents regression results following the method by Hendershott et al. (2011) but collapsing trade sequences at the 5th percentile of each stock's TI. The results in Panel A show that the estimated change in market capitalisation-weighted effective spreads following the Autoquote phase-in is close to zero, declining merely -1.09 basis points (insignificant at the 10% level). This is in comparison to the significant decline of 9.72 basis points for uncollapsed trade data (see Panel A of Table 4.3) and suggests higher AT is not associated with an improvement in liquidity once trade sequences are collapsed. The coefficients of the control variables also remain unchanged and continue to suggest high effective spreads are associated with high volatility, high tick-size and low market capitalisation. This suggests collapsing trade sequences is uncorrelated to these control variables. The estimated coefficient of volatility at 0.140 (significant at the 1% level) suggests a 1% increase in the daily high-low price range increases effective spreads by 0.14 basis points. The estimated coefficient of tick-size at 1.099 (significant at the 1% level) suggests a 100 basis point increase in relative tick-size increases effective spreads by 1.10 basis points. The estimated coefficient of the log of market capitalisation is -1.223 (significant at the 1% level) and suggests a 1% increase in market capitalisation decreases effective spreads by 1.223 basis points. Again, high turnover is associated with a significant increase in effective spread, however the magnitude of 0.000138 is very small and suggests on average for every $100 million increase in daily turnover effective spreads will increase by only 1.38 basis points. The results for turnover are not robust across size quintiles.

Panel B shows the change in effective spreads is insignificant across all size quintiles except for the smallest firms (which exhibit a significant *increase* in effective spreads of 126.97 basis points). The largest firms have an estimated coefficient corresponding to an increase in effective spreads of 2.66 basis points (insignificant at the 10% level) and the second quintile shows an average decline of 5.07 basis points but insignificant at the 10% level. This is in contrast to the results for uncollapsed trade data which show a significant decline of 14.8 and 16.4 basis points for the largest and second largest quintiles respectively (see Panel B in Table 4.3). Hence high AT is no longer associated with high liquidity after trades are collapsed. Again, across size quintiles high volatility, high tick size and low market capitalisation are overall positively correlated to higher effective spreads. Estimated coefficients for turnover are significant for the smallest quintile and insignificant for all other quintiles; estimated coefficients for volatility are positive and significant for all quintiles ranging between 0.171 to 1.139; estimated coefficients for tick size are positive and significant for all quintiles except the second smallest quintile and range between -0.113 to 1.547; estimated coefficients for the log of market capitalisation are negative and significant for all quintiles except the smallest quintile and range between -9.036 to 1.544.

Panel C shows the finding of insignificant change in liquidity also applies to fast trades. The fastest quintile indicates a decline in effective spreads by 0.98 basis points (insignificant at the 10% level) and the second fastest quintile shows an average reduction of 6.12 basis points (insignificant at the 10% level). In other words the fastest trades are no longer associated with improvement in market liquidity after Autoquote is phased-in. Only the 3rd quintile, with an estimated decline of 25.04 basis points, remains significant. The estimated coefficient for the slowest two quintiles are positive suggesting liquidity *deteriorated* for slow traders. I also note that looking at the estimated coefficients for turnover, the positive coefficient for the fastest trades suggest, *ceteris paribus*, during days with higher turnover the fastest trades are not associated with improvement in liquidity. In contrast, slower trades are associated with improved liquidity for days with high turnover. This suggest potentially only fast traders are shifting from liquidity provision to liquidity-taking strategies when markets are experiencing high turnover.

To help explain my finding of insignificant change in liquidity I also note the two opposing forces acting on effective spreads whereby adverse selection costs are almost entirely offset by gains in realised spreads. Panel C shows liquidity providers impose higher realised spreads on slow traders while faster liquidity takers are associated with a smaller reduction in adverse selection costs. In the cross-section, adverse selection significantly declined across all speed quintiles, monotonically decreasing as trade speeds slowed. The estimated decline ranges

Table 4.5: Regression Results After Collapsing Trade Sequences (at the 5th Percentile of TI)

The table regresses measures of liquidity on the Hendershott et al. (2011) Autoquote dummy variable. The liquidity measure is computed by collapsing sequences of consecutive buy or sell orders into a single transaction. For each stock trades are only collapsed if the time interval between consecutive trades is less than the 5th percentile. Sample period is from 1st January 2003 to 31st July 2003. The specification is: $L_{j,t} = \alpha_j + \gamma_t + \beta_1 AQ_{j,t} + \gamma_1 turnover_{j,t} + \gamma_2 volatility_{j,t} + \gamma_3 ticksize_{j,t} + \gamma_4 logmcap_{j,t} + \varepsilon_{j,t}$ where the dependent variable $L_{j,t}$ is measures of daily turnover-weighted liquidity in basis points: 1) half effective spreads; 2) half adverse selection; and 3) half realised spreads, α_j represents firm fixed effects, γ_t represents day dummy variables and $AQ_{j,t}$ is a dummy variable equal to +1 for periods with Autoquote phased-in and zero otherwise. The remaining factors are control variables: share turnover, volatility, tick size and the log of market capitalisation. Panel A shows market capitalisation-weighted results. Panel B results are quintile-specific based on market capitalisation. Panel C results are quintile-specific based on time interval between trades. Standard errors are robust to general cross-sectional and time-series heteroscedasticity and within-group autocorrelation (see Arellano and Bond, 1991). ***, **, * represent 1%, 5% and 10% significance level respectively.

Panel A: Market Capitalisation Weighted										
	$AQ_{j,t}$		$turnover_{j,t}$		$volatility_{j,t}$		$ticksize_{j,t}$		$logmcap_{j,t}$	
Dependent Variable: effective spreads (bps)										
	-0.0109		0.000138	***	0.140	***	1.099	***	- 1.223	***
Panel B: Quintile by Market Capitalisation										
Dependent Variable: effective spreads (bps)										
1 (smallest)	1.2697	***	- 0.045	**	1.139	***	1.547	***	1.544	***
2	- 0.2067		0.006		0.809	***	- 0.113	***	- 9.036	***
3	0.1286		- 0.002		0.293	***	0.200	***	- 5.260	***
4	- 0.0507		- 0.001		0.289	***	0.213	***	- 4.169	***
5 (largest)	0.0266		0.000		0.171	***	0.378	***	- 2.121	***
Panel C: Quintile sorted by Time Between Trades										
Dependent Variable: effective spreads (bps)										
1 (fastest)	- 0.0098		0.000	*	0.191	***	2.185	***	- 1.580	***
2	- 0.0612		- 0.003	***	0.402	***	0.258	***	- 3.142	***
3	- 0.2504	***	- 0.021	***	0.625	***	2.682	***	0.449	***
4	0.0735		- 0.046	***	1.013	***	1.319	***	- 2.564	***
5 (slowest)	1.8529	***	- 0.171	**	0.611	***	- 0.063	***	- 6.962	***
Dependent Variable: adverse selection (bps)										
1 (fastest)	- 0.1646	***	0.001	***	0.308	***	2.909	***	- 0.794	***
2	- 0.4235	***	0.001		0.617	***	0.603	***	- 1.498	***
3	- 0.7212	***	- 0.020	***	0.967	***	1.984	***	0.934	***
4	- 0.7692	***	- 0.024	*	1.408	***	0.867	***	- 0.869	**
5 (slowest)	- 0.8450	**	- 0.098		0.934	***	- 0.160	***	- 5.111	***

Panel C: (Continued)										
	$AQ_{j,t}$		$turnover_{j,t}$		$volatility_{j,t}$		$ticksize_{j,t}$		$logmcap_{j,t}$	
Dependent Variable: realised spreads (bps)										
1 (fastest)	0.1557	***	- 0.001	***	- 0.116	***	- 0.720	***	- 0.794	***
2	0.3872	***	- 0.004	***	- 0.210	***	- 0.341	***	- 1.646	***
3	0.4794	***	- 0.001		- 0.351	***	0.700	***	- 0.468	**
4	0.8460	***	- 0.022	*	- 0.406	***	0.450	***	- 1.748	***
5 (slowest)	2.6915	***	- 0.074		- 0.325	**	0.096	***	- 1.870	**

from 16.46 basis points (for the fastest trades) to 84.50 basis points (for the slowest trades). This suggests liquidity providers are better at avoiding adverse selection costs when trades are slower. However, compared to uncollapsed results (see Panel C in Table 4.3) estimates are biased downwards for all quintiles, supporting the findings of Kim and Murphy (2013). Estimated coefficients for collapsed (uncollapsed) trades are -0.1646 (-0.228), -0.423 (-0.643), -0.721 (-0.922), -0.769 (-1.173) and -0.845 (-1.068). Across TI quintiles, realised spreads also significantly increased across all quintiles, with a larger increase for slower trades. This suggests liquidity is more expensive for slower traders. The estimated increase ranges from 15.57 basis points (for the fastest trades) to 269.15 basis points (for the slowest trades). Estimated coefficients for collapsed (uncollapsed) trades are 0.1567 (0.140), 0.387 (0.435), 0.479 (0.595), 0.846 (1.055) and 2.6915 (1.760). There is no discernible bias in estimated realised spreads compared to the uncollapsed results (see Panel C in Table 4.3).

Overall, my results show that despite consistent findings with Hendershott et al. (2011) on the sign of adverse selection and realised spreads the estimated change in effective spreads is insignificant once trades are collapsed. This finding is robust across large firms and fast trades.

4.7. Conclusion

After an adjustment is made for order-splitting I find high AT as proxied by the phase-in of Autoquote is associated with insignificant change in effective spreads. This suggests the benefits of AT may be over-estimated. This is in contrast to the findings in Hendershott et al. (2011) which associate high AT with improvements in liquidity but is consistent with Kim and Murphy (2013) who argue measures of effective spreads may be biased downwards if order-splitting is unaccounted for.

To adjust for order-splitting I collapse consecutive buy or sell orders into one transaction. I only collapse trades that fall among the fastest five percent of all trades – this typically means for the largest (smallest) firms two consecutive trades are collapsed together only if the time interval between the trades is less than 20 seconds (2.88 minutes). My results show the new estimates of adverse selection costs are higher across all speed quintiles (relative to unadjusted results), and increases in realised spreads essentially offset the decline of adverse selection. This means liquidity on average has not improved despite an overall reduction in adverse selection.

My results are therefore consistent with the view that trading speeds potentially contribute less to market quality than previously thought and instead contribute to the shifting of liquidity costs from fast to slow traders (Lyle and Naughton, 2016; Gai, Yao and Ye, 2013). Hendershott et al. (2011) show, consistent with the advantage of additional speed, high AT is associated with less adverse selection "winner's curse" costs and an increase in the competitiveness of a liquidity provider's algorithm. My findings confirm this view, however across trading speeds I show liquidity providers are relatively better at avoiding adverse selection from slow traders but at the same time generate relatively higher revenues from slow traders. In other words slower traders incur relatively greater costs as trading speeds increase. Hence, despite similar results to Hendershott et al. (2011) regarding the effects of high AT on adverse selection costs and realised spreads, I present an overall different perspective in that effective spreads do not significantly change with high AT but rather shift the burden of liquidity costs from fast to slow traders.

CHAPTER 5: AVENUES FOR FUTURE RESEARCH AND CONCLUSIONS

5.1 Avenues for Future Research

In this concluding chapter I briefly discuss potential avenues for future research. In the context of PEAD research this thesis argues sophisticated participants do not trade away mispricing associated with PEAD due to unhedgeable idiosyncratic risk and transaction costs. This suggests frictions specific to practicing traders substantially influence trading behaviour and investment decisions. An avenue of further research is therefore analysing the trader's investment process and identifying whether, and to what degree, specific frictions affect the presence of financial anomalies; in the context of PEAD potential future research includes examining how anomaly effects are influenced by the taxation burdens of institutional and sophisticated traders, inventory constraints of algorithmic traders, short sales constraints and agency frictions between fund managers and fund investors.

With respect to the study of AT, one specific avenue for future research is extracting insights from exchange order-book data that distinguish algorithmic traders and high frequency traders from other traders. Such data can be used to validate the findings of this thesis and also expand on the relation between AT and PEAD; and provide more direct evidence on whether order-splitting biases empirical measures of liquidity.

In relation to Chapter 3 and Chapter 4, I note my proxies for AT are broad measures that rely heavily on both Autoquote and the AT measure by Hendershott et al. (2011). Obtaining exchange order-book data will aid in the classification of AT in terms of both quantity and quality. For example, as a general rule AT in the form of HFT originates substantially more order traffic than AT in the form of non-HFT activity. Hasbrouck and Saar (2010) classify the former as *agency algorithms* (AA) and the latter as *proprietary algorithms* (PA) and argue AA is a major originator of order-splitting but PA submits substantially more orders and cancellations. Generally, AA orders are also slower than PA orders. My classification of AT however does not differentiate between these two types of algorithms and the AT proxy by Hendershott et al. (2011) likely over-represents HFT activity (given the measure is positively associated with the number of order and trade messages). Hence, interpreted conservatively, my findings may be more a study on the relation between HFT and PEAD rather than between AT and PEAD. The degree by which high frequency traders are disproportionately represented in my AT measure is unexplored but HFTs generally are disinclined to hold overnight positions. Therefore one critique of my thesis is that my results are potentially over-weighting participants trading away *intra*-day inefficiencies while PEAD is a function of both *intra*-day and *inter*-day stock price movements. Further research which can classify and qualify AT is therefore desirable.

While my findings suggest AT may not reduce transaction costs I have not considered other facets of AT with respect to earnings announcements. For example, a critical area in academic and public policy debate extends to understanding the influence algorithmic traders have on market volatility and systemic risk. Earnings announcements are periods of uncertainty and one research avenue to address is whether the risk of illusory liquidity increases or decreases with AT, and under what circumstances. And does AT dampen or exacerbate volatility around earnings announcements and earnings surprises? For example, Chaboud et al., (2014) show AT often withdrawal liquidity provision during marcro news events but quickly replnish liquidity post-event. Hendershott et al. (2011) also note that the use of Autoquote as an instrument to proxy a large increase in AT may be biased towards capturing the effects of limit orders rather than market orders submitted by AT (one reason is the speed advantage of Autoquote enables AT liquidity providers to more swiftly cancel stale limit orders and therefore incentivises greater liquidity provision). While Autoquote may also incentivise liquidity-taking strategies I do not assess liquidity makers vis-à-vis liquidity takers. The literature however suggests market instability is often dual functions of the withdrawal of liquidity provision and the potential volatility-amplification effects of swift liquidity taking.

The proliferation of AT in the U.S. equities market is also inextricably linked to market fragmentation (in 2009 the exchanges NYSE and Nasdaq represented only 27.9% and 22.7% of total market turnover for their listed stocks (Foucault, 2012)). The U.S. equities market is unique in terms of having a high number of trading venues and each trading venue and ECN have specific trading rules and fee arrangement (some venues incentivise AT to post aggressive orders more so than others). I do not take into account the effects of AT on PEAD with respect to this multiplicity of trading venues, but generally speaking the more venues trading a security the more arbitrage and mispricing opportunities. Further, a debate exists as to whether algorithmic traders only trade on trade and quote information provided by these trading venues or do they also incorporate public information that has yet to be impounded into prices into their investment decision. One specific claim that I make is that AT potentially improves price discovery by extracting signals that predict earnings momentum (i.e. the autocorrelation of announcement news). The PEAD anomaly relates to many areas of these concerns and future research on the relation between AT and the attenuation of market anomalies have the potential to shed light on these questions.

5.2 Conclusions

This thesis, through three essays, assesses the relation between one of the most recent developments in financial markets with one of the oldest and most-studied financial anomalies. The first essay (Chapter 2) considers whether PEAD persists at the turn of the century by testing PEAD against a range of previously documented explanatory factors. The chapter addresses the extent anomalous PEAD effects remain unexplained and, given the relatively new test sample period, serves as an out-of-sample examination. My results show a portion of the PEAD anomaly is associated with low investor sophistication, high arbitrage risk and high transaction costs. One explanation for PEAD is therefore that investors with low sophistication systematically under-react to earnings surprises and sophisticated traders cannot arbitrage fully the mispricing due to trading risks (such as the high idiosyncratic risk that must be borne by undiversified or only partially diversified investors) and high transaction costs. My analysis augments standard event study methods to control for risk-mismeasurement bias as traditional event study models generally assume a constant firm beta (which produces model estimates unconditional to earnings surprise). Conditional on earnings surprise, I find average 60-day PEAD effects remains statistically and economically significant at approximately 4%; and my results show that after jointly controlling for other explanations PEAD nevertheless remains statistically significant at just under 2%.

In the second essay (Chapter 3) I conjecture algorithmic traders ought to attenuate PEAD effects given studies suggest AT is associated with lower bid-ask spreads, improved price efficiency and sophisticated trading. It therefore follows that AT and PEAD are potentially inversely related. I also argue if sophisticated algorithmic traders are better at extracting trading signals from earnings information then price discovery around earnings announcements should improve. I begin my analysis by first documenting the attenuation of PEAD starting in the early

2000s and find the decline is concentrated among NYSE-listed firms. I then present three explanations for the decline: 1) the phase-in of decimalisation; 2) the structural improvement in earnings quality in the early 2000s; and 3) the substantial increase in AT activity on the NYSE after May 2003. I then implement matched sampling test procedures to control for decimalisation and shifts in earnings quality and test whether a difference in PEAD across matched pairs can be explained by differences in AT; however my results show an insignificant relation. In the second part of my analysis I construct a proxy for price discovery as a function of PEAD and show price discovery significantly improves. I argue AT contributes to price discovery as a result of sophisticated investors extracting trading signals from earnings information.

In the third and final essay (Chapter 4) I assess whether AT significantly improves market liquidity once an adjustment is made for the potential under-estimation of effective spreads. One aspect of AT is that it encourages order-splitting and large orders are now camouflaged into sequences of small orders which may cause effective spreads to be under-estimated. I treat sequences of consecutive buy or sell orders as a single transaction and revisit the study by Hendershott et al. (2011) on the relation between AT and liquidity measures (the study finds improvements in liquidity are associated with the phasing-in of Autoquote); I find AT contributes substantially less to market quality than previously documented and effective spreads do not decline significantly. My results are consistent with studies demonstrating that order-splitting may cause the under-estimation of price impact and also demonstrates that fast liquidity providers are relatively better at avoiding adverse selection from slow traders (and the costs of liquidity are relatively higher for slow traders). This suggests algorithmic traders are opportunistic, taking advantage of their speed to mitigate price impact while imposing higher adverse selection costs on slower traders.

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APPENDIX A

A.1. PEAD and the Probability of Informed Trading

I follow Easley, Prado and O'Hara (2012) and compute the *volume-synchronised probability of informed trading* (VPIN) as a proxy for the probability of informed trading. This method is advanced by Easley et al. (2012) over the original PIN estimation method (Easley, Kiefer, O'Hara and Paperman, 1996) because of technical difficulties in implementing maximum likelihood estimation over large quantities of trade and quote data (such as data generated by high-frequency trading). Briefly, VPIN can be defined by the following[111]:

$$VPIN = \frac{\sum_{n=1}^{N} |V_n^S - V_n^B|}{nV} \tag{A.1}$$

$$V_n^B = \sum_{z=b(n-1)+1}^{b(n)} V_z \quad Z\left(\frac{P_z - P_{z-1}}{\sigma_{\Delta P}}\right) \tag{A.2}$$

$$V_n^S = V - V_n^B \tag{A.3}$$

Where for the z^{th} trade in the n^{th} bucket, V_z is the volume traded, $Z(\cdot)$ represents the cumulative normal distribution and $\Delta P = P_z - P_{z-1}$ is price change between the two successive trades. The intuition is that the probability of informed trading can be computed based on traded volume classification in probabilistic terms. Following Equation A.1 I compute, for each firm's earnings announcement, the average daily VPIN across the 40 trading days prior to earnings announcement. Below in Table A.1 I show results based on $N = 50$. Following Easley et al. (2012) I impose the constraint that, for each firm *i* and each trading day *t,* each of the 50 buckets have equal traded volume; any excess volume per trade is assigned to the next sequential bucket.

My results in Table A.1 that, with the exception of small cap firms, PEAD decreases with respect to VPIN. For example, across large firms estimated PEAD is 4.67% (significant at the

[111] A full discussion of the details to the method is found in Easley et al. (2012).

5% level) for low VPIN and declines to 1.49% (significant at the 5% level) for high VPIN. Hence, consistent with Vega (2004), a higher probability of informed trading reduces uncertainties surrounding ES and therefore attenuates PEAD. For robustness in unpublished results I also implement N = 200 and the results remain qualitatively unchanged.

Table A.1: Computed Good-minus-Bad 60-day PEAD and 3-day Response across VPIN Portfolios

I test for the difference of estimated alphas between good and bad news across each tercile group for VPIN. Rankings of low, mid, and high are based on quarterly within-quarter sort at the 33rd and 67th percentile. Following Fama and Macbeth (1973) I run quarterly regressions for the top and bottom ES quintiles within each tercile. I then take the difference in estimated alpha between the top and bottom quintiles and test whether the mean is significantly different from zero. The factors are market capitalisation ($Mcap_{i,q}$) and the volume-synchronised probability of informed trading ($VPIN_{i,q}$). Number of firm-quarter observations: 54,159.

		Good News minus Bad News			
$Mcap_{i,q}$	$VPIN_{i,q}$	3-day Response		60-day PEAD	
	low	0.0732	***	0.0630	***
low	mid	0.0731	***	0.0187	
	high	0.1121	***	0.0914	*
	low	0.0554	***	0.0369	**
mid	mid	0.0681	***	0.0162	
	high	0.0704	***	0.0179	
	low	0.0471	***	0.0467	**
high	mid	0.0509	***	0.0120	
	high	0.0560	***	0.0149	**

A.2. Variable Construction

A.2.1. Description of Explanatory Variables

The variable name and descriptions are outlined below in Table A.2. Variables are calculated based on each stock *i* and quarter *q*.

Table A.2: Description of Explanatory Variables

The table shows the description and data source of the explanatory variables. The variables are institutional ownership ($Insti_{i,q}$); number of announcements released on same day ($Distract\_U_{i,q}$); number of analysts issuing forecasts within the 90 days prior to the earnings announcement ($Analyst_{i,q}$); volatility of daily BHAR in the 40 trading days prior to earnings announcement ($Volatility_{i,q}$); arbitrage risk ($ArbRisk_{i,q}$); hedgeable risk ($ExpRisk_{i,q}$); average of Amihud illiquidity measured across 40 trading days prior to earnings announcement ($Illiq_{i,q}$); average of quoted spread at closing across 40 trading days prior to earnings announcement ($Spread_{i,q}$); stock price at the end of quarter, *q* ($Price_{i,q}$); average daily turnover (in millions of dollars) measured from 271 trading days to 22 trading days prior to earnings announcement ($Turn_{i,q}$); market capitalisation ($Mcap_{i,q}$); book-to-market ratio ($BM_{i,q}$); BHAR across the past 40 trading days prior to earnings announcement ($Mom_{i,q}$). BHAR are calculated using 5x5 size quintile and BM quintile matched portfolios. Data source refers to datasets obtained from the Wharton Research Data Service except FF which refers to the Fama-French factors obtained from Professor Kenneth French's website.

Variable	Description	Data Source
$Insti_{i,q}$	Fraction of shares outstanding held by institutions filing Form for the quarter prior to the earnings announcement (% multiplied by 0.01).	CDA Spectrum
$Distract_{i,q}$	Number of earnings announcements for each trading day.	I/B/E/S
$Analyst_{i,q}$	Number of analysts reporting quarterly earnings forecasts to I/B/E/S in the 90 days prior to earnings announcement. Only the most recent forecast per unique analyst is kept.	I/B/E/S
$Volatility_{i,q}$	Standard deviation of daily abnormal returns across 40 days prior to earnings announcement.	CRSP, FF
$ArbRisk_{i,q}$	Residual variance from market model regression (using returns from the S&P 500 index (dividends included)) estimated over 48 months ending 1 month prior to earnings announcement.	CRSP
$ExpRisk_{i,q}$	Explained variance from market model regression (using returns from the S&P 500 index (dividends included)) estimated over 48 months ending 1 month prior to earnings announcement.	CRSP
$Spread_{i,q}$	The average of bid-ask spread at close across past 40 trading days prior to earnings announcement (% multiplied by 0.01).	CRSP
$Illiquidity_{i,q}$	Illiquidity measure following Amihud (2002). The average of absolute value of daily return divided by the daily dollar share turnover. Measured across the 40 trading days prior to earnings announcement.	CRSP
$Price_{i,q}$	Stock price at the end of the announcement quarter (adjusted for stock splits)	Compustat
$Turn_{,q}$	Average daily share turnover between 271 and 22 trading days prior to earnings announcement ($million).	CRSP
$Mcap_{i,q}$	Number of shares outstanding multiplied by price as measured in the most recent June ($million).	Compustat
$BM_{i,q}$	Book-to-market ratio as measured in the most recent December.	Compustat
$Mom_{i,q}$	BHAR across the 40 days prior to earnings announcement.	CRSP, FF

A.2.2. Investor Sophistication (*$Insti_{i,q}$*)

Investor sophistication is proxied by the fraction of shares outstanding held by institutions. To calculate percentage of institutional ownership I follow Campbell et al. (2009) and obtain a firm's quarterly 13F filings.[112] The 13F filing is required by all institutions in the US with greater than $100 million of securities under discretionary management regardless of whether they are regulated by the SEC. All holdings greater than 10 000 shares or larger than $200,000 are disclosed. For each firm-CUSIP and date I sum up the shares held by all institutions to arrive at the total institutional ownership by the end of quarter. I obtain for each firm-quarter the total institutional ownership from the 13F filings and divide by the firm market capitalization calculated from the CRSP-Compustat merged database by multiplying the total shares outstanding with the stock price (both adjusted for stock splits). I follow Campbell et al. (2009) and remove any firm-quarter observation where the level of institutional ownership as a percentage of shares outstanding is greater than 100%.

A.2.3. Analyst Following (*$Analyst_{i,q}$*)

When dealing with analyst forecast data, I note that analysts may release multiple forecasts for quarterly earnings and therefore I exclusively select the latest forecast for each analyst per firm-quarter per firm from I/B/E/S. I remove any forecasts more than 90 calendar days old.

A.2.4. Arbitrage Risk (*$ArbRisk_{i,q}$*) and Hedgeable Risk (*$ExpRisk_{i,q}$*)

Arbitrage risk is defined as the idiosyncratic portion of a stock's volatility that arbitrageurs cannot diversify away by holding offsetting positions in index funds. The implicit assumption is that arbitrageurs hold large, but few, positions at any one time and therefore are not diversified investors.

[112] Obtained from WRDS.

Arbitrage risk is computed by the method of Wurgler and Zhuravskaya (2002) which runs a regression, per firm-quarter observation, of risk-free rate adjusted return on the risk-free rate adjusted return of the S&P 500. The residual variance of the regression proxies arbitrage risk while the explained variables proxy the hedgeable risk. My regression is estimated over 48 months and ends 1 month prior to the earnings announcement for each firm-quarter observation.

A.2.5. Illiquidity ($Illiquidity_{i,q}$) and Transaction Cost ($Spread_{i,q}$)

The illiquidity measure follows Amihud (2002) and is calculated by taking the daily absolute return multiplied by 1 million divided by the daily turnover. For proxy for transaction cost I follow Vega (2006) and take the average of the closing spread from 41 trading days to 2 trading days before earnings announcements.

A.3. Literature Review of Analyst Forecast Accuracy

The literature show analysts forecasts can both under- and over-react (Debondt and Thaler, 1990; Abarbanell and Bernard, 1992). Analysts are subject to selection bias as they tend to cover firms that have higher voluntary disclosure (Lang and Lundholm, 2013), less informational opacity (Bushman, Piotroski and Smith, 2004); fewer business segments; and lower complexity (Bhushan, 1989; Clement, 1999). Second, the number of analysts following is also correlated with firm size while forecast informativeness is negatively correlated with the cost of information processing (Frankel, Kothari and Weber, 2006). The quality of analyst forecasts varies too. For example, prestigious brokerage houses with more resources tend to attract higher skilled employees (Hong and Kubik, 2003) and therefore analysts from prestigious institutions tend to issue more accurate forecasts (Stickel, 1992; Clement, 1999). Analyst experience is also correlated with smaller forecast error (Mikhail, Walther and Willis, 1997 and 2003; Clement, 1999).

Firms are known to conduct earnings management to influence analyst forecast error (Abarbanell and Lehavy, 2003). Analyst forecasts and firm earnings are also correlated as analysts potentially exert pressure on managers to meet forecast expectations; or management may restrict access if analysts do not cooperate. Optimistic forecasts generate more clientele in the short term while more accurate forecasts generate higher reputation over the long run. Jackson (2005) shows analysts optimise across these conflicting interests. Hong and Kubick (2003) show brokerage houses reward optimistic analysts and are less likely to issue downgrades on securities that are held by their clients or have underwriting arrangements (Dechow, Hutton and Sloan, 2000; Lin and McNichols, 1998; Michaely and Womack, 1999). Easterwood and Nutt (1999) argue analysts under-react to negative earnings but over-react to positive news; and hence analysts are overall positively biased (Lys and Sohn, 1990; Brown, 1993). I note analysts also issue forecasts in the context of career advancement and trade/commission generation (Scharfstein and Stein, 1990; Laster, Bennet and Geoum, 1996, Jackson 2005).

A.4. Cross-Section of PEAD Across Factor Quintiles

This section shows a list of tables that serve as robustness tests to Table 2.4. I group my observations into 5x5 ES quintile by factor quintile portfolios and take the average of quarterly PEAD for each of the 25 portfolios. I compute the mean rather than estimate alpha returns across factor quintiles for each ES quintile given univariate test statistic on BHAR are well specified (Barber and Lyon, 1997)[113]. All results remain consistent with Table 2.4. For ease of reading I also plot cross-sectional means of PEAD returns for each factor quintile in Section A.5 of the Appendix. Overall the evidence suggests weaker PEAD effects for firms characterized by low investor sophistication, high structural uncertainty, and high limits of arbitrage.

[113] Barber and Lyon (1997) empirically demonstrate that common methods for calculating abnormal stock returns are mis-specified and that correcting buy-and-hold returns by matching sample firms to control firms based on similar size and book-to-market ratios yields well-specified test statistics.

Table A.3: Computed Good-minus-Bad 60-day PEAD and 3-day Response across Factor Quintiles and across ES Quintiles - *$Insti_{i,q}$*.

Each table represents PEAD across quintile factor groups. I compute PEAD as the difference between the mean of BHAR in the top ES quintile minus the mean of the BHAR for the worst ES quintile. BHAR is constructed by adjusting returns by 5x5 size quintile and BM quintile portfolio. ES breakpoints are computed in the previous quarter. Factor quintile breakpoints are computed based on within-quarter sort. The results below represent the average of the quarterly means. The variables are earnings surprise ($ES_{i,q}$); institutional ownership ($Insti_{i,q}$); number of announcements released on same day ($Distract\_U_{i,q}$); number of analysts issuing forecasts within the 90 days prior to the earnings announcement ($Analyst_{i,q}$); volatility of daily BHAR in the 40 trading days prior to earnings announcement ($Volatility_{i,q}$); arbitrage risk ($ArbRisk_{i,q}$); hedgeable risk ($ExpRisk_{i,q}$); average of Amihud illiquidity measured across 40 trading days prior to earnings announcement ($Illiq_{i,q}$); average of quoted spread at closing across 40 trading days prior to earnings announcement ($Spread_{i,q}$); stock price at the end of quarter, *q* (*Price*); average daily turnover (in millions of dollars) measured from 271 trading days to 22 trading days prior to earnings announcement ($Turn_{i,q}$); market capitalisation ($Mcap_{i,q}$); book-to-market ratio ($BM_{i,q}$); BHAR across the past 40 trading days prior to earnings announcement ($Mom_{i,q}$). Period: July 1995 to June 2011. ***, **, * represent t-test significance level at 0.01, 0.05 and 0.1 respectively.

		3-day Response		60-day PEAD		Good News (ES Quintile 5) minus Bad News (ES Quintile 1)			
$Insti_{i,q}$	ES Quintile	Mean of Quarterly Average		Mean of Quarterly Average		3-day Response		60-day PEAD	
1	1	- 0.026	***	- 0.042	***				
	2	- 0.013	***	- 0.014	***				
	3	0.003	**	- 0.009	*				
	4	0.012	***	- 0.005					
	5	0.026	***	0.013	*	0.052	***	0.052	***
2	1	- 0.029	***	- 0.021	**				
	2	- 0.013	***	- 0.004					
	3	0.002	*	- 0.004					
	4	0.014	***	0.007					
	5	0.031	***	0.020	***	0.060	***	0.042	***
3	1	- 0.029	***	- 0.009					
	2	- 0.016	***	- 0.000					
	3	0.001		- 0.001					
	4	0.018	***	0.006					
	5	0.039	***	0.022	***	0.068	***	0.031	***
4	1	- 0.035	***	- 0.007					
	2	- 0.020	***	- 0.007					
	3	0.001		- 0.004					
	4	0.019	***	0.001					
	5	0.034	***	0.021	***	0.069	***	0.028	***

		3-day Response		60-day PEAD		Good News (ES Quintile 5) minus Bad News (ES Quintile 1)			
$Insti_{i,q}$	ES Quintile	Mean of Quarterly Average		Mean of Quarterly Average		3-day Response		60-day PEAD	
	1	- 0.032	***	0.001					
	2	- 0.017	***	- 0.009	*				
5	3	0.004	***	- 0.004					
	4	0.022	***	0.003					
	5	0.037	***	0.005		0.069	***	0.004	

Table A.4: Computed Good-minus-Bad 60-day PEAD and 3-day Response across Factor Quintiles and across ES Quintiles - *Distract_U$_{i,q}$*.

See Table A.3 for explanation.

		3-day Response		60-day PEAD		Good News (ES Quintile 5) minus Bad News (ES Quintile 1)			
Distract_U$_{i,q}$	ES Quintile	Mean of Quarterly Average		Mean of Quarterly Average		3-day Response		60-day PEAD	
1	1	- 0.034	***	- 0.030	***				
	2	- 0.017	***	- 0.008					
	3	0.003	**	- 0.008	*				
	4	0.020	***	0.001					
	5	0.038	***	0.005		0.072	***	0.035	***
2	1	- 0.032	***	- 0.017	*				
	2	- 0.013	***	- 0.005					
	3	0.004	***	- 0.007					
	4	0.018	***	- 0.000					
	5	0.035	***	0.015	***	0.066	***	0.032	***
3	1	- 0.029	***	- 0.004					
	2	- 0.016	***	- 0.011	**				
	3	0.003	***	- 0.004					
	4	0.018	***	0.003					
	5	0.032	***	0.022	***	0.061	***	0.024	**
4	1	- 0.028	***	- 0.012	*				
	2	- 0.015	***	- 0.002					
	3	0.001		0.001					
	4	0.015	***	0.007	*				
	5	0.033	***	0.023	***	0.061	***	0.038	***
5	1	- 0.029	***	- 0.018	***				
	2	- 0.016	***	- 0.005					
	3	0.001		- 0.002					
	4	0.016	***	0.007					
	5	0.030	***	0.013	***	0.060	***	0.032	***

Table A.5: Computed Good-minus-Bad 60-day PEAD and 3-day Response across Factor Quintiles and across ES Quintiles - *Analyst$_{i,q}$*.

See Table A.3 for explanation.

		3-day Response		60-day PEAD		Good News (ES Quintile 5) minus Bad News (ES Quintile 1)			
Analyst$_{i,q}$	ES Quintile	Mean of Quarterly Average		Mean of Quarterly Average		3-day Response		60-day PEAD	
1	1	-0.029	***	-0.030	***				
	2	-0.016	***	-0.008					
	3	0.003	**	-0.006					
	4	0.015	***	-0.004					
	5	0.034	***	0.022	***	0.062	***	0.052	***
2	1	-0.034	***	-0.031	***				
	2	-0.016	***	-0.013	*				
	3	0.001		-0.006					
	4	0.020	***	0.001					
	5	0.036	***	0.009	*	0.072	***	0.040	***
3	1	-0.032	***	-0.010					
	2	-0.016	***	-0.003					
	3	0.001		-0.004					
	4	0.017	***	0.005					
	5	0.036	***	0.022	***	0.068	***	0.031	**
4	1	-0.035	***	-0.004					
	2	-0.017	***	-0.007					
	3	0.004	**	-0.003					
	4	0.018	***	-0.001					
	5	0.034	***	0.015	**	0.069	***	0.018	**
5	1	-0.024	***	-0.001					
	2	-0.014	***	-0.005					
	3	0.002		-0.004					
	4	0.015	***	0.008					
	5	0.029	***	0.012	**	0.053	***	0.016	**

Table A.6: Computed Good-minus-Bad 60-day PEAD and 3-day Response across Factor Quintiles and across ES Quintiles - *Volatility$_{i,q}$*.

See Table A.3 for explanation.

		3-day Response		60-day PEAD		Good News (ES Quintile 5) minus Bad News (ES Quintile 1)			
Volatility$_{i,q}$	ES Quintile	Mean of Quarterly Average		Mean of Quarterly Average		3-day Response		60-day PEAD	
1	1	- 0.023	***	- 0.010	*				
	2	- 0.014	***	- 0.004					
	3	0.002	***	- 0.004					
	4	0.015	***	0.005					
	5	0.023	***	0.011	**	0.047	***	0.024	***
2	1	- 0.030	***	- 0.021	***				
	2	- 0.014	***	- 0.001					
	3	0.002	**	- 0.002					
	4	0.015	***	0.002					
	5	0.034	***	0.014	***	0.065	***	0.036	***
3	1	- 0.030	***	- 0.005					
	2	- 0.016	***	- 0.009	*				
	3	0.002	*	- 0.005					
	4	0.019	***	0.005					
	5	0.036	***	0.015	**	0.066	***	0.020	*
4	1	- 0.033	***	- 0.013					
	2	- 0.017	***	- 0.011	*				
	3	0.000		- 0.005					
	4	0.019	***	0.001					
	5	0.039	***	0.016	**	0.071	***	0.030	***
5	1	- 0.034	***	- 0.027					
	2	- 0.018	***	- 0.008					
	3	0.004	*	- 0.006					
	4	0.016	***	0.000					
	5	0.035	***	0.025	**	0.069	***	0.052	***

Table A.7: Computed Good-minus-Bad 60-day PEAD and 3-day Response across Factor Quintiles and across ES Quintiles - $ArbRisk_{i,q}$.

See Table A.3 for explanation.

		3-day Response		60-day PEAD		Good News (ES Quintile 5) minus Bad News (ES Quintile 1)			
$ArbRisk_{i,q}$	ES Quintile	Mean of Quarterly Average		Mean of Quarterly Average		3-day Response		60-day PEAD	
1	1	- 0.019	***	- 0.009	*				
	2	- 0.011	***	- 0.003					
	3	0.002	*	- 0.002					
	4	0.012	***	0.003					
	5	0.022	***	0.010	*	0.041	***	0.022	***
2	1	- 0.029	***	- 0.017	***				
	2	- 0.015	***	- 0.006					
	3	0.003	***	- 0.002					
	4	0.017	***	0.007	*				
	5	0.031	***	0.008	*	0.061	***	0.026	***
3	1	- 0.030	***	- 0.012					
	2	- 0.015	***	- 0.009	*				
	3	0.002	*	- 0.003					
	4	0.017	***	0.001					
	5	0.034	***	0.013	*	0.064	***	0.025	**
4	1	- 0.038	***	- 0.018	*				
	2	- 0.019	***	- 0.010					
	3	0.005	***	- 0.011	***				
	4	0.022	***	0.005					
	5	0.040	***	0.021	***	0.078	***	0.039	***
5	1	- 0.034	***	- 0.021					
	2	- 0.017	***	- 0.005					
	3	- 0.002		- 0.003					
	4	0.017	***	- 0.004					
	5	0.040	***	0.028	***	0.074	***	0.049	***

Table A.8: Computed Good-minus-Bad 60-day PEAD and 3-day Response across Factor Quintiles and across ES Quintiles - $ExpRisk_{i,q}$.

See Table A.3 for explanation.

		3-day Response		60-day PEAD		Good News (ES Quintile 5) minus Bad News (ES Quintile 1)			
$ExpRisk_{i,q}$	ES Quintile	Mean of Quarterly Average		Mean of Quarterly Average		3-day Response		60-day PEAD	
1	1	-0.026	***	-0.030	***				
	2	-0.012	***	-0.011	**				
	3	0.002	*	-0.009					
	4	0.014	***	-0.002					
	5	0.030	***	0.009		0.056	***	0.041	***
2	1	-0.026	***	-0.026	***				
	2	-0.013	***	-0.008					
	3	0.004	**	-0.001					
	4	0.016	***	-0.001					
	5	0.028	***	0.011	**	0.054	***	0.038	***
3	1	-0.028	***	-0.012					
	2	-0.019	***	-0.004					
	3	0.003	***	-0.005					
	4	0.017	***	0.001					
	5	0.035	***	0.017	**	0.062	***	0.028	**
4	1	-0.035	***	-0.014					
	2	-0.015	***	-0.009					
	3	0.003	**	-0.007	*				
	4	0.020	***	0.003					
	5	0.038	***	0.019	**	0.074	***	0.033	***
5	1	-0.035	***	0.005					
	2	-0.021	***	-0.003					
	3	-0.002		0.001					
	4	0.019	***	0.011					
	5	0.037	***	0.026	**	0.072	***	0.021	

Table A.9: Computed Good-minus-Bad 60-day PEAD and 3-day Response across Factor Quintiles and across ES Quintiles - *Spread*$_{i,q}$.

See Table A.3 for explanation.

		3-day Response		60-day PEAD		Good News (ES Quintile 5) minus Bad News (ES Quintile 1)			
Spread$_{i,q}$	ES Quintile	Mean of Quarterly Average		Mean of Quarterly Average		3-day Response		60-day PEAD	
	1	-0.024	***	-0.006					
	2	-0.017	***	-0.013	***				
1	3	0.002	*	-0.002					
	4	0.017	***	-0.001					
	5	0.028	***	0.007	*	0.052	***	0.016	***
	1	-0.032	***	-0.009	*				
	2	-0.016	***	-0.004					
2	3	0.002	*	-0.007	*				
	4	0.015	***	0.007	*				
	5	0.033	***	0.014	***	0.065	***	0.023	***
	1	-0.032	***	-0.012					
	2	-0.018	***	0.000					
3	3	0.002		-0.007	**				
	4	0.019	***	0.007					
	5	0.036	***	0.012	**	0.068	***	0.024	**
	1	-0.030	***	-0.013					
	2	-0.016	***	-0.005					
4	3	0.004	***	0.001					
	4	0.017	***	-0.004					
	5	0.037	***	0.022	***	0.067	***	0.035	***
	1	-0.032	***	-0.036	**				
	2	-0.013	***	-0.011	*				
5	3	0.000		-0.005					
	4	0.017	***	0.003					
	5	0.033	***	0.026	**	0.065	***	0.062	***

Table A.10: Computed Good-minus-Bad 60-day PEAD and 3-day Response across Factor Quintiles and across ES Quintiles - *Illiq*$_{i,q}$.

See Table A.3 for explanation.

		3-day Response		60-day PEAD		Good News (ES Quintile 5) minus Bad News (ES Quintile 1)			
$Illiq_{i,q}$	ES Quintile	Mean of Quarterly Average		Mean of Quarterly Average		3-day Response		60-day PEAD	
	1	- 0.02	***	- 0.01	**				
	2	- 0.01	***	- 0.01					
1	3	0.00	*	- 0.01					
	4	0.01	***	0.00					
	5	0.02	***	0.00		0.05	***	0.01	**
	1	- 0.03	***	- 0.00					
	2	- 0.02	***	- 0.00					
2	3	0.00		- 0.00					
	4	0.02	***	0.01	*				
	5	0.04	***	0.02	***	0.06	***	0.02	***
	1	- 0.03	***	0.00					
	2	- 0.02	***	- 0.01	*				
3	3	0.00	**	- 0.01					
	4	0.02	***	- 0.00					
	5	0.03	***	0.02	***	0.07	***	0.01	
	1	- 0.04	***	- 0.02	**				
	2	- 0.01	***	- 0.01					
4	3	0.00		0.00					
	4	0.02	***	0.00					
	5	0.04	***	0.02	***	0.07	***	0.05	***
	1	- 0.03	***	- 0.05	***				
	2	- 0.01	***	- 0.01	*				
5	3	0.00		- 0.01	*				
	4	0.02	***	- 0.00					
	5	0.04	***	0.02	**	0.06	***	0.07	***

Table A.11: Computed Good-minus-Bad 60-day PEAD and 3-day Response across Factor Quintiles and across ES Quintiles - *Price$_{i,q}$*.

See Table A.3 for explanation.

		3-day Response		60-day PEAD		Good News (ES Quintile 5) minus Bad News (ES Quintile 1)			
Price$_{i,q}$	ES Quintile	Mean of Quarterly Average		Mean of Quarterly Average		3-day Response		60-day PEAD	
1	1	- 0.032	***	- 0.037	**				
	2	- 0.013	***	- 0.009					
	3	- 0.001		0.000					
	4	0.015	***	0.004					
	5	0.032	***	0.026	*	0.062	***	0.063	***
2	1	- 0.030	***	- 0.015					
	2	- 0.017	***	- 0.008					
	3	0.004	***	- 0.004					
	4	0.017	***	- 0.006					
	5	0.039	***	0.013	**	0.069	***	0.028	**
3	1	- 0.032	***	- 0.006					
	2	- 0.016	***	0.001					
	3	0.002	**	- 0.004					
	4	0.018	***	0.010	**				
	5	0.038	***	0.014	***	0.070	***	0.020	**
4	1	- 0.028	***	- 0.010	*				
	2	- 0.015	***	- 0.006					
	3	0.003	***	- 0.007					
	4	0.020	***	0.003					
	5	0.030	***	0.017	***	0.058	***	0.027	***
5	1	- 0.028	***	- 0.013	***				
	2	- 0.018	***	- 0.011	***				
	3	0.003	**	- 0.007					
	4	0.016	***	0.002					
	5	0.028	***	0.012	***	0.056	***	0.025	***

Table A.12: Computed Good-minus-Bad 60-day PEAD and 3-day Response across Factor Quintiles and across ES Quintiles - *Turn*$_{i,q}$.

See Table A.3 for explanation.

		3-day Response		60-day PEAD		Good News (ES Quintile 5) minus Bad News (ES Quintile 1)			
Turn$_{i,q}$	ES Quintile	Mean of Quarterly Average		Mean of Quarterly Average		3-day Response		60-day PEAD	
1	1	- 0.027	***	- 0.052	***				
	2	- 0.014	***	- 0.011	**				
	3	0.001		- 0.009					
	4	0.017	***	- 0.004					
	5	0.037	***	0.018	**	0.062	***	0.068	***
2	1	- 0.034	***	- 0.015					
	2	- 0.014	***	- 0.008					
	3	0.002		0.000					
	4	0.018	***	0.007	*				
	5	0.037	***	0.029	***	0.071	***	0.043	***
3	1	- 0.034	***	- 0.007					
	2	- 0.019	***	- 0.005					
	3	0.002	**	- 0.005					
	4	0.018	***	0.003					
	5	0.035	***	0.013	**	0.069	***	0.020	**
4	1	- 0.030	***	0.001					
	2	- 0.017	***	- 0.005					
	3	0.002	*	- 0.001					
	4	0.017	***	- 0.001					
	5	0.031	***	0.015	***	0.061	***	0.014	**
5	1	- 0.025	***	- 0.007					
	2	- 0.016	***	- 0.006					
	3	0.002	*	- 0.007	*				
	4	0.015	***	0.007					
	5	0.029	***	0.006		0.053	***	0.013	*

Table A.13: Computed Good-minus-Bad 60-day PEAD and 3-day Response across Factor Quintiles and across ES Quintiles - *$Mcap_{i,q}$*.

See Table A.3 for explanation.

		3-day Response		60-day PEAD		Good News (ES Quintile 5) minus Bad News (ES Quintile 1)			
$Mcap_{i,q}$	ES Quintile	Mean of Quarterly Average		Mean of Quarterly Average		3-day Response		60-day PEAD	
1	1	- 0.030	***	- 0.054	***				
	2	- 0.014	***	- 0.008					
	3	- 0.000		- 0.003					
	4	0.018	***	- 0.003					
	5	0.035	***	0.017	*	0.063	***	0.069	***
2	1	- 0.038	***	- 0.008					
	2	- 0.017	***	- 0.005					
	3	0.006	***	- 0.005					
	4	0.018	***	- 0.000					
	5	0.041	***	0.024	***	0.079	***	0.032	***
3	1	- 0.030	***	- 0.007					
	2	- 0.017	***	- 0.005					
	3	0.001		- 0.006					
	4	0.020	***	0.004					
	5	0.034	***	0.012	**	0.064	***	0.019	*
4	1	- 0.029	***	- 0.009	*				
	2	- 0.016	***	- 0.008	**				
	3	0.001		- 0.003					
	4	0.016	***	0.005					
	5	0.034	***	0.018	***	0.063	***	0.027	***
5	1	- 0.024	***	- 0.002					
	2	- 0.016	***	- 0.006	*				
	3	0.002		- 0.005					
	4	0.013	***	0.008	*				
	5	0.023	***	0.010		0.047	***	0.011	*

Table A.14: Computed Good-minus-Bad 60-day PEAD and 3-day Response across Factor Quintiles and across ES Quintiles - $BM_{i,q}$.

See Table A.3 for explanation.

		3-day Response		60-day PEAD		Good News (ES Quintile 5) minus Bad News (ES Quintile 1)			
$BM_{i,q}$	ES Quintile	Mean of Quarterly Average		Mean of Quarterly Average		3-day Response		60-day PEAD	
	1	-0.036	***	-0.009					
	2	-0.024	***	-0.011	**				
1	3	0.003	**	-0.005					
	4	0.025	***	0.004					
	5	0.042	***	0.010		0.076	***	0.022	***
	1	-0.035	***	-0.015	**				
	2	-0.020	***	-0.005					
2	3	0.002	*	-0.006					
	4	0.020	***	0.008	**				
	5	0.036	***	0.013	**	0.071	***	0.028	***
	1	-0.026	***	-0.018	**				
	2	-0.015	***	-0.008					
3	3	0.001		-0.003					
	4	0.017	***	0.002					
	5	0.030	***	0.015	***	0.056	***	0.033	***
	1	-0.030	***	-0.012					
	2	-0.009	***	-0.004					
4	3	0.004	***	-0.004					
	4	0.015	***	-0.004					
	5	0.032	***	0.025	***	0.062	***	0.037	***
	1	-0.026	***	-0.021					
	2	-0.012	***	-0.007					
5	3	-0.000		-0.003					
	4	0.009	***	0.002					
	5	0.029	***	0.017	*	0.055	***	0.038	***

Table A.15: Computed Good-minus-Bad 60-day PEAD and 3-day Response across Factor Quintiles and across ES Quintiles - *$Mom_{i,q}$*.

See Table A.3 for explanation.

		3-day Response		60-day PEAD		Good News (ES Quintile 5) minus Bad News (ES Quintile 1)			
$Mom_{i,q}$	ES Quintile	Mean of Quarterly Average		Mean of Quarterly Average		3-day Response		60-day PEAD	
1	1	-0.031	***	-0.016					
	2	-0.012	***	-0.002					
	3	0.008	***	-0.001					
	4	0.026	***	0.004					
	5	0.041	***	0.016		0.070	***	0.030	**
2	1	-0.028	***	-0.013					
	2	-0.013	***	-0.001					
	3	0.005	***	-0.001					
	4	0.019	***	0.003					
	5	0.035	***	0.020	***	0.064	***	0.034	***
3	1	-0.030	***	-0.013	*				
	2	-0.015	***	-0.005					
	3	0.002	**	-0.004					
	4	0.017	***	0.007	*				
	5	0.034	***	0.011	**	0.063	***	0.024	***
4	1	-0.030	***	-0.020	***				
	2	-0.020	***	-0.011	*				
	3	-0.001		-0.006					
	4	0.015	***	0.002					
	5	0.030	***	0.015	**	0.060	***	0.035	***
5	1	-0.033	***	-0.016	**				
	2	-0.020	***	-0.015	***				
	3	-0.004	***	-0.008	*				
	4	0.009	***	-0.004					
	5	0.027	***	0.019	***	0.060	***	0.035	***

Table A.16: Computed Good-minus-Bad 60-day PEAD and 3-day Response across Factor Quintiles and across ES Quintiles - *Dispersion$_{i,q}$*.

See Table A.3 for explanation.

Note: Only firm-quarter announcements with less than three analyst forecasts are removed. Number of observations: 46,336.

		3-day Response		60-day PEAD		Good News (ES Quintile 5) minus Bad News (ES Quintile 1)			
Dispersion$_{i,q}$	ES Quintile	Mean of Quarterly Average		Mean of Quarterly Average		3-day Response		60-day PEAD	
1	1	-0.041	***	-0.012					
	2	-0.023	***	-0.012	**				
	3	0.002		-0.002					
	4	0.023	***	0.007					
	5	0.040	***	0.027	***	0.082	***	0.039	***
2	1	-0.038	***	0.002					
	2	-0.019	***	-0.011	**				
	3	0.002	**	-0.006					
	4	0.024	***	0.008	*				
	5	0.038	***	0.020	***	0.076	***	0.018	
3	1	-0.029	***	-0.004					
	2	-0.015	***	-0.001					
	3	0.004	***	-0.004					
	4	0.017	***	0.001					
	5	0.033	***	0.005		0.062	***	0.010	
4	1	-0.023	***	-0.005					
	2	-0.012	***	-0.007					
	3	0.003	**	-0.008	**				
	4	0.015	***	-0.003					
	5	0.031	***	0.016	***	0.055	***	0.021	***
5	1	-0.021	***	-0.017	*				
	2	-0.011	***	0.003					
	3	0.000		-0.000					
	4	0.010	***	0.006					
	5	0.023	***	0.009		0.044	***	0.026	***

A.5. Plot of PEAD Across Factor Portfolios

I plot the mean of PEAD returns for each factor quintile as represented in Section A.4. Factors that proxy behavioural explanations are: 1) the percentage of shares owned by institutional investors, proxying investor sophistication; 2) the number of earnings announcements per trading day, proxying investor distraction. Factors that proxy structural uncertainty explanations are: 1) the number of analyst forecasts, proxying information diffusion; 2) the volatility of abnormal returns, proxying uncertainty; and 3) the book-to-market ratio, proxying informational opacity. Factors that proxy limits of arbitrage explanations are: 1) the residual variance from the stock's one-factor market model regression, proxying unhedgeable risk; 2) the Amihud (2002) illiquidity factor, proxying stock illiquidity; 3) the average bid-ask spread at close, proxying direct transaction cost; 4) the end-of-quarter stock price proxying trading commissions; 5) the average daily dollar volume of shares traded, proxying indirect trading costs and order processing costs. I also include 1) the explained variance from the stock's market model regression, proxying hedgeable risk;[114] 2) the market capitalisation, proxying size effects; and 3) the cumulative abnormal return for the 40 days prior to earnings announcement, proxying momentum effects.[115]

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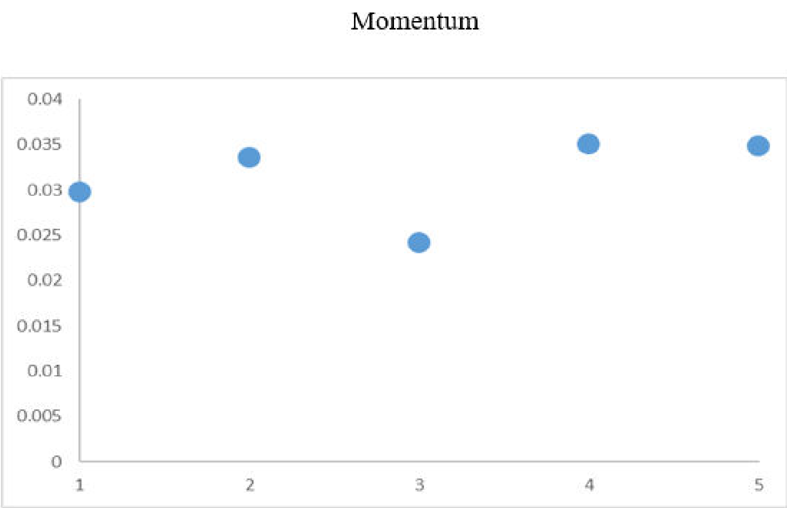
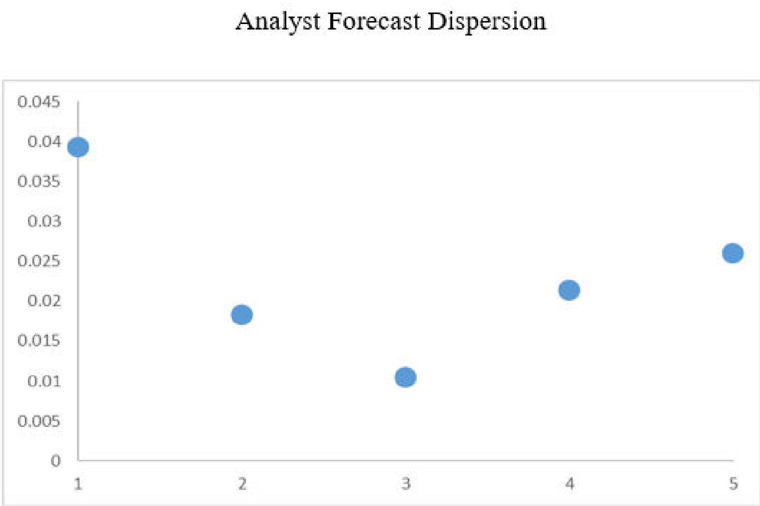
[114] Inclusion of this variable follows Mendenhall (2004), Livnat and Mendenhall (2006) and Chordia et al. (2009). An insignificant relationship with hedgeable risk affirms PEAD is not compensation for risks that can be hedged by the market portfolio.

[115] In Section A.1 of the Appendix I also consider 1) Volume-Synchronised Probability of Informed Trading (VPIN) as a proxy for the level of informed trading (Vega, 2006). The analysis of this factor results in a substantial loss of observations and therefore I consider it separately.

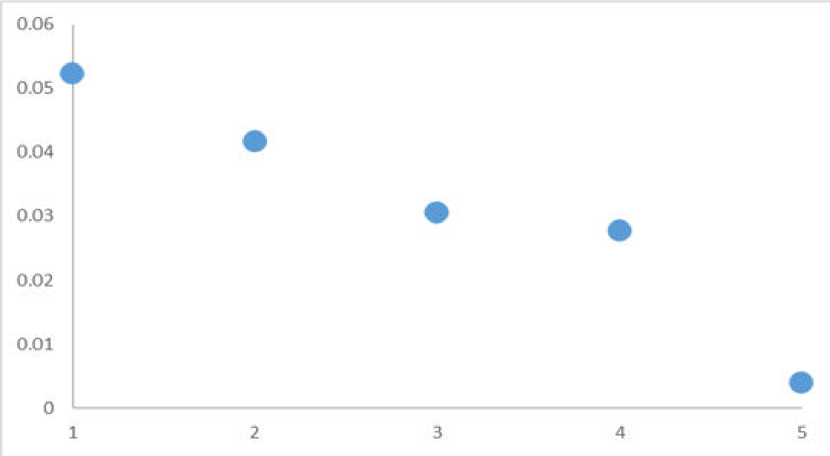
Figure A.1: Plot of PEAD across Factor Quintiles.

Each plot represents PEAD across factor quintile groups. I compute PEAD as the difference between the mean of BHAR in the top ES quintile minus the mean of the BHAR for the worst ES quintile. BHAR is constructed by adjusting returns by 5x5 size quintile and BM quintile portfolio. ES breakpoints are computed in the previous quarter. Factor quintile breakpoints are computed based on within-quarter sort. The results below represent the average of the quarterly means. The variables are earnings surprise ($ES_{i,q}$); institutional ownership ($Insti_{i,q}$); number of announcements released on same day ($Distract\_U_{i,q}$); number of analysts issuing forecasts within the 90 days prior to the earnings announcement ($Analyst_{i,q}$); volatility of daily BHAR in the 40 trading days prior to earnings announcement ($Volatility_{i,q}$); arbitrage risk ($ArbRisk_{i,q}$); hedgeable risk ($ExpRisk_{i,q}$); average of Amihud illiquidity measured across 40 trading days prior to earnings announcement ($Illiq_{i,q}$); average of quoted spread at closing across 40 trading days prior to earnings announcement ($Spread_{i,q}$); stock price at the end of quarter, q (*Price*); average daily turnover (in millions of dollars) measured from 271 trading days to 22 trading days prior to earnings announcement ($Turn_{i,q}$); market capitalisation ($Mcap_{i,q}$); book-to-market ratio ($BM_{i,q}$); BHAR across the past 40 trading days prior to earnings announcement ($Mom_{i,q}$). Period: July 1995 to June 2011.

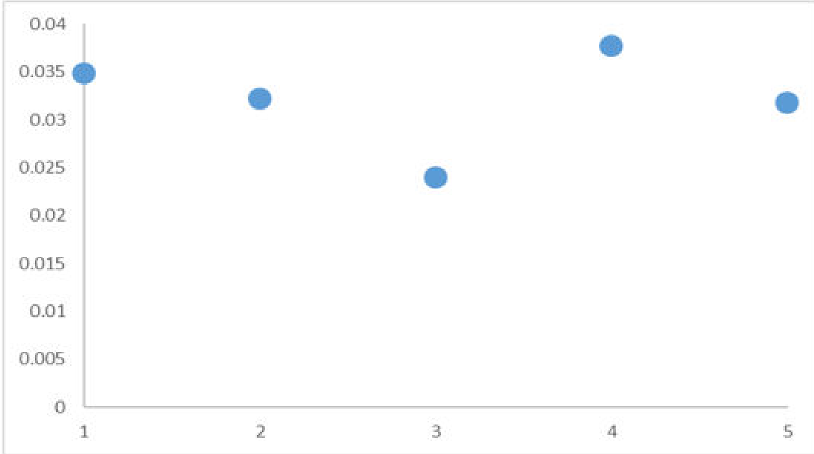




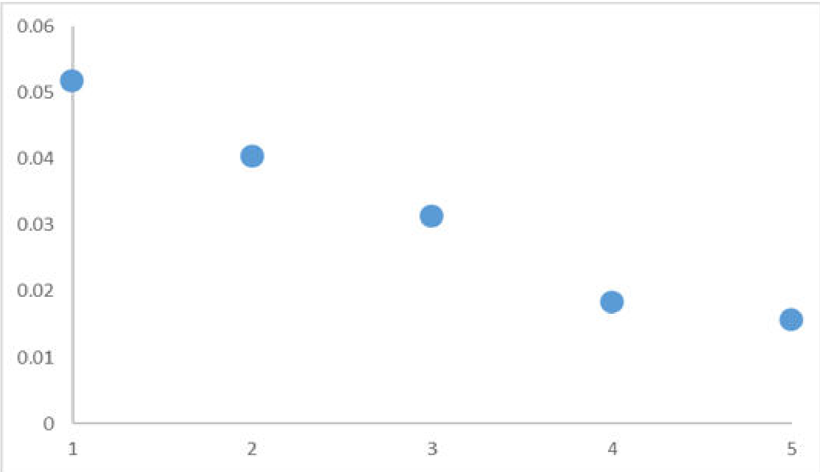
Institutional Ownership



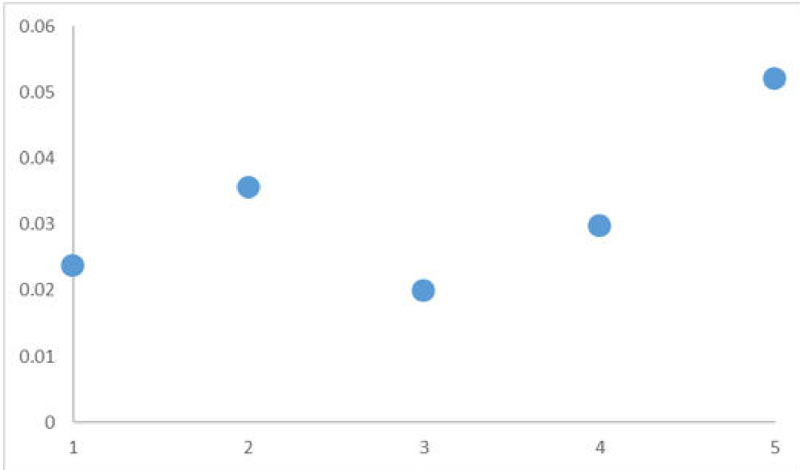
Number of Simultaneous Announcements



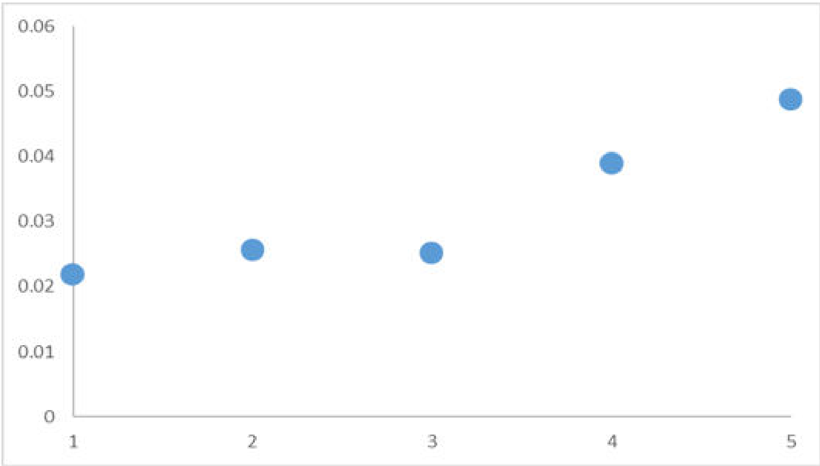
Number of Analysts



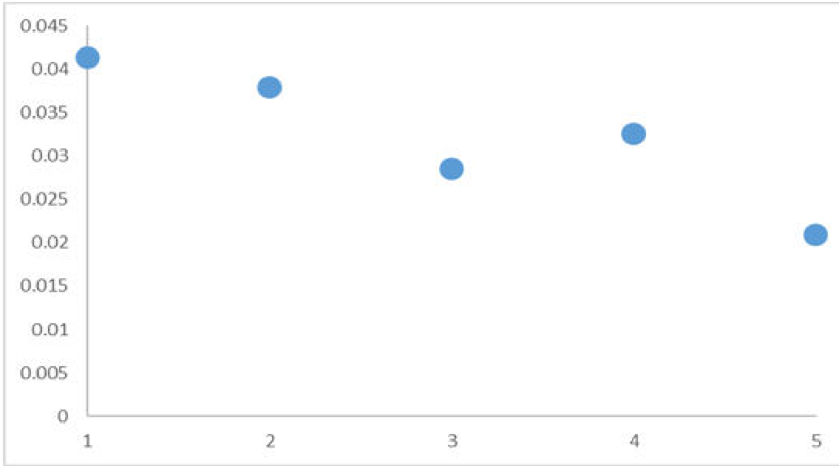
Volatility



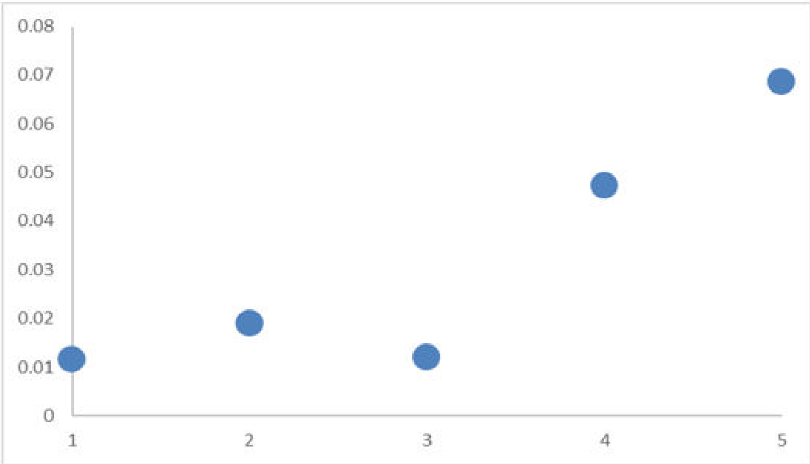
Arbitrage Risk



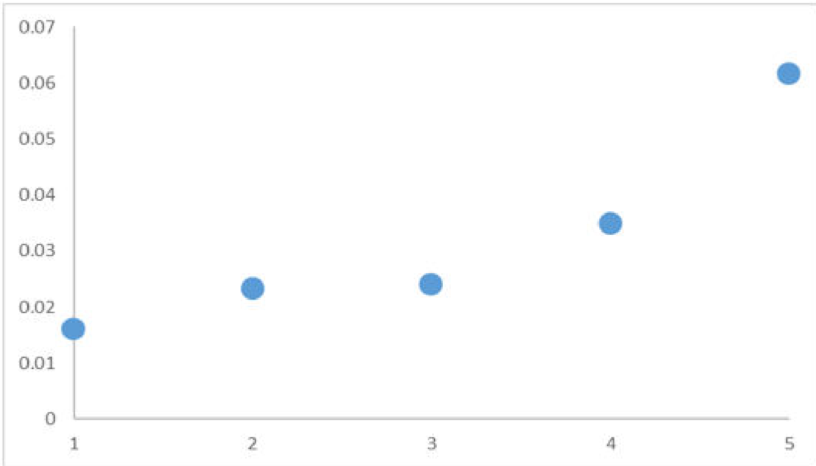
Hedgeable Risk



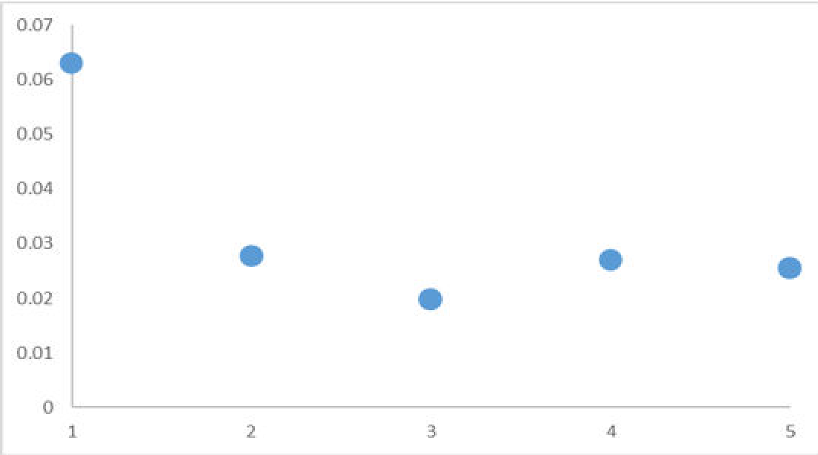
Amihud (2002) Illiquidity



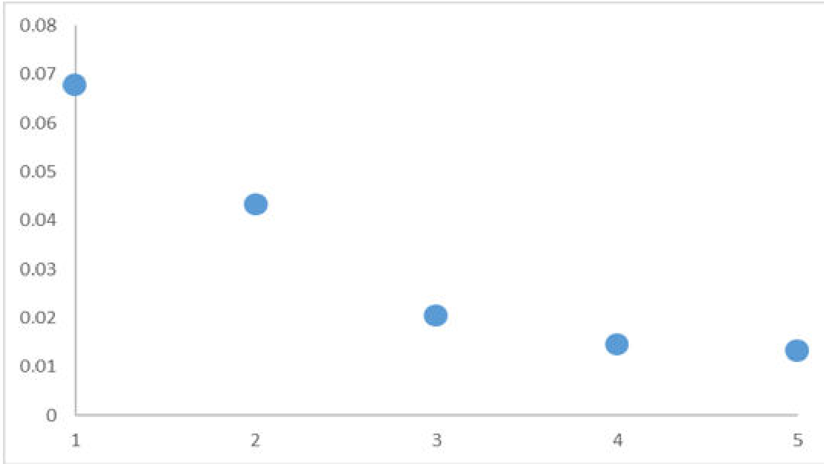
Bid-Ask Quote



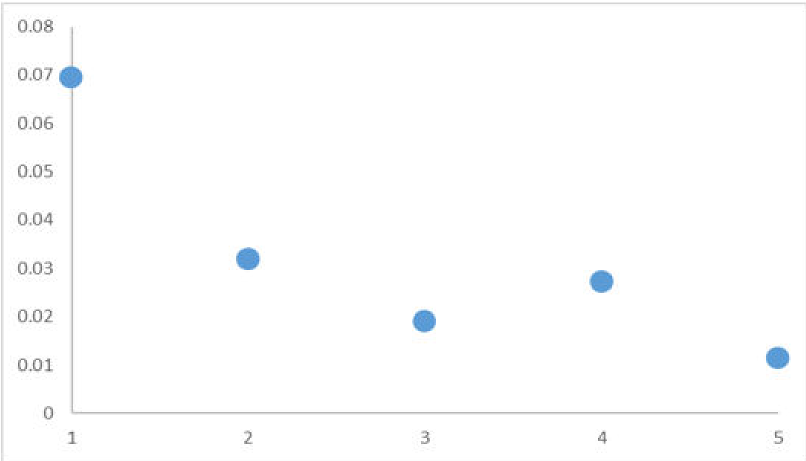
Stock Price



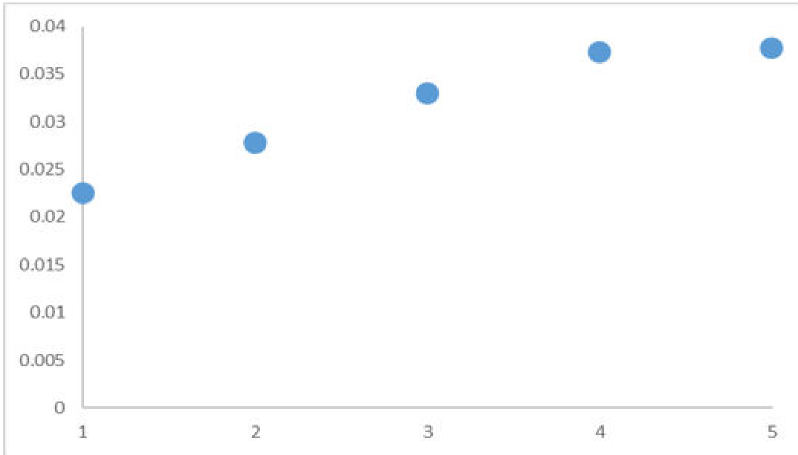
Turnover



Market Capitalisation



Book-to-Market Ratio



A.6. Correlation Matrix of Ranked Explanatory Factors

Table A.5: Full Sample Correlation Matrix of Scaled Factors Sorted Within-Quarter

The below values are computed correlation coefficients for variables in the period July 1995 to June 2011. All variables except $PEAD_{i,q}$ and $3DR_{i,q}$ are ranked. Therefore $ES_{i,q}$ is ranked to between 1, 2, 3, 4 or 5. Other explanatory factors are sorted within-quarter to a decile rank of between 1 and 10. The variables are, across firm *i* and in quarter *q*, earnings surprise ($ES_{i,q}$); institutional ownership ($Insti_{i,q}$); the decile rank based on number of announcements released on same day ($Distract_{i,q}$); number of analysts issuing forecasts within the 90 days prior to the earnings announcement ($Analyst_{i,q}$); volatility of daily BHAR in the 40 trading days prior to earnings announcement ($Volatility_{i,q}$); arbitrage risk ($ArbRisk_{i,q}$); hedgeable risk ($ExpRisk_{i,q}$); the logarithm of average Amihud illiquidity measured across 40 trading days prior to earnings announcement ($LogIlliq_{i,q}$); the logarithm of average of quoted spread at closing across 40 trading days prior to earnings announcement ($LogSpread_{i,q}$); stock price at the end of quarter, *q* ($Price_{i,q}$); average daily turnover (in millions of dollars) measured from 271 trading days to 22 trading days prior to earnings announcement ($Turn_{i,q}$); the logarithm of market capitalisation ($LogMcap_{i,q}$); book-to-market ratio ($BM_{i,q}$); BHAR across the past 40 trading days prior to earnings announcement ($Mom_{i,q}$); BHAR from the 2nd to the 61st trading day after earnings announcement ($PEAD_{i,q}$); and BHAR from the 1st trading day before earnings announcement to the 1st trading day after earnings announcement ($3DR_{i,q}$).

	$ES_{i,q}$	$LogIlliq_{i,q}$	$LogSpread_{i,q}$	$Insti_{i,q}$	$Analyst_{i,q}$	$Turn_{i,q}$	$Distract_{i,q}$	$Price_{i,q}$	$Volatility_{i,q}$	$Mom_{i,q}$	$ArbRisk_{i,q}$	$ExpRisk_{i,q}$	$LogMcap_{i,q}$	$BM_{i,q}$	$PEAD_{i,q}$	$3DR_{i,q}$
$ES_{i,q}$																
$LogIlliq_{i,q}$	-0.01															
$LogSpread_{i,q}$	-0.03	0.74														
$Insti_{i,q}$	0.05	-0.26	-0.21													
$Analyst_{i,q}$	0.01	-0.66	-0.44	0.24												
$Turn_{i,q}$	0.01	-0.96	-0.68	0.29	0.69											
$Distract_{i,q}$	0.02	-0.09	-0.09	0.05	0.05	0.08										
$Price_{i,q}$	0.03	-0.64	-0.73	0.22	0.35	0.57	0.10									
$Volatility_{i,q}$	0.00	0.34	0.47	0.04	-0.08	-0.21	-0.07	-0.46								
$Mom_{i,q}$	0.11	-0.06	-0.08	0.03	0.01	0.03	0.03	0.10	-0.03							
$ArbRisk_{i,q}$	0.03	0.40	0.49	0.08	-0.14	-0.28	-0.10	-0.52	0.68	-0.02						
$ExpRisk_{i,q}$	0.04	-0.02	0.09	0.17	0.11	0.11	-0.02	-0.13	0.29	0.01	0.38					
$LogMcap_{i,q}$	0.00	-0.94	-0.72	0.17	0.63	0.91	0.09	0.65	-0.39	0.06	-0.48	-0.01				
$BM_{i,q}$	0.05	0.33	0.29	-0.13	-0.19	-0.34	0.03	-0.32	0.02	-0.01	0.04	-0.03	-0.32			
$PEAD_{i,q}$	0.28	0.00	0.00	0.02	0.01	0.00	-0.01	0.01	0.00	-0.02	0.01	0.01	-0.01	0.00		
$3DR_{i,q}$	0.05	0.00	0.01	0.01	0.01	0.01	0.01	-0.01	0.01	-0.01	0.01	0.03	0.00	0.01	0.02	

APPENDIX B

Below I present alternative specifications for testing the attenuation of time-varying PEAD. Each test shows PEAD has significantly declined since the early 2000s. The test specifications include 1) Carhart (1997) four-factor test; 2) Multivariate Analysis; and 3) Unknown Structural Break Test.

B.1. Carhart (1997) Four-Factor Test

I consider a factor-based pricing model using Carhart (1997) four factors and test the change in PEAD alpha after the Autoquote phase-in. I obtain Carhart (1997) four factors from WRDS and Professor Kenneth French's website[116] and compute PEAD following the standard cumulative abnormal returns measure, where for firm *i* on announcement date t, $CAR_{i,t}$ is the cumulative abnormal returns: $CAR_{i,t} = \sum_n^N r_{i,t+n} - \sum_n^N r_{MM,t+n}$. I note $r_{i,t+n}$ is the daily stock return, $r_{i,t+n}^{MM}$ is the daily risk free rate, and *n* represents the holding period from the n^{th} day after the date of announcement to the N^{th} trading day. For computing PEAD, *n* is equal to 2 and *N* is equal to 61; for computing 3DR *n* is equal to -1 and *N* is equal to 1. I note the four factors of market risk premium, book-to-market ratio, size and momentum effects are also computed by summing daily returns from date *n* to *N.* For example $MKTRF$is the daily return of the S&P 500 index (including dividends) minus the risk free rate from the n^{th} trading day after earnings announcement to the N^{th}. I then only retain firm-quarter observations in the ES quintile equal to one or five and run the specification below:

$$CAR_{i,t} = \alpha + \rho_1 MKTRF_t + \rho_2 HML_t + \rho_3 SMB_t + \rho_4 UMD_t + \beta_1 GoodNewsDummy_i + \beta_2 AutoquoteDummy_t + \beta_3 GoodAfterAutoquote_{i,t} + \varepsilon_{i,t} \tag{B.1}$$

[116] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data library.html.

Where $GoodNewsDummy$ is equal to one for observations in quintile five and zero otherwise; $AutoquoteDummy$ is equal to one for all announcements post-Autoquote but zero otherwise; and the interaction term $GoodAfterAutoquote$ is equal to $GoodNewsDummy$ multiplied by $AutoquoteDummy$. Following Hirshleifer et al. (2009) the dummy variable coefficients can be interpreted by the following: 1) a significant β_1 means good news firms before Autoquote have significantly different drift from bad news firms before Autoquote; 2) a significant β_2 means bad news firms after Autoquote are significantly different from bad news firms before Autoquote; and 3) a significant β_3 means the difference between PEAD for good news firms and bad news firms is significantly different before Autoquote compared with after Autoquote. Hence a significant and negative β_3 is consistent with PEAD attenuation. I adjust standard errors for heteroskedasticity through clustering by both announcement date and firm level following the double-clustering method of Thompson (2011).

B.1.1. Results

The regression results are presented in Table B.1 and show PEAD attenuated by two-thirds after Autoquote was phased-in. Testing on only NYSE firms (in Panel A) I show PEAD was 3.62% (significant at the 1% level) before Autoquote and shrank by 2.47% after Autoquote (significant at the 1% level). I then implement the test on non-NYSE firms and impose $AutoquoteDummy_t$ equal to 1 for observations after 30th June 2003 but equal to zero otherwise. The results in Panel B indicate PEAD rose by 0.06% after 30th June 2003 (insignificant at 10% level) and therefore suggest PEAD did not attenuate for non-NYSE firms.

My results also show for both NYSE and non-NYSE firms 3DR accentuated. NYSE 3DR grew by 2.24% (significant at the 1% level) after the phase-in of Autoquote from 4.62% (significant at 1%); and non-NYSE 3DR grew 1.51% (significant at the 1% level) from 6.23% (significant at the 1% level). Hence 3DR significantly accentuated across all firms but PEAD only attenuated for NYSE firms.

Table B.1: Factor-Based Model: the Change in 3DR and PEAD after Autoquote

The table shows regression results from a factor-based pricing model employing Carhart (1997) four factors. For firm i on announcement date t, $CAR_{i,t} = \sum_{n}^{N} r_{i,t+n} - \sum_{n}^{N} r_{MM,t+n}$ where $r_{i,t+n}$ is the daily stock return and $r_{i,t+n}^{MM}$ is the daily risk free rate. For computing PEAD n equals 2 and N equals 61; for computing 3DR n equals -1 and N equals 1. The results are based on the following regression specification where only firm-quarter observations in the ES quintile equal to one or five are retained: $CAR_{i,t} = \alpha + \rho_1 MKTRF_t + \rho_2 HML_t + \rho_3 SMB_t + \rho_4 UMD_t + \beta_1 GoodNewsDummy_i + \beta_2 AutoquoteDummy_t + \beta_3 GoodAfterAutoquote_{i,t} + \varepsilon_{i,t}$ where $GoodNewsDummy$ is equal to one for observations in quintile five and zero otherwise; $AutoquoteDummy$ is equal to one for all announcements post-Autoquote but zero otherwise; and the interaction term $GoodAfterAutoquote$ is equal to $GoodNewsDummy$ multiplied by $AutoquoteDummy$. The four factors of market risk premium ($MKTRF_t$), book-to-market ratio (HML_t), size (SMB_t) and momentum (UMD_t) effects are computed by summing daily factor returns from date n to N. Standard errors are adjusted for heteroskedasticity across both announcement date and firm following the double-clustering method of Thompson (2011). ***, **, * represent significance level at 0.01, 0.05 and 0.1 respectively.

Dependent Variable:	Risk-Free Rate Adjusted 3DR		Risk-Free Rate Adjusted PEAD	
	Panel A: NYSE Firms			
Intercept	-0.0215	***	-0.00297	
$MKTRF_t$	1.172	***	1.017	***
HML_t	0.774	***	0.610	***
SMB_t	0.650	***	0.671	***
UMD_t	-0.345	***	-0.496	***
$GoodNewsDummy_i$	0.0462	***	0.0362	***
$AutoquoteDummy_t$	-0.0118	***	0.00830	**
$GoodAfterAutoquote_{i,t}$	0.0224	***	-0.0247	***
	Panel B: non-NYSE Firms			
Intercept	-0.0290	***	0.0199	***
$MKTRF_t$	1.087	***	1.071	***
HML_t	0.141	**	-0.093	***
SMB_t	1.124	***	1.344	***
UMD_t	-0.357	***	-0.410	***
$GoodNewsDummy_i$	0.0623	***	0.0336	***
$AutoquoteDummy_t$	-0.0112	***	-0.0286	***
$GoodAfterAutoquote_{i,t}$	0.0151	***	0.0006	

B.2. Multivariate Analysis

I now control for a range of explanatory factors (listed in Section 3.3). To do so I employ a multivariate test with scaled interaction terms using the buy-and-hold abnormal returns measure to proxy for PEAD: $BHAR_{i,q,t} = \prod_{n=2}^{61}(1 + r_{i,q,t+n}) - \prod_{n=2}^{61}(1 + r_{i,t+n}^{MM})$ where the adjustment-portfolio $r_{i,t+n}^{MM}$ represents 5x5 size and BM matched portfolios (details of the specification are explained in Section 2.5.1 in Chapter 2):

$$
\begin{aligned}
BHAR_{i,q} \quad = \quad & a_q \\
& + \beta_1 ES_{i,q}^{Scaled} \\
& + \textstyle\sum_{z=1}^{Z}\left[\gamma_z InteractionTerm_{z,i,q}^{Scaled}\right] + \varepsilon_{i,q} \qquad \text{(B.2)}
\end{aligned}
$$

I then run Fama and MacBeth (1973) quarterly regressions and conduct a two-sample pooled student-t test where I compare the distribution of estimated β_1 prior to the 2nd quarter of 2003 with the estimated β_1 after the 4th quarter of 2003. The results in Table B.2 show that after controlling for the full set of explanatory factors the mean of $\hat{\beta}_1$ reduced by 1.41% (significant at the 10% level) from 2.59% (significant at the 1% level) to 1.17% (significant at the 10% level). The right column shows the findings excluding quarters under recession. I do note this test may be inefficient if $\hat{\beta}_1$ is trending downwards across time (Vega, 2006), and that the test statistic may be under-estimated. To assess the robustness of my findings I therefore also consider whether the mean of PEAD has declined across 25 portfolios based on 5x5 sorts of arbitrage risk and institutional ownership. This extends my analysis in Chapter 2 that arbitrage risk and institutional ownership are robust explanatory factors for PEAD. The results are in Table B.3 and show PEAD declined for 17 of the 25 portfolios. The remaining 8 portfolios are concentrated in portfolios with low institutional ownership and high arbitrage risk (which are proxies for small-cap firms).

For example, for the quintile with the highest arbitrage risk three of five quintiles experienced a rise in PEAD (the second institutional ownership (IO) quintile at 0.14%, the third IO quintile at 0.003% and the largest IO quintile at 0.12%). Further, for the portfolios at the lowest institutional ownership (IO quintile equals 1), three of five portfolios are positive. The smallest arbitrage risk (AR) quintile shows 0.27%, second smallest AR quintile shows 1.08% and third smallest AR quintile shows 0.38%. The remaining portfolios almost entirely indicate a decline in PEAD.

B.3. Unknown Structural Break

Finally, I test for a structural change in PEAD and assess whether an unknown break point corresponds to a known structural change. To do so I follow the unknown structural break test of Andrews (1993) where the break point is selected across times series data by maximising the QLR statistic (Quandt, 1960): $QLR\ Statistic = \max[F - statistic(\lambda)]$ where λ_i=m_i/n is the unknown break date; and n is the number of breaks. The maximising function maximises with respect to m_i over $[m_a, m_b]$ where *a* and *b* are the min and max selected break points.

I follow Andrews' (1993) "naive" approach and set m_a to the date period closest to the 15th percentile of the data period and m_b closest to the 85th. I then run the specification:

$$CAR_{i,t} = \alpha + \beta * MKTRF_t + \gamma * GoodNewsDummy_i + \varepsilon_{i,t} \qquad \text{(B.3)}$$

Where $CAR_{i,t}$ is defined under Section B.1, $MKTRF_t$ the daily return of the S&P 500 index minus the risk free rate from the 2nd day after earnings announcement to the 61st day and $GoodNewsDummy$ is equal to 1 for good news observations and zero otherwise.

I conduct the test on only NYSE firm-quarter observations and my results show that periods close to the introduction of Autoquote are selected as the structural break. For yearly break dates (30th June of every year are the reference break points), 30th June 2003 is chosen with a

QLR Statistic of 90.9 which is significant at the 1% level.[117] For quarterly break dates I find the selected break date is 30th June 2002 (with a QLR statistic of 73.3) and again significant at the 1% level.[118] Hence the unknown structural break of time-varying PEAD of NYSE firms corresponds to the phase-in of Autoquote.

To visualise this break in Figure B.1, I plot the annual difference in PEAD between the top and bottom ES quintiles. I calculate PEAD as measured by the cumulative abnormal return $CAR_{i,t}$ as defined under Section B.1.[119] The graph shows PEAD averaged consistently at just below 4% before the year 2001 and then experienced a sharp decline in the early 2000s. The plot of 3DR shows inversely that 3DR has trended upwards over time.

[117] The 1% level is 13.39 (Andrews, 1993).

[118] For the quarterly break test I first purge the firm-quarter observations for quarters under economic recession (as defined by NBER).

[119] I note computing 3DR and PEAD by either CAR or BHAR does not change my findings.

Table B.2: Change in Fama-Macbeth coefficient after Autoquote

The table show the mean of $\hat{\beta}_1$ estimates for sample period before and after 30th June 2003. $\hat{\beta}_1$ is estimated from the specification $BHAR_{i,q} = a_q + \beta_1 ES_{i,q}^{Scaled} + \sum_{z=1}^{Z}\left[\gamma_z InteractionTerm_{z,i,q}^{Scaled}\right] + \varepsilon_{i,q}$ where the dependent variable is PEAD ($PEAD_{i,q}$) of NYSE firms. All factor deciles are scaled to between -0.5 to +0.5. The variables are: earnings surprise quintile ($ES_{i,q}^{Scaled}$); institutional ownership ($Insti_{i,q}^{Scaled}$); number of announcements released on same day ($Distract_{i,q}^{Scaled}$); number of analysts issuing forecasts within the 90 days prior to the earnings announcement ($Analyst_{i,q}^{Scaled}$); volatility of daily BHAR in the 40 trading days prior to earnings announcement ($Volatility_{i,q}^{Scaled}$); arbitrage risk ($ArbRisk_{i,q}^{Scaled}$); hedgeable risk ($ExpRisk_{i,q}^{Scaled}$); average of quoted spread at closing across 40 trading days prior to earnings announcement ($Spread_{i,q}^{Scaled}$); stock price at the end of quarter, q ($Price_{i,q}^{Scaled}$); average daily turnover (in millions of dollars) measured from 271 trading days to 22 trading days prior to earnings announcement ($Turn_{i,q}^{Scaled}$); market capitalisation ($Mcap_{i,q}^{Scaled}$); book-to-market ratio ($BM_{i,q}^{Scaled}$); BHAR across the past 40 trading days prior to earnings announcement ($Mom_{i,q}^{Scaled}$). The results represent Fama and Macbeth (1973) regressions where the computed mean is based on the average of estimated coefficients from quarterly regressions. Period: July 1995 to June 2011. ***, **, * represent t-test significance level at 0.01, 0.05 and 0.1 respectively.

	All Quarters		Exclude Quarters Under Recession	
Pre-Autoquote	0.0259	***	0.0259	***
Post-Autoquote	0.0117	*	0.0134	***
Two sample t-test	-0.0141	*	-0.0124	*

Table B.3: Cross-Sectional Analysis of the Change in 3DR and PEAD after Autoquote

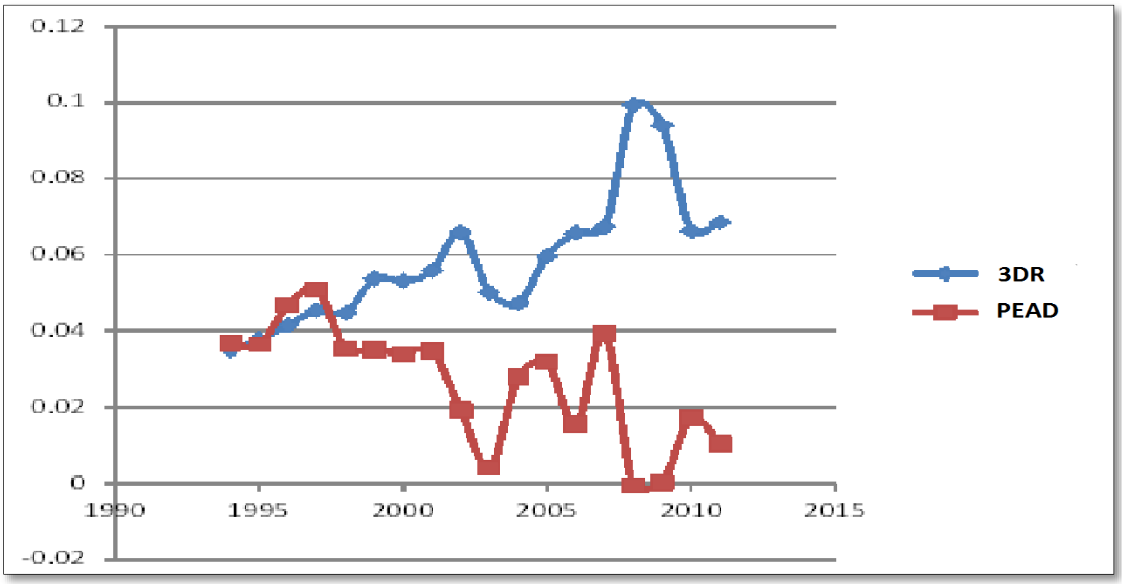
The table below computes the sample mean of 3DR and PEAD before and after Autoquote. Means are computed across arbitrage risk quintiles and institutional ownership quintiles. To compute means, earnings announcements are sorted within-quarter by arbitrage risk ($ArbRisk_{i,q}$) and institutional ownership ($Insti_{i,q}$) into quintiles; and only firm-quarter observations in the top and bottom ES quintiles are retained. 3DR and PEAD are then computed by taking the quarterly difference in mean between the top and bottom ES quintiles. The sample data is separated into before and after Autoquote based on 30th June 2003.

		3DR			PEAD		
$ArbRisk_{i,q}$	$Insti_{i,q}$	*Pre-Autoquote*	*Post-Autoquote*	*Post-Autoquote minus Pre-Autoquote*	*Pre-Autoquote*	*Post-Autoquote*	*Post-Autoquote minus Pre-Autoquote*
Low Arbitrage Risk	Low IO	0.0096	0.0182	0.0086	0.0118	0.0145	0.0027
	2	0.0112	0.0209	0.0097	0.0180	0.0130	-0.0051
	3	0.0169	0.0219	0.0050	0.0119	0.0068	-0.0051
	4	0.0129	0.0292	0.0163	0.0132	0.0020	-0.0112
	High IO	0.0155	0.0215	0.0060	0.0197	-0.0040	-0.0237
	mean	0.0132	0.0223	0.0091	0.0149	0.0064	-0.0085
2	Low IO	0.0099	0.0286	0.0187	0.0087	0.0195	0.0108
	2	0.0184	0.0302	0.0118	0.0355	0.0161	-0.0194
	3	0.0154	0.0296	0.0142	0.0074	0.0034	-0.0041
	4	0.0187	0.0342	0.0155	0.0130	0.0135	0.0005
	High IO	0.0194	0.0398	0.0204	-0.0019	0.0044	0.0063
	mean	0.0164	0.0325	0.0161	0.0126	0.0114	-0.0012
3	Low IO	0.0202	0.0333	0.0131	0.0270	0.0308	0.0038
	2	0.0249	0.0365	0.0116	0.0185	0.0032	-0.0154
	3	0.0189	0.0342	0.0153	0.0043	0.0025	-0.0017
	4	0.0208	0.0397	0.0188	0.0109	-0.0025	-0.0135
	High IO	0.0286	0.0413	0.0126	0.0012	-0.0073	-0.0084
	mean	0.0227	0.0370	0.0143	0.0124	0.0053	-0.0070
4	Low IO	0.0242	0.0370	0.0128	0.0225	0.0208	-0.0017
	2	0.0263	0.0446	0.0183	0.0315	-0.0235	-0.0550
	3	0.0282	0.0324	0.0042	0.0180	0.0348	0.0168
	4	0.0264	0.0428	0.0163	0.0026	-0.0001	-0.0027
	High IO	0.0260	0.0446	0.0185	0.0026	-0.0068	-0.0095

		3DR			PEAD		
$ArbRisk_{i,q}$	$Insti_{i,q}$	*Pre-Autoquote*	*Post-Autoquote*	*Post-Autoquote minus Pre-Autoquote*	*Pre-Autoquote*	*Post-Autoquote*	*Post-Autoquote minus Pre-Autoquote*
	mean	0.0263	0.0403	0.0140	0.0154	0.0050	-0.0104
High Arbitrage Risk	Low IO	0.0201	0.0350	0.0150	0.0343	0.0239	-0.0104
	2	0.0289	0.0472	0.0184	0.0095	0.0109	0.0014
	3	0.0376	0.0479	0.0103	0.0203	0.0203	0.00003
	4	0.0311	0.0452	0.0141	0.0206	0.0026	-0.0180
	High IO	0.0221	0.0482	0.0261	0.0016	0.0028	0.0012
	mean	0.0279	0.0447	0.0168	0.0173	0.0121	-0.0052

Figure B.1: Plot of Annual PEAD and 3DR

The figure plots annual 3DR and PEAD across time. The plot represents the annual difference in mean between firm-quarter observations in the top and bottom ES quintiles. 3DR and PEAD are measured by the cumulative abnormal return measure: $CAR_{i,t} = \sum_n^N r_{i,t+n} - \sum_n^N r_{MM,t+n}$ where $r_{i,t+n}$ is the daily stock return and $r_{i,t+n}^{MM}$ is the daily risk free rate. For computing PEAD *n* equals 2 and *N* equals 61; for computing 3DR *n* equals -1 and N = +1. The vertical axis represents return and the horizontal axis represent calendar year.



APPENDIX C

C.1. Description of Variables

The variable name and descriptions are outlined below. Variables are calculated based on each stock *j* and each trading day *t*.

Variable	Description	Data Source
$qspread_{j,t}$	turnover-weighted quoted half-spread (bps)	TRTH
$espread_{j,t}$	turnover-weighted effective half-spread (bps)	TRTH
$rspread_{j,t}$	turnover-weighted realised half-spread (bps) at 5 minutes	TRTH
$adv\_selection_{j,t}$	turnover-weighted adverse selection half-spread (bps) at 5 minutes	TRTH
$messages_{j,t}$	number of order book changes (/day)	TRTH
$turnover_{j,t}$	daily share turnover ($million)	TRTH
$volatility_{j,t}$	daily price range standardized by the daily close price (%)	CRSP
$price_{j,t}$	daily closing price ($)	CRSP
$ticksize_{j,t}$	0.01 divided by $price_{j,t}$.	
$market\_cap_{j,t}$	number of shares outstanding times price as of June 2003 ($billion)	Compustat
$trade\_count_{j,t}$	number of trades (/day)	TRTH
$trade\_size_{j,t}$	mean daily trade size ($1,000)	TRTH
$volume_{j,t}$	number of shares transacted (1,000)	TRTH

C.2. Cleaning TRTH data

Following Boehmer, Fong and Wu (2015) I conduct the following filters on the SIRCA TRTH data.

Trade data must satisfy:

a) Trades must be inside regular trading hours (9:30 to 16:00)
b) Regular sales conditions[120]
c) Trades with positive trade price (price>0) and positive trade size (size>0)
d) Trades with absolute change in trade price from the previous trade price of less than or equal to 10%.

Quote data must satisfy:

a) Quotes must be inside regular trading hours (9:30 to 16:00)
b) Regular quotes (on-market quote)
c) Quotes with positive bids (bid>0), positive ask price (offer>0), ask price greater than bid price (offer>bid), positive bid size (bidsize>0) and positive offer size (offersize>0)
d) Quotes with relative quoted spreads of less than or equal to 20%
e) Quotes with absolute change in bid price from the previous bid price (in same trading day) of less than or equal to 10% and with absolute change in ask price from the previous ask price (in same trading day) of less than or equal to 10%.

[120] Qualifiers include either: "[PRC_QL2]", "[CTS_QUAL]; [PRC_QL2]", "[CTS_QUAL]; [PRC_QL2];High", "[CTS_QUAL]; PRC_QL2];Low"

C.3. Adverse Selection and Realised Spreads

Adverse Selection declined after Autoquote and realised spreads increased after Autoquote. To show this result I test the following specification:

$$L_{j,t} = \alpha_j + \gamma_t + \beta_1 AQ_{j,t} + \gamma_1 turnover_{j,t} + \gamma_2 volatility_{j,t} + \gamma_3 ticksize_{j,t}$$

$$+\gamma_4 logmcap_{j,t} + \varepsilon_{j,t} \qquad (\text{C.1})$$

Where $L_{j,t}$ is the daily turnover weighted liquidity measure, α_j represents firm fixed effects, γ_t represents day dummy variables for day t, and $AQ_{j,t}$ is the Hendershott et al. (2011) dummy variable equal to +1 for periods with Autoquote phased-in and zero otherwise. I also include the following control variables: share turnover, tick size, the log of market capitalisation and volatility based on daily price range standardized by the daily stock price $(P_{j,t}^{High} - P_{j,t}^{Low})/P_{j,t}$ (see Parkinson, 1980). The estimated standard errors are robust to general cross-sectional and time-series heteroscedasticity and within-group autocorrelation (see Arellano and Bond, 1991). Table C.1 show results for adverse selection and realised spreads across size quintiles. The change in adverse selection range between -0.513 basis points for the largest firms and -1.002 for the smallest firms (all significant at the 1% level). The change in realised spreads range between 0.365 basis points for the largest firms and 1.603 for the smallest firms (all significant at the 1% level). In other words overall asymmetric information declined after Autoquote and realised spreads increased after Autoquote.

Table C.1: Regression Results following Hendershott et al. (2011)

The table regresses measures of liquidity on the Hendershott et al. (2011) Autoquote dummy variable. Sample period is from 1st January 2003 to 31st July 2003. The specification is: $L_{j,t} = \alpha_j + \gamma_t + \beta_1 AQ_{j,t} + \gamma_1 turnover_{j,t} + \gamma_2 volatility_{j,t} + \gamma_3 ticksize_{j,t} + \gamma_4 logmcap_{j,t} + \varepsilon_{j,t}$ where the dependent variable $L_{j,t}$ is measures of daily turnover-weighted liquidity in basis points and 1) half adverse selection, and 2) half realised spreads, α_j represents firm fixed effects, γ_t represents day dummy variables and $AQ_{j,t}$ is a dummy variable equal to +1 for periods with Autoquote phased-in and zero otherwise. The remaining factors are control variables: share turnover, volatility, tick size and the log of market capitalisation. Market capitalisation break points are computed based using market capitalisation at the end of June 2003. Standard errors are robust to general cross-sectional and time-series heteroscedasticity and within-group autocorrelation (see Arellano and Bond, 1991). ***, **, * represent 1%, 5% and 10% significance level respectively.

	$AQ_{j,t}$		$turnover_{j,t}$		$volatility_{j,t}$		$ticksize_{j,t}$		$logmcap_{j,t}$	
Panel A: Adverse Selection By Market Capitalisation Quintile										
Dependent Variable: adverse selection (bps)										
1 (smallest)	- 1.002	***	- 0.026		1.800	***	0.184	**	- 3.765	***
2	- 0.846	***	- 0.011		1.361	***	- 0.201	***	- 6.194	***
3	- 0.765	***	0.003		0.359	***	0.413	***	- 2.082	***
4	- 0.613	***	0.000		0.501	***	0.283	***	- 1.580	***
5 (largest)	- 0.513	***	0.001	**	0.334	***	0.295	***	- 1.434	***
Panel B: Realised Spreads By Market Capitalisation Quintile										
Dependent Variable: realised spreads (bps)										
1 (smallest)	1.603	***	- 0.020		- 0.630	***	1.327	***	4.565	***
2	0.669	***	0.018	*	- 0.561	***	0.087	***	- 2.822	***
3	0.738	***	- 0.004		- 0.089	*	- 0.193	***	- 2.923	***
4	0.456	***	- 0.001		- 0.220	***	- 0.110	***	- 2.651	***
5 (largest)	0.365	***	- 0.001		- 0.158	**	0.090	***	- 0.833	***

C.4. Summary Statistics of TI at the 5th percentile

Table C.2 shows the distribution of TI at the 5th percentile. For the largest quintile at the 5th percentile the median ranked firm has an upper bound TI of 0.055 minutes (3.32 seconds). In other words, for half of all large firms a trade is eligible to be collapsed only if its TI is less than 3.32 seconds. In comparison, the first row of Table C.2 shows the median ranked firm for the smallest quintile has an upper bound of 0.333 minutes (20 seconds). Table C.2 also shows 95% of large firms have a TI upper bound of less than 20 seconds (hence for 95% of large firms a trade is eligible to be collapsed only if the associated TI is less than 0.337 minutes or 20 seconds) and in comparison 95% of small firms have a TI upper bound of less than 2.876 minutes.

Table C.2: Distribution of Time Interval At The 5th Percentile

The table shows the summary statistics of each firm's $TI_{j,t}$ upper bound at the 5th percentile. $TI_{j,t}$ is computed by taking, for each stock j, the n^{th} trade's timestamp minus the timestamp of the immediate previous trade. $TI_{j,t}$ is computed only if both trades occurred on the same day. The upper bound is then chosen by sorting, for each stock, $TI_{j,t}$ and selecting the 5th percentile. Values are computed based on 913 NYSE-listed stocks sorted into market capitalisation quintiles where 1 is the smallest firms and 5 is the largest firms. The sample period is 1 January 2003 to 31 July 2003.

		mean	1st	5th	25th	median	75th	95th	99th
Market Cap Quintile	1 (smallest)	0.774	6.67×10^{-5}	0.016	0.066	0.333	0.974	2.876	4.863
	2	0.477	3.33×10^{-5}	0.015	0.053	0.203	0.613	1.777	3.099
	3	0.320	$<1.00\times10^{-5}$	0.014	0.044	0.143	0.404	1.173	2.078
	4	0.195	$<1.00\times10^{-5}$	0.012	0.036	0.093	0.236	0.705	1.272
	5 (largest)	0.100	$<1.00\times10^{-5}$	0.001	0.023	0.055	0.123	0.337	0.604

C.5. Relaxing TI Upperbound

Further to the results in Section 4.6.1 I relax the TI upper and find results that remain consistent with my findings. In other words, changes in effective spreads as a result of Autoquote remains insignificant if sequences of consecutive buy or sell orders are collapsed at a slower trade speed. The results are in Table C.3 and show, collapsing trades up to each stock's 25th TI percentile, the change in market capitalisation-weighted effective spreads following the Autoquote phase-in is close to zero, declining 0.47 basis points (insignificant at the 10% level). This is in comparison to the significant decline of 9.72 basis points for uncollapsed trade data (see Panel A of Table 4.4) and suggests higher AT is not associated with an improvement in liquidity once trade sequences are collapsed. Panel B shows the change in effective spreads is also insignificant across all size quintiles except for the smallest firms (which exhibit a significant *increase* in effective spreads of 137 basis points). Panel C shows the fastest trades experienced significant rise in realised spreads (an increase of 15.6 basis points and significant at the 1% level) and experienced the least reduction in asymmetric information (a decline of 16.1 basis points (significant at the 1% level).

Relaxing the TI upper bound too much however may also introduce bias. While Kim and Murphy (2013) did not impose an upper-bound for TI (their study was on the highly active and liquid S&P 500 ETF), I show in Table C.4 that an appropriate upper-bound is likely necessary when adjustments are made for order-splitting.[121] Collapsing trades without considering the size of TI, Panel A in Table C.4 show market capitalisation-weighted effective spreads significantly *increases* following Autoquote, rising by 42.3 basis points. Panel B show the largest firms experienced a rise in effective spreads (38.0 basis points and significant at the 5% level) while Panel C show the fastest trades were subject to a significant rise in realised spreads

[121121] I note I do not discuss model calibration with respect to TI upperbound in this thesis.

(an increase of 14.3 basis points and significant at the 1% level) as well as a significant rise in asymmetric information (an increase of 34.0 basis points and significant at the 1% level). In other words, the selection of an appropriate TI upper bound is likely a relevant consideration (and especially relevant for low-liquidity stocks with long periods of market inactivity) when collapsing trade data: while computed effective spreads that are un-adjusted for order splitting are potentially subject to under-estimation bias, over-adjustment for order splitting can also lead to over-estimation bias.

Table C.3: Regression Results After Collapsing Trade Sequences (at the 25th Percentile of TI)

The table regresses measures of liquidity on the Hendershott et al. (2011) Autoquote dummy variable. The liquidity measure is computed by collapsing sequences of consecutive buy or sell orders into a single transaction. For each stock trades are only collapsed if the time interval between consecutive trades is less than the 25th percentile. Sample period is from 1st January 2003 to 31st July 2003. The specification is: $L_{j,t} = \alpha_j + \gamma_t + \beta_1 AQ_{j,t} + \gamma_1 turnover_{j,t} + \gamma_2 volatility_{j,t} + \gamma_3 ticksize_{j,t} + \gamma_4 logmcap_{j,t} + \varepsilon_{j,t}$ where the dependent variable $L_{j,t}$ is measures of daily turnover-weighted liquidity in basis points: 1) half effective spreads; 2) half adverse selection; and 3) half realised spreads, α_j represents firm fixed effects, γ_t represents day dummy variables and $AQ_{j,t}$ is a dummy variable equal to +1 for periods with Autoquote phased-in and zero otherwise. The remaining factors are control variables: share turnover, volatility, tick size and the log of market capitalisation. Panel A shows market capitalisation-weighted results. Panel B results are quintile-specific based on market capitalisation. Panel C results are quintile-specific based on the time interval between trades (collapsing at the 25th percentile of TI). Standard errors are robust to general cross-sectional and time-series heteroscedasticity and within-group autocorrelation (see Arellano and Bond, 1991). ***, **, * represent 1%, 5% and 10% significance level respectively.

	$AQ_{j,t}$		$turnover_{j,t}$		$volatility_{j,t}$		$ticksize_{j,t}$		$logmcap_{j,t}$	
Panel A: Market Capitalisation Weighted										
Dependent Variable: effective spreads (bps)										
	- 0.0047		0.0001	***	0.1386	***	1.0695	***	- 1.2031	***
Panel B: Quintile by Market Capitalisation										
Dependent Variable: effective spreads (bps)										
1 (smallest)	1.3695	***	- 0.0489	***	1.1526	***	1.5275	***	2.0264	***
2	- 0.1779		0.0050		0.8117	***	- 0.1121	***	- 8.9480	***
3	0.1332		- 0.0024		0.2875	***	0.3226	***	- 4.8554	***
4	- 0.0536		- 0.0008		0.2598	***	0.2110	***	- 3.9594	***
5 (largest)	0.0427		0.0003		0.1755	***	0.3728	***	- 2.1028	***
Panel C: Quintile sorted by Time Between Trades										
Dependent Variable: effective spreads (bps)										
1 (fastest)	- 0.0081		0.0002	*	0.1916	***	2.1591	***	- 1.5782	***
2	- 0.0524		- 0.0028	***	0.3986	***	0.2600	***	- 3.1410	***
3	- 0.2322	***	- 0.0213	***	0.6297	***	2.6252	***	0.3765	**
4	0.1037		- 0.0467	***	0.9933	***	1.3139	***	- 2.5392	***
5 (slowest)	1.9116	***	- 0.1963	**	0.5871	***	- 0.0509	***	- 5.9965	***
Dependent Variable: adverse selection (bps)										
1 (fastest)	- 0.1645	***	0.0010	***	0.3094	***	2.8804	***	- 0.7955	***
2	- 0.4153	***	0.0012		0.6130	***	0.6039	***	- 1.4971	***
3	- 0.7032	***	- 0.0203	***	0.9628	***	1.9638	***	0.9215	***

Panel C: Quintile sorted by Time Between Trades										
4	- 0.7338	***	- 0.0245	*	1.3952	***	0.8644	***	- 0.8496	**
5 (slowest)	- 0.8558	**	- 0.1208		0.8336	***	- 0.1462	***	- 4.1023	***
Dependent Variable: realised spreads (bps)										
1 (fastest)	0.1572	***	- 0.0008	***	- 0.1164	***	- 0.7168	***	- 0.7911	***
2	0.3878	***	- 0.0043	***	- 0.2092	***	- 0.3405	***	- 1.6456	***
3	0.4796	***	- 0.0007		- 0.3411	***	0.6630	***	- 0.5277	**
4	0.8408	***	- 0.0218	*	- 0.4132	***	0.4467	***	- 1.7417	***
5 (slowest)	2.7611	***	- 0.0764		- 0.2487		0.0941	***	- 1.9169	**

Table C.4: Regression Results After Collapsing Trade Sequences (No Upper Bound)

The table regresses measures of liquidity on the Hendershott et al. (2011) Autoquote dummy variable. The liquidity measure is computed by collapsing sequences of consecutive buy or sell orders into a single transaction. For each stock trades are only collapsed irrespective of the time interval between consecutive trades. Sample period is from 1st January 2003 to 31st July 2003. The specification is: $L_{j,t} = \alpha_j + \gamma_t + \beta_1 AQ_{j,t} + \gamma_1 turnover_{j,t} + \gamma_2 volatility_{j,t} + \gamma_3 ticksize_{j,t} + \gamma_4 logmcap_{j,t} + \varepsilon_{j,t}$ where the dependent variable $L_{j,t}$ is measures of daily turnover-weighted liquidity in basis points: 1) half effective spreads; 2) half adverse selection; and 3) half realised spreads, α_j represents firm fixed effects, γ_t represents day dummy variables and $AQ_{j,t}$ is a dummy variable equal to +1 for periods with Autoquote phased-in and zero otherwise. The remaining factors are control variables: share turnover, volatility, tick size and the log of market capitalisation. Panel A shows market capitalisation-weighted results. Panel B results are quintile-specific based on market capitalisation. Panel C results are quintile-specific based on the time interval between trades (collapsing without a TI upper-bound restriction). Standard errors are robust to general cross-sectional and time-series heteroscedasticity and within-group autocorrelation (see Arellano and Bond, 1991). ***, **, * represent 1%, 5% and 10% significance level respectively.

	$AQ_{j,t}$		$turnover_{j,t}$		$volatility_{j,t}$		$ticksize_{j,t}$		$logmcap_{j,t}$	
Panel A: Market Capitalisation Weighted										
Dependent Variable: effective spreads (bps)										
	0.4234	***	- 0.0003	***	- 0.0148		0.2249	***	- 0.7783	***
Panel B: Quintile by Market Capitalisation										
Dependent Variable: effective spreads (bps)										
1 (smallest)	0.6415		- 0.0126		- 0.4231		1.2381	***	0.4454	
2	0.8203	***	0.0038		- 0.2085		0.0452	**	- 4.5702	***
3	1.2244	***	- 0.0052		- 0.0839		- 0.1380	**	- 3.0833	***
4	0.7670	***	- 0.0013		0.0130		0.2787	***	- 0.0745	
5 (largest)	0.3804	**	- 0.0006		0.0169		- 0.3462	***	- 1.6119	***
Panel C: Quintile sorted by Time Between Trades										
Dependent Variable: effective spreads (bps)										
1 (fastest)	0.4848	***	- 0.0004	***	0.0151		- 0.0142		- 1.2646	***
2	0.6762	***	- 0.0056	***	0.0359		- 0.2482	***	- 1.8419	***
3	0.8300	***	- 0.0160	***	- 0.0396		1.4814	***	- 0.2280	
4	1.3938	***	- 0.0565	***	- 0.0215		1.0506	***	- 0.8028	
5 (slowest)	0.2811		- 0.1506		- 0.2430		0.0417		- 0.4999	
Dependent Variable: adverse selection (bps)										
1 (fastest)	0.3404	***	0.0004	*	0.1371	***	0.9189	***	- 0.3288	***
2	0.2385	***	- 0.0003		0.2770	***	0.4874	***	0.1046	

Panel C: Quintile sorted by Time Between Trades										
3	0.1403	*	-0.0206	***	0.3956	***	1.1113	***	0.3643	
4	0.1274		-0.0439	***	0.4037	***	0.8483	***	0.4087	
5 (slowest)	-0.2115		-0.0169		-0.5156	***	-0.2522	***	-4.1802	***
Dependent Variable: realised spreads (bps)										
1 (fastest)	0.1426	***	-0.0008	***	-0.1173	***	-0.9272	***	-0.9435	***
2	0.4564	***	-0.0056	***	-0.2397	***	-0.7314	***	-1.9545	***
3	0.6915	***	0.0045		-0.4294	***	0.3515	***	-0.6395	*
4	1.2705	***	-0.0120		-0.4400	**	0.1976	**	-1.2552	**
5 (slowest)	0.5086		-0.1610		0.3953		0.2905	***	3.6422	**