MARKET MICROSTRUCTURE AROUND THREE CORPORATE ANNOUNCEMENTS

Skander Lazrak

A Thesis

In

The John Molson School of Business

Presented in Partial Fulfillment of the Requirements

For the Degree of Doctor of Philosophy at

Concordia University

Montreal, Quebec, Canada

April 2005

© Skander Lazrak, 2005

Library and Archives Canada

Published Heritage Branch

395 Wellington Street
Ottawa ON K1A 0N4
Canada

Bibliothèque et Archives Canada

Direction du Patrimoine de l'édition

395, rue Wellington
Ottawa ON K1A 0N4
Canada

Your file Votre référence
ISBN: 0-494-05718-1
Our file Notre référence
ISBN: 0-494-05718-1

NOTICE:
The author has granted a non-exclusive license allowing Library and Archives Canada to reproduce, publish, archive, preserve, conserve, communicate to the public by telecommunication or on the Internet, loan, distribute and sell theses worldwide, for commercial or non-commercial purposes, in microform, paper, electronic and/or any other formats.

The author retains copyright ownership and moral rights in this thesis. Neither the thesis nor substantial extracts from it may be printed or otherwise reproduced without the author's permission.

AVIS:
L'auteur a accordé une licence non exclusive permettant à la Bibliothèque et Archives Canada de reproduire, publier, archiver, sauvegarder, conserver, transmettre au public par télécommunication ou par l'Internet, prêter, distribuer et vendre des thèses partout dans le monde, à des fins commerciales ou autres, sur support microforme, papier, électronique et/ou autres formats.

L'auteur conserve la propriété du droit d'auteur et des droits moraux qui protège cette thèse. Ni la thèse ni des extraits substantiels de celle-ci ne doivent être imprimés ou autrement reproduits sans son autorisation.

In compliance with the Canadian Privacy Act some supporting forms may have been removed from this thesis.

While these forms may be included in the document page count, their removal does not represent any loss of content from the thesis.

Conformément à la loi canadienne sur la protection de la vie privée, quelques formulaires secondaires ont été enlevés de cette thèse.

Bien que ces formulaires aient inclus dans la pagination, il n'y aura aucun contenu manquant.

Canada

ABSTRACT

MARKET MICROSTRUCTURE AROUND THREE CORPORATE ANNOUNCEMENTS

Skander Lazrak, Ph.D. in Administration

Concordia University, 2005

This thesis examines various aspects of the market microstructure around three important corporate events. These important corporate events are stock splits, corporate acquisitions and earnings announcements.

The second chapter (first essay) investigates the microstructure effects of stock splits. We find that the price range theory explains the stock splits of high price stocks and information plays an essential role in the explanation of stock splits for low price stocks. While global liquidity decreases post-split, trading activity as measured by the number of trades increases. The temporary component of the spread increases while the directional change for the permanent component is indeterminate. Uninformed traders intensify their trading activities relatively more than informed traders after stock splits. While the probability of new information arrival remains unchanged, the probability of a bad event and of informed trading decreases after stock splits. In addition, temporary volatility increases while true price volatility decreases post-split. Consistent with the extant literature, stock splits attract small or uninformed traders. Whether attracted by the lower per-share price, the newly promoted stock or the decrease in the probability of informed trading, uninformed traders are the essential cause of the increase in trading activity, trading cost and return volatility after stock splits.

The third chapter (second essay) investigates the microstructure effects of acquisitions. The intensification of trading activity upon announcement of such offers is more dramatic for targets

than for bidders. Investors are more inclined to sell targets upon announcement using direct market orders against ask limit orders when the tender offers involve cash due to portfolio rebalancing and profit realization motives. Liquidity improves for targets with a fall in trading costs , and with an increase in quoted dollar and share depth. Both trading costs and quoted depth fall continuously over the tender offer cycle to successful completion for the acquirers. Increased trading causes the temporary trading cost to fall farther for targets than for acquirers. Permanent trading costs decline over the tender offer cycle, and especially for targets for cash tender offers and for acquirers for share tender offers. These findings based on method of payment are related to the good and bad news, respectively, that are revealed by the announcement and realization of the tender offer, respectively.

The fourth chapter (third essay) analyzes trading on the various trading venues for Canadian firms that are cross-listed on the main US trading venues around earning announcement dates. We first show that the Canadian trading venues lost their trade advantage in terms of trade cost compared to their US counterparts for trading Canadian cross-listed shares. However, the Canadian market still retains the dominant part of trade volume and Canadian dealers offer greater market depth. There is also no preference ordering among the top three US listing venues for Canadian shares based on trade cost. Both trading legs have similar proportions of informed trading during off-announcement days. They both react simultaneously to earnings news. However, on announcement day, most informed traders trade on the domestic Canadian market. We claim that the domestic Canadian market is much more informative during announcement dates than its US competitors.

Acknowledgements

I am extremely grateful to my thesis supervisor, Dr. Lawrence Kryzanowski, for his invaluable guidance. Dr. Kryzanowski trained me to become a researcher in Finance. He is the model I will do my best to follow in the academic world. Dr. Kryzanowski showed me that it is through hard work that objectives can be achieved. Without his guidance, this thesis may never have been done.

I would also like to thank my other thesis committee members, Dr. Abraham Brodt, Dr. Simon Lalancette for valuable comments and advise during my doctoral studies. I would also thank Dr. Bryan Campbell for his valuable feedback.

I would also thank the various professors who taught me various courses at Concordia, McGill and University of Montreal. These courses contributed much to what I am at this stage of my academic career. I want to especially thank Dr. Francois Leroux from HEC.

I want also to express my grateful thanks to my PhD colleagues, especially Mohamed Ayadi and Lawrence He. They gave my valuable advice and comments both about this thesis and about the long PhD process.

This thesis is dedicated to my parents for every thing they gave me. I owe them much and nothing I can do is enough to pay my debt for them. I would also thank my brother and sisters for their patience and support.

Last but not least, I want to thank my wife, Martine. This thesis would not be finished without her unconditional love and support. She was my true emotional motivation to finish this task. Martine, I want to tell you how much I appreciate your help and support. This thesis is also dedicated to you. Thank you.

Table of Contents

List of Tables, List of Figures

MARKET MICROSTRUCTURE AROUND THREE CORPORATE ANNOUNCEMENTS

CHAPTER 1

INTRODUCTION

Investors trade for several reasons. Black (1986) classifies trades as either information or noise motivated. Informed traders possess private information about the company and take advantage by trading with less informed traders. On the other hand, noise traders trade for a different set of reasons. They may enter into transactions simply out of liquidity reasons or they may trade because they believe they are acting on some private information when such is not the case. Trading based on technical analysis would belong to this category as an illustration. Unlike informed trades, which get prices closer to true fundamental values, noise trades basically only add noise to the price. Hence, trading by both trader types has a material impact on the price formation process.

In markets with only noise traders, prices are not strongly related to fundamental values while in markets with only informed traders, trading is fully revealing and prices equal true values. However, as Grossman and Stiglitz (1980) note, both trader types are needed for the market to function. If only informed traders are present, then there will be no incentive to trade since prices are fully revealing and it does not pay to incur the cost to acquire private information. If only uninformed traders are trading, prices can fade away from true values. Furthermore, if the proportion of informed traders is high enough to discourage uninformed traders from trading, then markets can cease. In turn, this eliminates mark-to-market pricing and the price discovery process.

In an ideal world, the market should be liquid enough to permit trading and pricing. However, there should be enough informed traders to prevent such traders from moving prices considerably and for long periods away from true fundamental values. In this way, market efficiency is preserved to some extent. This thesis is a continuation of this main idea.

The general goal of the thesis is to study the trading behaviour of both trading populations (i.e., informed and uninformed) and their contribution to the liquidity and efficiency of markets. However, we limit the analysis to corporate announcement events for a number of reasons. First, examining periods where trading activity is heavier should reveal more about the trading motivations of various market participants. As a result, corporate event announcements present natural experimentation opportunities since both trading populations usually intensify their trading activity around these events. For the informed, the news announcement can be seen as a signal to acquire more information while for the uninformed it can be the source of portfolio rebalancing or noise trading (as defined by Black). Secondly, both trading activity and the information structure change around such events. By definition, public news announcements are intended to reveal part of the private information held by the company's management to the investing public. Hence, we expect that the level of information asymmetry should decrease at the news announcement. Moreover, we usually observe leaking of the material information to the investing community even before the public announcement. Such information revelations are expected to change the informed trading base since their informational advantage is reduced because part of the private information is made publicly available to the remaining group of investors. However, this result is weakened by the fact that some investors who did not know about the company until it is in the "news", decide to pay more attention to the company and acquire private information to trade the company. This is related to the Merton (1987) argument that states that investors trade only stocks they know about.

Similarly, there are at least three reasons why uninformed investors should trade more frequently after corporate announcements. First, several uninformed investors will rebalance their portfolios due to the incorporation of the released news into prices. Secondly, as noted by Black, some uninformed investors may think that the information is not yet totally reflected in prices and will try to benefit from the incomplete price discovery process. Third, predicated on the updated belief that they are less likely to being taken advantage of by informed traders, uninformed investors will be less hesitant to trade, which increases the probability of their trading with other uninformed investors.

From an academic and theoretical perspective, this thesis presents empirical tests of the changing liquidity around these announcements. It also relates these changes to the announcement nature and content. For example, an acquisition announcement is more informative than a stock split and hence the trading change is asymmetric for these two events. For stock splits, we show that the main force driving the liquidity pattern change is uninformed trading while for acquisitions we have a strong information component, especially for targets. This thesis also presents a (modified and adapted) test of the relation between trading activity, liquidity and volatility. The relation between these variables is well documented in the financial literature, as in Karpoff (1987), Gallant, Rossi and Tauchen (1992), Jones, Kaul and Lipson (1994) and Anderson (1996). In this thesis, we decompose volatility into their short- and long-term components, where the former is induced by noise trading or price bouncing, while the latter is closely related to informed trading and thus corresponds to the "true" volatility.

We also investigate several market places that use different trading designs. For example, we investigate the trading on the NYSE (characterized by the presence of a monopolistic specialist assigned to each stock), the NASDAQ (a pure dealers market) and the TSX market (a combination of both with several registered traders playing the role of the specialist). This thesis also empirically investigates the effect of shares being cross-listed from the market microstructure perspective. To the contrary of the literature, which investigates the market microstructure on the domestic market place just after the cross-listing decision, we analyze the liquidity and information asymmetry on both trading venues for shares already cross-listed. This is an important issue since it can show how information is imbedded into prices through feedback effects between the two trading venues. This is also a different way to test for the implications of market fragmentation.

From a practical perspective, the conclusions of this thesis should interest all parties involved in the trading process, mainly traders, market makers and regulating authorities such as exchange commissions. First, uninformed traders are interested in knowing the depth of the market just at the release of the news. Usually, there is dominant trading on one side of the market after the announcement. For example, we observe more uninformed seller-initiated relative to buyer-initiated trading after cash acquisitions. Uninformed traders are interested in knowing the outstanding buying limit orders, the bid depth of the market makers, and the trading reaction of informed traders. Uninformed traders are smart as O'Hara (2003) has pointed out. They can act strategically and time their trades. If the news release is such that it heavily reduces information asymmetry, uninformed traders can exploit the situation by executing all their trades at that point in time. This is an argument that conforms to the Admati and Pfleiderer (1988) theory. Secondly, informed traders are interested in quantifying their informational advantage loss caused by the news release. Paradoxically, we show that informed trading increases after news announcements. In each of the three essays (chapters two through four), we generally find that, even if the probability of trading against an informed agent is reduced after the corporate announcement, the intensity of trading by informed traders is not reduced. This is consistent with the trading pattern theory of Admati and Pfleiderer (1988) where informed traders realize that there are more uninformed traders trading so that the informed traders are motivated to either acquire more information or to refine their own information. This is caused by the fact that with the uninformed being aggressive and realizing that the extent of information asymmetry is reduced, the informed traders have a greater opportunity to better hide their trades. Although informed traders possess several pieces of private information, the reduction in the information asymmetry caused by the news announcement is related only to the information that is enclosed in the public news release and not to any other outstanding privately held information.

Market makers are the third body of market participants who are interested in the results of this thesis. These liquidity providers make their living from trading. As is the case for uninformed traders, the worst transaction that a market maker can make is to trade against a better informed trader. Market makers prefer to trade against uninformed traders and they protect themselves against those who are privately informed by raising the bid-ask spread they charge by an amount that compensates for their expected loss from trading with informed traders. For that reason, market makers are interested in how the public release of information regarding a company impacts the trading activities of informed traders. If informed trading is reduced, then market makers would lower their posted bid-ask spread. As a consequence, the liquidity on the market improves and trading frequency increases.

The fourth and last practical motivation of the thesis involves the regulatory authorities. These authorities aim to protect the market from major failures, such as a market shutdown due to informed trading dominance. Protecting the general and supposedly uninformed trading public is a primary goal of such bodies. This is the main reason why public companies need to issue statements and press releases on a regular basis. This thesis shows that issuing such public news announcements actually stimulates the trading activity of the uninformed investors. The fact that informed trading also increases shows that not all private information is being revealed and that more can be done in terms of disclosure by the firm's management either on a voluntary basis or in response to more stringent regulatory disclosure policies.

The structure and main findings of the thesis are as follows. In chapter two (essay one), we analyze the market microstructure impact of stock split announcements and realizations for Canadian companies listed on the TSX. We conclude that the main reason for such corporate decisions is to bring the per share price into a pre-determined range. Information is only secondary. Using Canadian stock splits spanning the period 1985 to 1999, we find that splits heavily stimulate uninformed traders compared to informed traders. In chapter three (essay two), we investigate the market microstructure around mergers and acquisition announcements for both targets and bidders. We find that these announcements have a dramatic impact on the liquidity of targets as opposed to bidders. Also, the impact is sharper for cash acquisitions than for transactions conducted using shares or a mixture between cash and shares. A surprising result is the high selling pressure on targets acquired through cash. The last essay (chapter four) relates to the liquidity of Canadian shares cross-listed on the major US exchanges. We examine the microstructure differences for both trading legs around earnings announcement periods. We find that the domestic Canadian market no longer presents a cost advantage over the US markets. However, the Canadian market still retains most of the market depth, which explains why it also retains most of the trading activity. As expected, most of the informed (and uninformed) trading is conducted on the Canadian market. However, the US trading venues retain a proportional part of the trading of each group so that the probability of trading against informed traders is identical. Moreover, both markets react almost simultaneously to the news announcement in term of liquidity and trading activity, which is critical for the survival of both markets.

CHAPTER 2

Stock Split Rationales and the Effect of Stock Splits on the Behavior of Markets and Uninformed Traders

2.1 Introduction

Since stock splits result in no cash transfer or shift in corporate policies, they are often considered as being purely cosmetic events with no real impact on firm value. Stock splits could even be considered as being value destroying since issuing new shares is usually costly. Nevertheless, many empirical studies find that stock splits are associated with positive abnormal returns around both their announcement and ex-dates.[1]

The literature classifies the reasons for stock splits into two main groups. The first group is information related. McNichols and Dravid (1990) argue that managers use the split factor to signal a firm's future earnings. Brennan and Hughes (1991) develop a model where managers split their shares to capture the attention of financial analysts who produce more research reports and issue more client recommendations. In turn, this increases liquidity by attracting the newly interested clients. Since trade costs increase and market making costs decrease after stock splits (Schultz, 2000), dealers and financial analysts appear to have incentives to promote newly split stocks. This explanation is consistent with the Merton (1987) model where investors only trade securities of firms that they know. Thus, stock splits can be seen as a tool to mitigate the information asymmetry between informed managers and uninformed traders. In contrast, Desai, Nimalendran and Venkataraman (1998) argue that the increase in the number of financial analysts following the stock post-split will increase the number of informed traders and increase information asymmetry.

---

[1] This includes the pioneering work of Fama, Fisher, Jensen and Roll (1969), and subsequent papers by Grinblatt, Masulis and Titman (1984), Eades, Hess and Kim (1984), Lamoureux and Poon (1987), amongst others.

Kryzanowski and Zhang (1996) find that small traders increase their board-lot trading and move to the buy side of the market after Canadian stock splits. Schultz (2000) confirms this finding for split stocks listed on the NYSE/AMEX and NASDAQ. Conrad and Conroy (1994) report that the change in trade direction post split moves trade prices from the bid to the ask side, which causes returns to be inflated by the bid-ask spread. Grinblatt and Keim (2000) confirm this change in trade pattern, and argue that this shift is only partially responsible for the observed abnormal returns for low price stocks.

The second group of reasons for stock splits relates to an optimal range for share prices. The underlying belief is that managers decrease share prices to attract small, uninformed investors who can buy board lots after stock splits. For example, Angel (1997) argues that the share price itself is of no importance but that managers care about the relative tick size. He finds wide variation in share prices but much less variability in relative tick sizes across international markets.

Several empirical studies beginning with Ohlson and Penman (1985) find that volatility increases after stock splits. Brennan and Copeland (1988) find an increase in systematic risk or beta for both announcement and effective dates. Dubofsky (1991) finds that the volatility increase disappears when weekly data for AMEX stocks is used. Kryzanowski and Zhang (1993) find that the volatility increase is due to noise and can be explained by the increase in per-dollar trading costs.

Desai, Nimalendran and Venkataraman (1998) examine the trading activity of (un)informed traders following stock splits using the George, Kaul and Nimalandran (1991) (GKN hereafter) spread decomposition model. Based on the finding of an increase in both transitory and permanent costs, they conclude that stock splits amplify information asymmetry. Using the variance ratio, they find that both the short and long term components of volatility increase post-split. Since this indicates that both types of traders increase their trading activity post-split, this raises the question of interest in this essay; namely: Why do uninformed liquidity investors trade more frequently post-split given the possibility that the probability of being taken advantage of (bagged) by an informed trader is higher?

To address this question, this chapter (essay) investigates the trading cost components around Canadian stock splits using six spread decomposition models. The examination of Canadian stock splits avoids problems associated with data snooping by examining a non-U.S. sample of splits drawn from a market that is well integrated with U.S. markets and has numerous institutional similarities (e.g., see Kryzanowski and Zhang, 2002). These spread decomposition models include the models of GKN, Neal and Wheatley (1998) (NW), Masson (1994), Glosten and Harris (1988) (GH), Lin, Sangher and Booth (1995) (LSB), and Madhavan, Richardson and Roomans (1996) (MRR). Since none of the existing spread decomposition models capture all of the complexities of price formation, including price discovery, the use of various models helps to alleviate the impact of spread decomposition model mis-specification on empirical inference.

While the temporary spread component per dollar as a proportion of the quoted spread clearly increases post-split, the adverse information component appears to decrease slightly on balance after the split. This contradicts the hypothesis of Desai, Nimalendran and Venkataraman (1998) who find that both components increase for U.S. stock splits. The level of per-share prices is an important factor for determining the direction of the change in the permanent spread component. The permanent cost decreases and increases for high and low stock price levels, respectively. This result is consistent with the price range theory. For stocks trading in a high price range, the split is essentially a tool to bring the price back into a "normal" range or the relative tick size towards its optimal value.

By using the Easley, Kiefer, O'Hara and Paperman (1996) (EKOP) model as in Easley, O'Hara and Saar (2001) for NYSE-listed split stocks, we find that trading intensities increase for both informed and uninformed traders post-split. Admati and Pfleiderer (1988) explain such observed trading patterns as the interaction between informed and strategic uninformed traders. The uninformed trade together simultaneously in a deep and thick market to avoid any material adverse price change. Informed traders hide their trades in thick markets to take advantage of their information. This creates trading concentration. If the relative increase in the number of informed traders is lower post-split, then the probability of any particular uninformed trader being taken advantage of (or bagged) by an informed trader is lower. This leads to larger market participation by both groups of traders.

We also find that the transaction volume of the uninformed traders increases relatively more than for informed traders, and that the probability of trading with an informed trader is lower post-split. Thus, uninformed liquidity traders trade newly split stocks given the knowledge that absolute informed trading activity has intensified post-split.

As in Desai et al, we investigate the transitory noise-driven (short-run) and the permanent information-driven (long-run) volatility around stock splits given their link with the spread components through trading. However, unlike Desai et al. (1998), we do not use the variance ratio for this purpose due to the problem of deciding what is the appropriate frequency of measurement of the returns. In contrast, the MRR model and the component GARCH model of Engle and Lee (1999) are used to identify the volatility components because the distinction between long and short-term is endogenous under this approach. We observe that most of the growth in volatility is temporary, and that long- and short-run volatility decrease and increase, respectively, on a proportional basis post-split. This is consistent with a broader participation of uninformed traders in the trading process post-split. As reported by Brennan and Copeland (1988), systematic risk increases post-split. However, we find such an increase only for down markets.

2.2 Data Description

The sample includes all Canadian stock splits as reported by the TSE Monthly Review over the period 1985-2000. Splits that do not meet either of two retention filters are removed from the initial sample. Thus, any split stock that has no trades for 10 consecutive days is dropped, and shares with multiple splits during a 365-day period also are removed. The final sample of 306 stock splits is distributed by split factor as follows: 1 four-for-three split, 22 three-for-two splits, 221 two-for-one splits, 47 three-for-one splits, 7 four-for-one splits, 5 five-for-one splits, 1 six-for-one split, and 2 seven-for-one splits.

Table 1 reports descriptive statistics for various characteristics of our sample firms. The characteristics are the average per-share price for the five trading days preceding the effective split date, size or market value of equity at month end aggregated across all share classes, number of trades and traded share volume. The last three characteristics are averaged over the 12 trailing months preceding the effective split date. Based on table 1, all the distributions are positively skewed and leptokurtotic. Thus, the higher the price per share, the bigger the size, and the more liquid the stock, and the more likely it will split. The average firm has a per-share price of $32.39, a market equity of $1.6 billion, a monthly trading volume of over 800,000 shares, and 687 trades or 1,160 shares traded per trade.

[Please insert Table 1 about here.]

Table 2 summarizes the changes in the liquidity and trading activity around stock splits based on the Equity Trades and Quotes History or ETQH database from the Toronto Stock Exchange or TSX. The data are checked using the commonly used filters.[2] Reported quotes with a bid exceeding the offer are eliminated. When only the bid or ask is reported, a backward search not exceeding five minutes is made to obtain the latest missing quote if the bid is lower than the ask.[3] If none is found, the original partial quote is eliminated. The final data set contains a total of 3,323,027 lines of which 1,494,331 are trades.

[Please insert Table 2 about here.]

[2] Trades that are reported with negative numbers of shares or prices or are subject to special restrictions and conditions are omitted. Trades with big reversals (return higher than 50%) also are eliminated.

[3] Because the data contain only the best outstanding bid and offer quotes and not those of a particular dealer or registered trader, a missing quote is due primarily to an update to one side of the publicly displayed quote. Thus, we assume that the missing side of the quote did not change.

For each split, the event window consists of 60 trading days where the pre-split pane ends 20 days before the announcement date and the post event pane starts 20 days after the effective date. If the stock split announcement is considered to be a signal, then any market reaction should immediately follow the announcement and not be reflected after the effective date. Most studies similarly define the event as being the announcement itself. For example, Desai and Jain (1997) examine long-run abnormal returns after the announcement month. Grinblatt, Masulis and Titman (1984) study returns around both dates, and Nayar and Rozeff (2001) examine returns around the record, when-issued and ex-dates. In contrast, studies that examine changes in volatility around stock splits concentrate on such behavior around the effective date, although Brennan and Copeland (1988) report an increase in beta around both the announcement and ex-dates.

Information on announcement days is collected from the Lexis-Nexis, Dow Jones Interactive and Bloomberg databases, and on effective dates from the TSE Monthly Review and cross-checked using the TSX ETQH database. The period between announcement and effective dates varies from three to 317 days with a median of 61.5 days.

The changes in the quoted spreads are reported in panel A of table 2. Columns 2, 4 and 6 correspond to the quoted dollar spreads, and columns 3, 5 and 7 refer to the proportional or per-dollar quoted spreads. The mean (median) quoted spread drops from 57.12 (41.92) to 36.15 (28.50) cents over the split. The mean (median) proportional spread increases from 1.96% (1.59%) to 2.35% (1.97%) over the stock split. The decrease in the dollar spread and the increase in the proportional spread are significant based on the matched t- and the Wilcoxon sign tests, and are robust to an examination of the stock splits in the pre- and post-TSX-decimalization periods. These results confirm the earlier literature for the changes in liquidity costs around stock splits.[4]

As a test of robustness, various sub-samples are investigated, such as the 266 stock splits with no more than five consecutive days without a trade (hereafter, the 5-day sub-sample). In addition,

[4] This includes Kryzanowski and Zhang (1993) for TSX firms, Desai et al (1998) for NASDAQ firms, and Easley, O'Hara and Saar (2001) for NYSE firms.

the firms who split their shares during the year are split into three categories based each on size, on price and on volume. To illustrate, the 44 splits for the first year in our sample (1985), are divided into 15 small, 14 medium and 15 large size firms according to their average monthly market equity values for the calendar year 1984. The sorts are done on a revolving yearly basis to avoid any possible problems due to the positive tendency of the sorting variables. Based on unreported results, the spread patterns are consistent for all of the ten sub-samples. Based on panel B of table 2, the preceding results also hold for the effective spreads. The mean (median) effective spreads decrease from 37.9 (29.2) to 24.0 (20.2) cents, while the mean (median) proportional effective spreads increase from 1.35 (1.11) to 1.65 (1.38) percent. All of these spread measures are positively skewed.

The changes in the second liquidity dimension, depth, and the dollar volume are reported in panel C of table 2. Mean (median) overall quoted depth is reduced from about 55 (38.6) to 47.6 (32.1) thousand dollars. This reduction is significant based on the Wilcoxon non-parametric test but not for the paired t-test. Such mixed results occur for all of the sub-samples studied herein. The increase in the dollar volume after stock splits is unexpected. Mean (median) trading volume increases by 6% (13%), or by more than $100,000 per day.[5]

Based on panel D of table 2, both the number of trades and volume as measured by number of shares increase post-split. The mean (median) increase in the number of trades is 91% (46%) and in the number of shares traded per day is more than 200% (98%). Given that the average split factor exceeds two, we expect both the number of trades and the number of shares traded to double if the dollar volume is held constant. In summary, we observe a reduction in liquidity as measured by both trading costs and market depth, and a slight increase in trading activity on a post-split basis.

---

[5] As a check of robustness, the sample period is divided into two sub-periods based on the initiation of decimalization and the reduction of the tick size on the TSX on April 15, 1996. Although the spread decomposition results are not materially different, the increase in trading volume is solely a post-TSX-decimalization phenomenon. The volume increase post-TSX-decimalization is mitigated for the sub-sample of highly liquid stocks.

2.3 Changes in Spread Components Around Stock Splits

To further investigate trading cost changes after stock splits, we examine the behavior of two specific payments for immediate trading, that is, for order processing and adverse information. Although Ho and Stoll (1981) document a third component called inventory holding cost, this component is estimated jointly with order processing cost and is referred to as the temporary spread component, or what the dealer earns on a round-trip trade. The component is not estimated separately because it is perceived as being very small in relative magnitude, and its price impact is temporary due to the bid-ask bounce.[6]

Desai et al (1998) use the GKN approach to decompose the spread because the approach mitigates the time varying expected return that may induce positive autocorrelation and bias the spread and its component estimates. We start with this approach, and then use several other spread decomposition methods as tests of robustness. The results for the spread decomposition models for the full sample of 306 stock splits are presented in table 3, where each model is identified in the first column. The results for the pre- and post-split periods are reported in panels A and B, respectively, and changes in these statistics are reported in panel C. The results for the spread decomposition models are discussed next.

[Please insert table 3 about here.]

2.3.1 Spread decomposition using the model of George, Kaul and Nimalendran (GKN)

In the George, Kaul and Nimalendran (1991) model, the first-order autocovariance from the differences between returns based on trade prices and bid quotes is calculated for each sample firm. Since quotes are reported ahead of prices, looking backward for any posted bid recorded before the trade identifies subsequent bids. If none is found, a forward search is made for the first qualifying bid that follows the trade.

[6] Stoll (1989) finds that inventory cost is 10% of the spread compared to 47% and 43% for the order processing and the information components, respectively. In contrast, Huang and Stoll (1997) attribute 28% of the total spread cost to the inventory component. However, they note that trade size has an important impact on this cost.

Based on the results reported in Table 3 for a cross-sectional regression with 303 observations, the temporary component increases from 77.40% to 83.61%, and the temporary and permanent costs fall from 44.21 and 12.91 cents to 30.23 and 5.92 cents, respectively, post-split.[7] In proportional terms, the temporary component increases from 1.34% to 1.68% and the permanent component decreases from 0.39% to 0.33% post-split. The latter result differs from that of Desai et al. For the reduced sample of 266 splits containing no more than five consecutive days with no trades (the 5-day sub-sample), the proportions increase only for the permanent spread component (from 0.19% to 0.58%). As a further test of robustness, the estimates for the temporary component for the sub-samples based on each of size, volume and price are examined. Based on unreported results, some estimates are not feasible because they exceed one and imply negative estimates for the permanent component.[8] This may explain why the change in both components is not consistent. This may be due to various problems associated with the George et al decomposition model, such as: the constant spread assumption,[9] trading volume is not deemed a spread determinant, and trades within the quoted spread are ignored.

2.3.2 Spread decomposition model of Neal and Whetley (NW)

Neal and Whetley (1998) estimate the George et al model using a time-series regression that allows the spread to be time varying. The well-known Lee and Ready (1991) algorithm is used to sign the trades for this (and all other) trade indicator models in this essay. Each transaction price is compared to the prevailing mid-quote, where prevailing quotes for any given transaction should be reported at least five seconds before the price. [10]

---

[7] Three stock splits are removed due to positive first-order autocorrelation in their return differences.
[8] For instance, our estimate of the temporary component as a proportion of the quoted spread is 107% for the medium price sub-sample. This leads to negative estimates of the adverse information trading cost. As a result, little weight is placed on the GKN estimates reported in table 4.
[9]For intraday data, Chan, Christie and Schultz find that the spread is lower at the close on the Nasdaq. Brock and Kleidon (1992), McInish and Wood (1992), and Lee, Mucklow and Ready (1993) document a U-shaped spread pattern on the NYSE. Chordia, Roll and Subrahmanyam (2001) find evidence of daily time series variation in liquidity measures, including quoted and effective spreads.
[10] Odders-White (2000) finds that the Lee and Ready algorithm correctly classifies 85% of the trades in the NYSE. Ellis, Michaely and O'Hara (2000) report an accuracy rate of 81% for NASDAQ trades. Both papers report systematic misclassifications for specific trades (close to the midpoint or outside the quotes).

Based on the NW results presented in Table 3, both the temporary and the permanent components are lower in cents but higher on a per-dollar basis post-split. These results are robust to firm size, share price and trading volume partitioning. Overall, the proportional information and temporary cost components increase by 23 and 16 basis points or bps post-split for the full sample, and by 24 and 8 bps for the 5-day sub-sample. The contribution of each component to the total increase in trading cost differs by split. These results are not completely in agreement with those of Desai et al who attribute a larger portion to the information-related component post-split. The contribution of the temporary component to the total spread as measured by π increases marginally by 325 basis points on average. This is due to the high cross-sectional variability of the estimates.

The changes in the spread components for the NW decomposition model for the sub-samples based on per-share price are summarized in table 4. Each panel reports the change of the spread component estimates around the splits (as in panel C of table 3). For the three price-sorted sub-samples, the average adverse information component does not change for the highest price sub-sample, and all of the increase in the proportional spread is due to higher temporary trading costs that increase on average (median) by 19 (12) bps. The adverse information costs only increase for the low price sub-sample, and this increase exceeds that of the temporary component. This may be due to the smaller investor following for low price stocks. For the medium price sub-sample, the change in the proportional permanent component is not significantly different from zero, although the proportional temporary component increases significantly post-split. These results hold for both the parametric and the non–parametric tests.

[Please insert table 4 about here.]

Ellis et al propose a modified algorithm where trades that do not match the bid or the ask quotes are classified using a categorized tick rule. This improves classification accuracy to 82%. In our sample, 1,326,516 (88.8%), 127,105 (8.5%) and 40,710 (2.7%) of the trades take place at, inside and outside the prevailing quotes, respectively.

Based on the results for the NW decomposition model for the full sample reported in table 3, both the post-split increases in the mean and median π are significant at the 0.10 level. While the mean and median of the proportional temporary component cost increase significantly at the 0.01 level post-split, the mean and median of the proportional permanent component cost also increases significantly post-split, albeit at the 0.10 level. Thus, the marginally significant increase in total cost post-split appears to be primarily attributable to the very significant increase in its temporary component post-split. Desai et al also find similar results. As is shown in Table 4, the increase in π is essentially due to the medium price sub-sample of stock splits.

Based on the results reported for the NW decomposition model for the price sub-samples reported in table 4, only the changes (increases) in the mean of total cost for the low price sub-sample are significant. All of the changes in the means and medians of the temporary component cost as a proportion of the total quoted spread are increases that are significant at the 0.05 level. While all of the mean and median changes in the permanent component cost as a percent of the total quoted spread are increases, only those for the low price sub-sample are significant (at the 0.05 and 0.10 levels for their mean and median, respectively). We conclude that stock splits carry an information effect only for the low price sub-samples of split stocks.

2.3.3 Spread decomposition model of Masson

Masson (1994) estimates the realized spread using the revision in the beliefs about the payoffs for the traded security of the market maker immediately post-trade. This approach assumes that the unconditional means of the spread components are constant over time. Cross-sectional mean and median estimates and estimates of the theoretical variance of the estimated spread components, which are calculated for the full sample and each sub-sample, are assumed to be distributed as independent Poisson processes.

Based on the findings reported in Table 3, both spread components decrease in absolute terms and increase on a per-dollar basis. This result holds for all sub-samples, including the price-sorted sub-samples (see table 4). Globally, the proportional temporary and adverse information components increase by 28 and 11 bps, respectively. Based on panel A of table 4, the corresponding increases for the low price sub-sample are a very significant 42 and 20 bps, respectively, for both tests. In contrast, only the mean (median) temporary proportional trading costs increase of 16 (12) bps are significant for the high price sub-samples. The average change in the proportional permanent cost for this sub-sample of 3 bps is not significant.

2.3.4 Spread decomposition model of Glosten and Harris (GH)

Glosten and Harris (1988) use a trade indicator model coupled with a volume measure. Based on Table 3, all dollar spreads and their components decrease, as expected, post-split. On a per-dollar basis, the temporary component accounts for the total increase in the implied spread. While the adverse information cost remains at 0.22%, the temporary component moves from 0.69% to 0.92%. This result is systematic for all of the 10 sub-samples. The contribution of the adverse information cost to total trade cost, as measured by the parameter π_1, declines significantly post-split by an average 374 bps for the full sample. The sign test results confirm the significance of the increase and decrease of the proportional temporary and permanent components, respectively, and the inconclusiveness of the change in the per-dollar permanent cost.

As for the price-sorted sub-samples, only the proportional temporary component changes significantly (see table 4). The per-dollar permanent cost component does not change significantly post-split. This clearly suggests that all of the increase in the trading cost is caused by an increase in the temporary component.

2.3.5 Spread decomposition model of Lin, Sangher and Booth (LSB)

The main property of the Lin, Sangher and Booth (1995) model is its ability to infer the adverse information component from the relation between the mid-quote changes and the effective signed half-spread. Thus, this model accounts for trades negotiated inside the best quoted spread. As in LSB, the estimate of λ, which denotes the adverse selection component as a percentage of the total spread, is used to infer the temporary and permanent dollar and proportional trading costs.

Based on the results reported in table 3, the average dollar temporary component decreases and its per-dollar counterpart increases from 1.51% to 1.91% post-split. Both the dollar and proportional permanent components decrease post-split, and this pattern is somewhat robust across the 11 sub-samples. The average increase in the proportional permanent cost as a proportion of total trading costs is 440 bps for the full sample, and is greater for the 5-day sub-sample. The increase in the π estimate is robust to size, volume and price sorting, and to the use of the nonparametric sign test. Thus, this spread decomposition model clearly finds that the proportion of information asymmetry compared to noise trading decreases post-split.

The same conclusions, as are reached above using the Glosten and Harris and the Masson models, hold for the various sub-samples. Most (if not all) of the change in the per-dollar posted spread is due to the temporary component. For the high price sub-sample, the proportional permanent cost actually decreases.

2.3.6 Spread decomposition model of Madhavan, Richardson and Roomans (MRR)

The moment conditions of the full spread decomposition model of Madhavan, Richardson and Roomans (1996) are used to estimate seven parameters for each splitting stock. Based on the main results reported in table 3, the dollar spread and its components systematically decrease post-split.

On a per-dollar basis, the implied spread increases from 0.70% to 0.83% post-split. While the temporary component increases on average from 0.27% to 0.63%, the permanent component decreases on average from 0.43% to 0.20%. The cost reduction of 23 bps for the permanent component is more than offset by the increase of 36 bps in the temporary component. This type of change behavior is robust for all of the sub-samples. To illustrate, the adverse information and temporary components decrease and increase on average by 6 and 22 bps, respectively, for the medium per-share price sub-sample (see table 4). The contribution of the adverse selection component to the total spread falls from 71.54% to 46.67% on average, and decreases by more than 34% as a percentage of the total implied spread for the full sample and by a greater percentage for the sub-samples.

For the price-sorted sub-samples, the per-dollar temporary cost increase and the permanent proportional cost decrease are significant based on the t-test of the mean changes for the high and low price sub-samples. The increase in the temporary proportional cost is higher for the low compared to the high price sub-sample. The mean (median) changes are 54 (15) bps for the low price sub-sample compared to 31 (3) bps for the high price sub-sample.

2.3.7 Recapitulation

The evidence shows that the proportional temporary cost increases post-split. This result is very robust across all spread decomposition models and all sub-samples.[11] In contrast, depending on the model used and whether or not the sample is price-sorted, the proportional permanent cost component is either unchanged or lower post-split. Based on the GKN, NW and Masson models, the proportional permanent cost component increases post-split only for the low price sub-sample. For the GH, LSB and MRR models, the proportional permanent cost does not change post-split.

The above results for the six spread decomposition models provide weak support for both the price range and information-based explanations for stock splits. For high price stocks, the split is used mainly to bring the per-share price back into a "normal" or optimal range compared to the tick size as argued by Angel (1997). As reported herein, this does not affect information-based trading or increase the adverse information cost. However, the managers of low per-share price stocks do not aim to achieve an optimal relative tick compared to price but rather to convey

[11] While none of these spread decomposition models explicitly accounts for dealer monopoly returns, one can assume that such rents are captured in the temporary cost component since they are not related to information. An interesting avenue for future research is to formulate and test a spread decomposition model that has an explicit component to capture dealer monopoly rents as well as inventory and order-processing costs.

information. This explains why the proportional permanent cost increases for the low price stocks.

If managers use a split as a signaling mechanism, then the extent of adverse information should be reduced once the split is announced. If the split is used to capture the attention of traders and financial analysts, then information asymmetry should be reduced and liquidity should be improved. Such a pattern is found for the high price sub-sample. For the low price sub-sample, the higher level of permanent proportional cost can be explained by the fact that investors still consider such stocks to be risky since the signal is ambiguous. As some investors might decide to pay and acquire the new information, this increases the extent of the information asymmetry. In turn, this leads to a higher adverse selection trading cost.

A slight decrease in adverse information costs that is more than offset by an increase in temporary costs after stock splits is strongly confirmed for all six models. The increase in temporary costs indicates that either immediacy trade cost is increased or that liquidity is decreased. Unlike Desai, Nimalendran and Venkataraman (1998), Easley, O'Hara and Saar (2001) find that the adverse information problem is reduced after stock splits using a different approach, but similarly note that the gain is not material compared to the increase in volatility and in the total spread.

2.4 Changes in Trading Intensity Around Stock Splits

In this section, we build on the EKOP methodology to infer the trading intensity of both uninformed and informed traders in order to understand the extent of information and noise trading around stock splits. EKOP develop a trading model where the spread results from information asymmetry between informed traders and the market maker (see appendix B for the full model). To estimate the arrival intensity parameters and the probability of informed trading, the logarithm of the likelihood function given by (1) is maximized:

$$L\langle (B,S)|\Theta\rangle = \prod_{i}^{I}\left[L\langle (B_i,S_i)|\Theta\rangle\right] \tag{1}$$

where B_i and S_i are the number of buyer and seller initiated trades on day i, respectively,

$L\langle (B_i,S_i)|\Theta\rangle$ is the likelihood of observing B_i buys and S_i sells on day i conditional on the information set Θ. This includes the probability α that an event occurred at the beginning of day i, that conditional on this occurrence the probability that it has a negative impact is δ, and that the intensities of trading by the informed and uninformed traders are μ and ε, respectively.

The last four trading parameters for both pre-announcement and post effective periods of 60 trading days each are estimated for each splitting stock.

[Please insert table 5 about here.]

Panels A, B and C of table 5 report statistics relative to the pre-split period, the post-split period, and changes from the pre-to-post-split period, respectively, for the full sample and the 5-day sub-sample.[12] The cross-sectional averages for the set of parameters and the probabilities of informed trading (PIN) reported therein show that trading activity for both informed and uninformed traders has increased. The average daily arrival rate of informed traders increases on average by about 67.52% from 18.4 to 22.0 post-split. The arrival rate for uninformed traders increases on average by 116.47% from 11.78 to 20.80. Although both types of traders trade more intensely after stock splits, the uninformed trade more frequently. These findings are robust across the various sub-samples. For the 5-day sub-sample, the increase in the arrival of informed and uninformed traders is about 65% and 97%, respectively. The low volume sub-sample exhibits

[12] Since the EKOP model is not linear, the use of the standard errors from the sampling distributions for its parameter estimates may lead to incorrect inferences. To test for this possibility, the "true" standard errors obtained using the Bollerslev-Woolridge correction of the inverse of the Hessian for the EKOP model are calculated. This has no material effect on the inferences drawn herein. To save valuable journal space, these results are not reported herein.

the highest growth rate in informed and uninformed traders of 92% and 189%, respectively. These changes are all statistically significant.

Depending upon the change in information production, the previously mentioned change in the composition of the pool of traders will have a different impact on the probability that a single trade involves an informed trader. If the (exogenous) probability of information arrival α does not change post-split, then the total probability of trading against an informed trader is reduced since the increase in the number of uninformed traders is larger than that of informed traders. Thus, information based trading is diluted even though the total number of informed traders increases after the split. Formally, the probability of informed trading is given by:

$$\text{PIN} = \frac{\alpha\mu}{\alpha\mu + 2\varepsilon} \qquad (2)$$

Based on Table 5, α increases marginally from 37% to 40% post-split, and the increase in ε is almost double that in μ. This leads us to conjecture that the PIN variable should fall. Our estimate of the probability of information trading decreases from 32.41% to 30.41% post-split. This is a significant drop of 200 bps, and is consistent with the inference from the sign test.

The change in the δ parameter estimate is of some importance, even if it is not linked to the intensity of informed trading, and thus to the probability of informed trading. δ is the probability that the event has a negative impact. δ decreases from 50.10% to 39.37% post-split. The mean difference of 10.72 % is significant at the 0.05 level. This indicates that splitting firms tend to experience a greater proportion of positive-information events just after the split than before it. This is consistent with the signaling and information-based explanations of stock splits.

[Please insert table 6 about here.]

Focusing on the price-sorted sub-samples, we find that the higher α, lower δ, higher μ, higher ε and lower PIN post-split also occurs for the low and high price sub-samples in table 6. However, the reduction in the probability of informed trading is larger for the high price sub-sample, and the drop in PIN is not as significant for the low price sub-sample. This supports our previous spread decomposition results that the price range is the main reason for splits for stocks with higher pre-split prices. Since this leads to more trading activity by uninformed investors and no new information is being signalled, then the PIN is reduced. However, even if information is suspected as being linked with the split, it is in the form of a more promising future given the reduction in δ of 15.11 bps. The corresponding figure for the low price sub-sample is much lower at 6.45 bps.

2.5 Changes in Volatilities Around Stock Splits

2.5.1. Change in volatility as measured using a GARCH approach

Ohlson and Penman (1985) find that volatility increases post-split. Dubofsky (1991) attributes the higher volatility increases after stock splits for NYSE versus AMEX stocks to measurement errors induced by spreads or the clientele effect. Since stock splits are accompanied by higher trading costs, volatility should increase simply because of the bid-ask bounce, ceteris paribus. Furthermore, as noted by Black (1986), if stock splits attract small and uninformed traders through a clientele effect, then noise trading (and volatility) will increase. This increase in volatility should only be temporary as the market will correct through information-based trading and the release of new public information. Desai, Nimalendran and Venkataraman (1998) use one minus the variance ratio over a three-day period (due to the positive autocorrelation of daily returns) as a measure of the contribution of noise or temporary volatility to total volatility. They find that both temporary and permanent volatility increase after stock splits.

The impact of stock splits on volatility components is captured herein using an ARCH model where the conditional mean return is computed using a market model. The volatility components methodology is used to decompose the volatility into an information-based permanent component and a transitory noise-trading-induced component.

Wiggins (1992) finds that stocks with high (low) historical betas have higher (lower) betas during up than down markets. Bhardwaj and Brooks (1993) use a dual bull and bear beta model and are able to explain the size effect. Applying the same methodology, Howton and Peterson (1998) find a strong beta-return relation even in the presence of Fama and French (1993) factors.

Pettengill, Sundaram and Mathur (1995) find that conditioning the (realized returns version of the) CAPM on the risk premium sign improves model performance. When the excess return on the market is negative (positive), a negative (positive) relation between beta and return should exist. In Pettengill et al (2002), they argue that the market premium categorization is sufficient and that using up and down market betas is not a necessary condition. Since we use a market model for the return equation, we rely on the dual beta market framework. Unlike Howton and Peterson who define bull and bear markets by comparing the market return to its unconditional mean over the period under study, we classify up and down market as in Pettengill, Sundaram and Mathur (1995, 2002).

The market model used herein is given by:

$$\begin{aligned} R_{i,t} &= \alpha_i + \beta_i^{up} \times R_{m,t}^{up} + \beta_i^{down} \times R_{m,t}^{down} + \beta_i^{*up} \times R_{m,t}^{up} \times I_{a,t} \\ &+ \beta_i^{*down} \times R_{m,t}^{down} \times I_{a,t} + \kappa_1 \times I_{announc,t} + \kappa_2 \times I_{effect,t} + \varepsilon_{i,t} \end{aligned} \tag{3}$$

where $R_{i,t}$ is the excess return of stock i during day t, where the risk-free rate is proxied by the daily rate for one month treasury bills as published by the Bank of Canada,

$R_{m,t}^{up}$ is the market excess return if positive, and is zero otherwise,

$R_{m,t}^{down}$ is the market excess return if negative, and is zero otherwise,

$I_{a,t}$ is a dummy variable equal to 1 if after the announcement date, and is zero otherwise,

$I_{announc,t}$ is a dummy variable equal to 1 for the day preceding, the day of and the day after the split announcement, and is zero otherwise,

$I_{effect,t}$ is a dummy variable equal to 1 for the day preceding, the day of and the day after the split effective date, and is zero otherwise, and

$\varepsilon_{i,t}$ is an error term with the usual assumed properties.

The approach of Scholes and Williams (1977) is used to correct for the nonsynchronous trading problem by estimating betas on lagged, lead and contemporaneous market returns. All excess returns are computed as nominal daily compounded returns less the one-month treasury bill rate for equal pre-announcement and post-effective periods of one year. The parameters of interest are the pre-split systematic risk measures β_i^{up} and β_i^{down}. On a post-split basis, stock i has a systematic risk of $\beta_i^{up} + \beta_i^{*up}$ during up markets and $\beta_i^{down} + \beta_i^{*down}$ during down markets. The parameters κ_1 and κ_2 capture any abnormal returns that may occur around announcement and effective split dates, respectively.

Volatility is modeled using the component GARCH model of Engle and Lee (1993, 1999) with an asymmetric effect on volatility of shocks to return, as in Glosten, Jagannathan and Runkle (1993). The long-run volatility is not time invariant but follows a (hypothetically) highly persistent and slowly evolving autoregressive process. Three other specifications for volatility also are used; namely, the usual GARCH(1,1) specification, a GARCH coupled with an asymmetric effect of the return shocks, and a component GARCH without leverage effect.

Let $h_{i,t}$ denote the conditional variance of $R_{i,t}$. Then $h_{i,t} = E\left(\varepsilon_{i,t}^2 \mid F_{t-1}\right)$ where F_{t-1} is the information set available for prediction at time t. If $q_{i,t}$ is the permanent or long-term time t component of the volatility for stock i, then the transitory or short-term component is given by $h_{i,t} - q_{i,t}$, and is equal to:

$$h_{i,t} - q_{i,t} = \mu \times \left(\varepsilon_{i,t-1}^2 - q_{i,t-1}\right) + \gamma \times \left(\varepsilon_{i,t-1}^2 - q_{i,t-1}\right) \times I_{\varepsilon_{i,t-1}} + \psi \times \left(h_{i,t-1} - q_{i,t-1}\right) + \theta_2 \times I_{a,t} \qquad (4)$$

The parameter θ_2 captures any impact that the stock split has on the temporary volatility component. $I_{\varepsilon_{i,t-1}}$ is a dummy variable that is equal to 1 if $\varepsilon_{i,t-1} > 0$, and is zero otherwise.

Only the temporary component of the volatility is affected by the asymmetric effect. As in Engle and Lee (1999), who find a significant asymmetric effect for transitory volatility only, we do not assume nor estimate the leverage effect for permanent volatility. When investigating a model with no asymmetry at all, γ is constrained to be equal to zero.

The permanent component of volatility is given by:

$$q_{i,t} = \omega + \rho \times (q_{i,t-1} - \omega) + \phi \times (\varepsilon_{i,t-1}^2 - h_{i,t-1}) + \theta_1 \times I_{a,t} \qquad (5)$$

The change in the permanent volatility due to the stock split is measured by the parameter θ_1.

To achieve convergence and to gain in estimation efficiency, any firm with more than one stock split during any 800 consecutive days or any stock with less than 500 observations is eliminated from our initial sample. This reduces the final sample to 105 stock splits.

The main results for daily returns are presented in table 7, where the first column refers to the common GARCH(1,1) model, the second column to the GARCH(1,1) with leverage effect, the third column to the component volatility GARCH without asymmetry, and the fourth column to the full model. For the systematic risk coefficients, the average up-market beta is higher than the average down-market beta. Based on unreported one-side Wald test results for a test if $\beta_i^{up} = \beta_i^{down}$, the null is rejected in 86 out of the 105 cross-section splits.

[Please insert table 7 about here.]

A binomial sign test suggests that the up-market beta is higher than the down market beta for splitting firms. This implies that if a stock experiences an upward beta jump when the market is up (market timing), then properly accounting for this beta jump may explain why it exhibits a higher than average return. To this end, we examine the estimates of κ_1 and κ_2. For the GARCH(1,1) specification, both are significantly positive. When asymmetry is accounted for, the announcement date effect is not significantly different from zero. For the full model, neither estimate is significant at the 0.05 level.[13]

Only the change in systematic risk in down markets is significantly different from zero and positive. On average, the stock split induced bear market beta increases by 0.30 and 0.21 for the simple GARCH(1,1) specification and the full component model with leverage effect, respectively. This significant increase in the down-market beta reduces the gap between the two pre-split betas.

The low level of persistence of volatility for all of the estimated models using daily returns is unexpected. For the GARCH(1,1), the average $\left(\overline{\rho}+\overline{\phi}\right)$ is about 0.66, well below 1. For the component volatility model, the average $\overline{\rho}$ of 0.75 is well below the value of about 0.99, which Engle and Lee report as indicating highly persistent long-term volatility for their sample. This may be due to the shorter time horizon examined herein (specifically, two years of daily returns compared to half a century of daily returns in Engle and Lee). The θ_1 coefficient, which captures any change in the volatility due to the stock split, is significant and positive. This corroborates the increase in the risk on an ex-date basis. Based on the values reported in the second set of parameters in column 7 of table 7, asymmetry is present in the volatility structure. The γ coefficient is positive and significant. When the leverage effect is considered, the impact on volatility is even higher, and ϕ_1 increases by 40% with a higher t-statistic. Based on column 10 of table 7, the short or transitory component of volatility increases significantly on average, while its long-term counterpart does not after stock splits. Column 11 indicates that the leverage effect is significant, as noted by Engle and Lee.

Based on the results reported in table 7 for embedded leverage, long-term volatility decreases significantly. The average θ_1 and θ_2 coefficients are significantly negative and positive,

[13] Using a matched sample and an extended three-factor model, Byun and Rozeff (2003) conclude that there are no long-term abnormal returns after stock splits for a large sample of splitting CRSP stocks.

respectively. Nevertheless, the magnitudes of the t statistics are lower for the long-term volatility. The sum of the two coefficients, $\theta_1 + \theta_2$, which represents the impact on total volatility of the split, is significantly positive as expected. Overall, the split has a mitigating effect on long-term volatility and increases short-term volatility. This is consistent with findings reported earlier for the spread decomposition and trading intensity measures. The noise or liquidity based trading increases much more than the information based trading after stock splits.

The issue is further investigated by examining the true price volatility caused by the arrival of new public information and noise trading volatility as deduced from the MRR model. Mean and median estimates of the four main volatility components (namely, public information, noise trading, asymmetric information and price discreteness induced volatility) for the whole sample and the low and high price sub-samples for the pre- and post-split periods and their ratios are reported in panel A of table 8.[14] These volatilities as proportions of the total volatility pre- and post-split and their differences between these two periods are presented in panel B of table 8. Since the volatility estimates are based on changes in transaction prices, this variable is adjusted by the split factor for the post-split period.[15]

[Please insert table 8 about here.]

Based on panel A of table 8, all of the volatility components increase significantly in magnitude post-split. While the noise and the discreteness-induced volatility double in value, the asymmetric volatility component increases by only 16%. The patterns of change are similar for both the low and high price sub-samples. The volatility due to the arrival of new public information increases by 43% for the overall sample, and increases by a higher percentage for the low price sub-sample. This is consistent with our previous findings for the estimations of the

[14] The volatility resulting from the interaction between asymmetric information and noise trading is not reported to conserve valuable journal space.

[15] All negative volatility estimates and a few outliers are eliminated. Since the GMM system is just identified with only one solution set, restrictions on the parameters or changes in the variables are not feasible. This reduces the number of cross-sectional data points with the most severe case being the interaction volatility component where only 148 data points remain.

EKOP and the spread decomposition models, and the inference that a split is motivated to achieve an optimal price range for high priced stocks.

Based on panel B of table 8, public information induced volatility is the largest component of volatility (38.98%) and is of the same relative magnitude as in MRR. Somewhat unexpectedly, the volatility induced by discreteness in prices accounts for about 25% of total volatility.[16] There are a number of possible reasons why our estimate far exceeds the maximum estimate of 3.8% that MRR report for a sub-sample of NYSE-listed stocks. The first possible reason is that the average stock in our sample is substantially less liquid than that in the MRR sample where each stock needs at least 250 trades for each 75-minute interval. The second possible reason is that MRR exclude split stocks in order to avoid any big adjustment or structural change in the price difference series.

Noise trading induced volatility increases for each of the three price-sorted sub-samples, and especially for the low price sub-sample where the share of this volatility component moves significantly from an average of 14.28% to 17.00%. In contrast, the change for the high price sub-sample from 19.47% to 20.08% is smaller but still significant. Asymmetric information volatility as a proportion of total volatility increases (significantly) only for the low price sub-sample (from 3.80% to 4.01%). These findings also are consistent with the changes in the spread component estimates reported earlier.

2.5.2 Test of robustness using the realized volatility

This section uses an alternative measure of volatility to test whether the conclusions reached above are sensitive to the chosen measure. The change in volatility is investigated using the realized volatility computed from high frequency data. One reason for doing so is that the

[16] French and Foster (2002) find that price discreteness does not affect the variance after stock splits. For this reason we do not insist on analyzing the change in this volatility component around these events. In fact, panel B of table 8 shows this. However, it is interesting to compare the estimates with those reported in the literature.

volatility measures obtained from both the GARCH and the MRR estimation used above are both based on a latent error, which is the residual return from an empirically estimated model.[17]

Barndorff-Nielsen and Shephard (2002a and 2002b) derive the properties of the realized volatility measure. Assuming that the (change in) price follows a semi-martingale, they use the fundamental result that the realized volatility is a consistent estimator of the quadratic variation when sampling tends to be continuous. Anderson, Bollerslev, Diebold and Labys (2003) show that if prices are formed by a predictable component and a local martingale, then the sum or the integration of the quadratic variations over a given period can be used to measure price or return volatility. They show that the realized volatility measure of the most common exchange rates performs better than other competing measures, including the ARCH specification, in term of forecasting. Ferland and Lalancette also found that forecasting using realized volatility dominates using GARCH methodology.

However, the use of the realized volatility has some limitations. The most important one is that the use of tick-by-tick data does not just capture the "true" price volatility but it also captures the volatility induced by microstructure effects. Anderson et al and Barndorff-Nielsen and Shephard (2002b) note this in an indirect fashion. In their empirical analysis, Anderson et al use foreign exchange rates sampled at a thirty-minute frequency. They justify this choice by noting:

> "For our exchange rate series, preliminary analysis based on the methods of ABDL (2000b) suggests that the use of equally-spaced thirty minutes returns strikes a satisfactory balance between the accuracy of the continuous-record asymptotics underlying the construction of our realized volatility measures on the one hand, and the confounding influences from market microstructure frictions on the other …".

Barndorff-Nielsen and Shephard (2002b) also conclude that the realized volatility measure is noisy even when the sampling frequency is continuous (i.e., that the number of terms summed up

[17] For a review on volatility measures and their classification, please see Anderson, Bollerslev and Diebold (2002).

for the quadratic variation is infinite). Bandi and Russel (2003b) show that adding up the quadratic variations in the presence of microstructure effects simply adds noise to the volatility measure, and the estimate diverges to infinity. Bandi and Russel (2003a) provide a rational for using sampling at a given frequency depending on trade frequency. Ait-Sahalia, Mykland and Zhang (2003) try to overcome the problem by modeling the noise added to the pricing function by sampling at two different frequencies to compute the realized volatility of true prices.

However, we are interested in measuring both components of volatility. Specifically, our aim is to measure the impact of a stock split on both (i) the true price volatility or the long-term volatility which is information driven, and (ii) the liquidity driven or transitory volatility, which is related to uninformed trading activity. The realized volatility measure from all trading activity is the sum of both of these components. To identify the impact of each component, we fit an ARMA(1,1) model to the realized volatility. For each of the 105 stock splits, we estimate the following model:

$$RV_t = \sum_{i=2}^{n_t} \left(p_{ti} - p_{t,i-1}\right)^2$$

$$Log\left(1 + RV_t\right) = \varpi + \alpha Log\left(1 + RV_{t-1}\right) + \varepsilon_t + \beta\varepsilon_{t-1} + \theta_1 . I_{a,t} + \theta_2 . I_{e,t} \qquad (6)$$

where $Log\left(1+RV_t\right)$ is the natural logarithm of one plus the realized volatility during day t,[18]

n_t is the number of trades during day t,

$p_{t,i}$ is the logarithm of the ith trade during day t,

$I_{a,t}$ is a dummy variable equal to 1 if post-announcement date, and is zero otherwise,

$I_{e,t}$ is a dummy variable equal to 1 for the day preceding, the day of and the day after the split becomes effective, and is zero otherwise, and

[18] One is added to the realized volatility to include cases where trading during a single day occurs at one price, and hence no strictly positive quadratic variation occurs.

θ_1 and θ_2 correspond to the impact of the stock split on the true and the temporary volatility, respectively.

The choice of the dummy variables is now justified. Since the true volatility is related to information flow, any impact from the split on the true volatility will be observed on the announcement date. Also, since information flow is cumulative, the impact is expected to be long term and to persist after the announcement date. On the other hand, uninformed (especially, small) traders who contribute to the transitory liquidity are more likely to act once the split becomes effective and the per-share price decreases so that the size of a round lot is smaller. Since transitory volatility is short lived, we limit its effect to the days around the effective date.

[Please insert table 9 about here.]

The results from the ARMAX model are reported in table 9. Both the moving average and the autorgressive coefficients are highly significant. Most interestingly, the estimated coefficient on the $I_{e,t}$ dummy variable is positive and significant. This clearly indicates that volatility increases temporarily around the effective date. In contrast, the coefficient on the $I_{a,t}$ dummy variable is not significant. These results for a test of robustness confirm our previous findings.

2.6 Concluding Remarks

Stock splits are shown herein to be more than purely cosmetic events due to their real impacts on the fundamentals of the equity of splitting firms. Since stock splits are endogenous and voluntary events, managers consider several factors when deciding to split stocks. Thus, possible explanations for stock splits are unlikely to be exclusive alternatives.

In our empirical findings, we document that the change in the amount of information asymmetry alternates between increasing and decreasing depending on the model used. The strongest result reported herein is for the increase in the noise or liquidity trading after a stock split. We also find a decrease in the probability of any single trader trading against an informed trader. This does not mean necessarily that stock splits reduce information asymmetry. In fact, it may well be the case that some of the additional investors who get attracted to the newly split stock decide to become more informed (or receive finer signals) about the stock. However, the rest of the investors will trade the stock for liquidity purposes only. So even if the extent of the information asymmetry worsens, the risk of getting bagged by an informed investor is reduced.

The evidence reported herein suggests that splits are essentially a tool for bringing price back to an optimal range for stocks with high prices pre-split. Any signaling is used to reduce the level of information asymmetry and to encourage trading. Thus, noise trading increases for this sub-sample of stock splits. In contrast, information signaling is definitely present for the low price sub-sample of stock splits.

CHAPTER 3

Trading Activity, Trade Costs and Informed Trading for Acquisition Targets and Acquirers

3.1 Introduction

Acquisitions are major events for both targets and acquirers, which induce major changes at various levels. The major motivation for acquisitions appears to be the achievement of efficiencies through cost economies or synergies. The published literature includes numerous papers that examine value creation after mergers and acquisitions and the determinants of such.

This literature finds that acquisitions represent material events that significantly affect prices and result in abnormal returns.[19] Targets achieve positive abnormal returns, which are relatively higher when the method of payment is in cash. In contrast, acquirers earn negative and neutral abnormal returns when the method of payment is shares and cash, respectively. If the bidder is cash rich, Harford (1999) uses agency cost theory to explain the decline in post-acquisition performance and the negative abnormal returns on the announcement date for cash-rich acquirers. Martin (1996) investigates the relation between investment opportunities (as measured by growth) and the payment method and finds that bidders with high potential growth tend to use shares as a mean of payment. He explains this by the constraints that cash payments impose on the achievement of profitable investment opportunities for acquirers. Gosh and Ruland (1998) argue that managerial preference for shares as the payment method increases as managerial ownership of the target firm increases, and that this managerial behavior is motivated by the increased probability of these managers keeping their jobs. Song and Walking (2000) fail to reject the acquisition probability hypothesis, which stipulates that the competitors of target firms enjoy

[19] See, for example, Bradley, Desai and Kim (1983), Jensen and Ruback (1983), Malatesta (1983), Franks, Harris and Titman (1991), Agrawal, Jaffe and Mandelker (1992), and Loughran and Vijh (1997).

positive abnormal returns because of the increased probability that they will become targets themselves. Shleifer and Vishny (2003) argue that acquisitions are driven by market misevaluations, and that the incentive to use shares as a payment method by rational managers increases with higher misevaluations.

Most surprisingly is the paucity of literature on the market microstructure around the announcement and effective dates for corporate acquisitions. Since news of a possible or actual acquisition has considerable materiality, its release should drive trading and therefore affect market liquidity and trade behavior. As is widely accepted in the literature,[20] investors trade for various reasons. Since the expectations of investors about the future cash flows of firms are affected by news, investors adjust or rebalance their holdings to conform to their updated expectations. Investors, who previously did not follow the firm, may decide to commence following the firm after receiving the news release. Investors who had private information about the firm prior to the release have their previous privileged position with regard to knowledge about the firm dissipated.

In contrast, the literature contains many examinations of liquidity and other microstructure changes around generally less material corporate news announcements. Lee, Mucklow and Ready (1993) find that liquidity is lower immediately before and after earnings announcements. While Krinsky and Lee (1996) find that earning announcements have no impact on the total bid-ask spread, they argue that this is due to offsetting increases and decreases in the permanent adverse selection and temporary components, respectively, of the spread. Kosky and Michaely (2000) investigate liquidity and information asymmetry around dividend and ex-dividend dates and find that liquidity is lower and that trades have higher impact on prices during announcement periods compared to the ex-date period. Desai, Nimalendran and Venkataraman (1998) use the George, Kaul and Nimalendran (1991) spread decomposition model to investigate changes in cost

[20] O'Hara (1995) is the main reference for the microstructure literature. Madhavan (2000) provides a literature survey on market microstructure.

components around stock splits. Easley, O'Hara and Saar (2001) use a variant of the model of Easley, Kiefer, O'Hara and Paperman or EKOP (1996) to study changes in trading intensity by informed and uninformed traders around splits. Ellis, Michaely and O'Hara (2000a) investigate the trading and the liquidity provided by the lead-underwriter and the co-managers around IPOs.

Given this deficiency in the literature, the primary purpose of this essay is to investigate changes in trading activity and liquidity for successful tender offer acquisitions around their announcement and effective dates. The examination is of both acquirers and targets listed on both the NYSE and NASDAQ and differentiated by proposed method of payment. Our conjecture is that the announcement of a tender offer reveals some portion of the private information formerly held by insiders and other privately informed investors. Therefore, we expect that the permanent component of the trading cost (i.e., the portion related to asymmetric information) drops after such an announcement. We also expect that the drop in the permanent cost will be larger for the cash versus the share method of payment for targets. The method of payment is a signal, and cash represents a much stronger positive signal than shares. Cash tender offers are a stronger signal that the acquirer considers the target to be undervalued or that its value can be enhanced if managed differently.[21]

This essay makes six main contributions. The first contribution is that we confirm, as expected, that there is a pronounced increase in trading activity and liquidity on the tender offer announcement dates for targets. Volume measured using various proxies is about ten times higher than it was pre-announcement. Although depths drop, spreads (quoted, effective, and weighted by volume) decline substantially, thereby confirming the improved liquidity. Acquirers experience the same directional but a more muted change in trading activity and liquidity on the tender offer announcement dates.

---

[21] A data snooping problem may arise here. Since the literature reports that targets receiving cash payments experience higher returns (Calvet and Lefoll, 1987; Travlos, 1987), assuming that method of payment is a signal can be viewed as problematic from an empirical point of view. However, this problem is mitigated somewhat since we rely on recent (out-of-sample) data that was not used in the previous literature to identify this relationship.

The second contribution is the striking result of increased selling pressure for targets although their prices increase sharply upon announcement, especially when the method of payment is cash. This is linked to liquidity trading, portfolio rebalancing caused by the abnormal returns, and the limited arbitrage arguments of Shleifer and Vishny (1997), and Baker and Svaşoglu (2002).

The third contribution, which is closely related to the previous one, deals with the change in executions against limit orders at both ends of the inside bid and ask quotes. We find that executions against limit buy orders increase for targets, and especially for cash tender offers. Executions against sell limit orders also increase for some groupings of targets but more modestly. The changes are smaller for acquirers. These results are consistent with our conjecture that many pre-announcement shareholders dispose of some of their holdings to convert uncertain gains into certain gains. These shareholders contribute to the pressure by selling against the limit buy orders. These results can also be related to the submission of more aggressive limit buy orders by arbitrageurs who know that opportunities still exist for positive abnormal returns.

The fourth contribution is to provide estimates of the quoted and implied spread components using five spread decomposition models. This multi-model approach provides a test of robustness since none of the models account for all of the complexities of the price formation and discovery mechanisms, and all of the models make different simplistic assumptions about the price discovery process. The temporary and permanent components of the spread decrease significantly for the targets. The decline is less significant for the temporary component due to the huge increase in trading activity. Since the order processing cost is essentially a fixed cost, higher volume results in lowers costs. The permanent cost drops because of the reduction in information asymmetry. The temporary component also declines in a less pronounced manner for acquirers due to increased trading activity. Weak evidence also exists for a decline in the permanent component for acquirers. However, the decline is more pronounced for share versus cash tender offers because of their association with almost no news and negative news, respectively, for acquirers.

The fifth contribution is to provide estimates of trading intensity for both informed and uninformed traders and the inferred probability of informed trading (PIN), as in Easley, Kiefer, O'Hara and Paperman or EKOP (1996). The PIN declines for targets because the increase in trading intensity is greater for uninformed than for informed traders, and the PIN remains relatively constant for acquirers because the increases in trading intensity are relatively equal for uninformed and informed traders.

The sixth and final contribution is to relate the abnormal returns observed around tender offer announcements to the corresponding changes in adverse information. Abnormal returns and information asymmetry are negatively related, as expected, since news is reflected in the price. However, this relation is not robust since it is subsumed by other variables when they are added to the postulated relationship.

3.2. Samples and Data Collection

The sample consists of firms listed on the NYSE or NASDAQ that participated in a completed acquisition transaction during the calendar year 2001. After implementing a number of filters, the final sample consists of 111 NYSE-listed targets, 252 NASDAQ-listed targets, 191 NYSE-listed acquirers and 277-NASDAQ listed acquirers.

Data on announcement and effective dates are obtained from the SDC Financial Thomson database. The sample is limited to completed tender offer transactions in order to be able to measure the impact after effective acquisitions. The first offer made by the final acquirer is set as the announcement date for both targets and acquirers. This reduces the impact of pre-acquisition expectations that are discounted in the microstructure measures. The nature of the considerations involved and the percentage of equity the acquirer was seeking are also collected.

Acquisitions below a minimum transaction value of 5 million dollars are deleted from further consideration. This minimum value corresponds to the minimum market value of publicly held shares that are required to maintain a listing on the NASDAQ market. Any acquirer or target that switches listing venue during the period under investigation also is not retained in the sample. This filter eliminates targets that shifted their listings between the NASDAQ and the NASDAQ SmallCap and/or the Over-the-Counter Bulletin Board or the Pink sheets. Such firms are deleted because a listing venue shift changes the trading mechanisms and impacts both trading and liquidity.

Companies also are deleted if they have a (reverse) stock split or a stock dividend during the period starting six months before the acquisition announcement and ending six months after the realization of the acquisition. Although this does not ensure that the sample is "pure" in terms of removing all other events, stock splits and dividends need to be eliminated since liquidity is highly related to the price level and the literature documents the impact that deterministic or discretionary price changes such as splits and stock dividends have on liquidity.[22,23]

Four time periods (event windows) are considered for each acquiring firm. The pre-announcement event window consists of the 45 trading days preceding a period of 20 days before the intention to acquire announcement, and the announcement window consists of the three trading days centered on the announcement day. If the announcement occurs on a holiday, the day before and the two days after are used. The effective window consists of the three days centered on the effective day of the acquisition. The post-effective window consists of the 45 trading days beginning 20 trading days after the effective acquisition date. In contrast, since most of the targets

---

[22] The literature on the impact of splits on liquidity and trading activity includes Kryzanowski and Zhang (1993, 1996), Angel (1997), Easley, O'Hara and Saar (2001), and Desai, Nimalendran and Venkataraman (1998). In contrast, cash or stock dividends generally have a much smaller impact on the per-share price than splits.

[23] No firm in the sample announced a large special cash dividend or a liquidating dividend. This is particularly relevant for targets since large cash dividends are one of the measures that managers can use to defend against hostile takeovers.

(85%) are de-listed around the effective date, only pre- and announcement windows (similarly-defined) are examined for the targets.[24]

The trades and quotes data, which are posted during normal trading hours from 9:30 am to 4:00 p.m., for both acquirers and targets for only common shares with voting power are extracted from the TAQ database. This includes trades that are initiated and executed on all trading venues including the regional exchanges. However, for quotes, only those posted at the company's primary listing venue (i.e., NYSE or NASDAQ) are retained, as in Chordia, Roll and Subrahmanyam (2001). This deletion filter reduces the number of passive autoquotes posted automatically by inactive dealers.

The data are further cleaned by deleting all quotes where the bid price is higher than the ask price, all zero quotes, all non firm quotes, quotes during trading halts, quotes with percentage spreads higher than 30%, trades with zero price or volume, trades with absolute intradaily returns higher than 50%, and trades with special settlement conditions. These filters remove less than 0.07% of the total data.[25]

The Lee and Ready algorithm is used to sign the trades. This is basically the combination of the quote and the tick test rules. If the traded price is higher (lower) than the prevailing mid-quote, then the trade is classified as buyer- (seller-) initiated. For trades at the prevailing mid-quote, the price is compared to the previous trade's price. If price moved up (down), then the trade is classified as a buyers (seller-) initiated. One of the problems in applying the quote rule is the choice of the prevailing quotes. Lee and Ready (1991) advocate the use of quotes reported at least five seconds ahead of trades since trades are reported more promptly. Both five and two second delays are used herein to cope with fast market maker reactions, especially during opening

[24] As such, the beginning and ending dates are: July 13, 1999 to March 26, 2002 for NYSE-listed acquirers; January 10, 2000 to March 26, 2002 for NASDAQ-listed acquirers; May 26, 1999 to January 3, 2002 for NYSE-listed targets; and September 1999 to January 2002 for NASDAQ-listed targets.

[25] The data lost due to filtering are not evenly distributed. The loss is higher for firms listed on NASDAQ (0.19%) versus NYSE (0.006%), for acquiring (0.152%) versus targeted firms (0.039%), and for quotes (0.257%) versus trades (0.011%).

market periods right after the acquisition announcement. The Ellis, Michaely and O'Hara (2000b) algorithm also is used because it performs better during such periods of fast trading. Basically, this algorithm uses the quote rule for the trades that exactly match bid or ask quotes, and the tick rule for all other trades including those outside the posted quotes.

Descriptive statistics for the different samples are presented in table 10. NYSE-listed stocks (whether acquirers or targets) trade on average at a significantly higher per-share price than NASDAQ-listed stocks. Using total assets and total market capitalization as proxies for size, the average NYSE-listed company is bigger than the average NASDAQ-listed company for both targets and acquirers. The average acquiring firm has on average 37% and 7% more assets than the average target firm for NASDAQ- and NYSE-listed firms, respectively. Even more pronounced, the average acquiring firm has a market equity capitalization that is approximately 3.5 and 2.5 times that of targets for NASDAQ- and NYSE-listed firms, respectively. Based on table 10, trading volume is higher for acquiring than target firms and for NYSE– versus NASDAQ-listed firms when measured before the announcement of the intention to acquire.[26]

[Please insert table 10 about here.]

3.3. Changes in Liquidity and Trading Activity for the Acquisition Parties

Two dimensions of liquidity are measured, namely spreads and depth. The spread measures are: dollar quoted spread, or ask quote less bid quote for admissible quotes; proportional quoted spread, or dollar quoted spread divided by the midspread; dollar effective spread, or twice the absolute value of the difference between trade price and the prevailing mid quote; proportional effective spread, or the dollar effective spread divided by the prevailing mid-quote; dollar effective weighted spread, or every effective spread weighted by the dollar value of each involved trade; and proportional effective weighted spread, or every proportional effective spread weighted by the dollar value of each involved trade. The average is first calculated for each spread measure

[26] The unreported statistics for dollar volume are similar.

for each stock for each trading day, and then averaged for each stock over each of the four windows. Cross-sectional averages for each window are reported. Average dollar depth, which is defined as the sum of the dollar depth at the ask plus bid divided by two, is also calculated using the same averaging procedure as is used for spreads. Dollar depth at the bid (ask) is equal to the bid (ask) quote times its corresponding depth in number of shares. Trading activity is measured by the daily number of trades (total and buyer- and seller-initiated), daily volume in numbers of shares, daily dollar volume (total, buyer- and seller-initiated and per trade), and using the same averaging procedure as for the spread measures. The average dollar value per trade provides information on level of aggressiveness of traders.

Throughout this essay, the pre-announcement window is used as the benchmark against which all other windows are compared. As noted earlier, one and three windows are compared against this benchmark for the samples of targets and acquirers, respectively. For percentage (level) variables like the proportional quoted spread (dollar quoted spread), a univariate test is conducted of the difference (ratio) of the estimated matched averages between (of) the window under study and the benchmark window. The univariate tests use the matched sample t-test and the Wilcoxon signed rank test of whether the mean and the median differences or ratios are different from zero or one, respectively. For the acquirers, a multivariate test of any difference in each liquidity and trade activity measure across the four windows for each firm is conducted.[27] The multivariate tests rely on the Wilks' lambda from a repeated ANOVA design, and the non-parametric Friedman test. Because of the size of the table, the differences or the ratios are not reported and only the significance level is reported for the multivariate statistics by appending them to the mean (median) statistics for the parametric (non-parametric) tests. For the multivariate tests, these appear under the first column of each variable that is related to the pre-announcement or benchmark window.

[27] Multivariate is related to our use of four windows for acquirers, which corresponds to four repeated samples. The univariate test refers to the unique sample formed by matching the event windows two by two. In all our analysis, the variables are examined separately.

3.3.1 Changes in liquidity and trading activity for the targets

The cross-sectional averages for each of the two windows are reported in table 11 for the targets, where panels A and B relate to NASDAQ- and NYSE-listed stocks, respectively. The spread measures for targets decrease dramatically after acquisition intentions are announced. For NASDAQ-listed targets, the mean quoted spread decreases from 17 to 11 cents, and the median from 13 to 8.7 cents. For NYSE-listed targets, the mean quoted spread decreases from 13.3 to 9.9 cents, and the median from 11.8 to 9.2 cents. The ratio of the average quoted spread during the announcement to pre-announcement window is tested using the matched sample t-test and the non-parametric Wilcoxon signed rank test. The hypothesis of constant quoted dollar spreads around the announcements of acquisition intentions is strongly rejected. For example, for NYSE listed targets, the average ratio of 0.748 is significantly below one.

[Please insert table 11 about here.]

Since proportional spreads relate trading costs to traded value, they are more relevant for traders than quoted spreads. Because the literature reports that on average targets enjoy abnormal returns that materialize over the announcement window, the expectation is that the per-dollar spreads drop given our result that dollar spreads decrease. In accordance with this conjecture, we find that the mean and median proportional quoted spreads decline on average from 3.0% and 2.3% to 1.8% and 1.1%, respectively, for the full sample of targets. The differences between the averages during the announcement and pre-announcement windows for each target are tested. As reported in panel B of table 11, the mean and median proportional spreads drop from 1.2% and 0.6% to 0.8% and 0.4%, or by a strongly significant -0.4% and -0.2%, respectively.

Unlike the quoted spread, the effective spread better reflects trades that occur inside or outside the posted quotes. The unsigned effective spreads also fall around the announcement period for NASDAQ-listed targets. Based on panel A of table 11, the mean and median effective spreads fall from 14.6 and 11.7 cents pre-announcement to 9.6 and 7.1 cents, respectively, in the announcement window. The weighted effective spreads for NASDAQ-listed targets decrease significantly on average from a mean and median of 14.8 and 11.7 cents to 9.7 and 7.5 cents, respectively. In contrast, the mean dollar and weighted effective spreads for NYSE-listed targets increase significantly at the announcement date. These results appear to be induced by outliers since the medians for the effective and weighted effective spreads decrease significantly from 8.1 and 10.4 cent to 7.8 and 9.1 cents, respectively.

As for quoted spreads, the expectation is that the proportional (weighted) effective spread will fall. For the NASDAQ-listed targets, the per-dollar effective spread falls significantly from a mean and median of 2.6% and 2.1% to 1.6% and 1.0%, respectively. These numbers are identical for the weighted counterpart. For the NYSE-listed targets, the mean and median proportional unweighted and weighted effective spreads decrease significantly by the same 20 and 10 basis points, respectively, as is reported in panel B of table 11.

The mean and median depths move from $7,608 and $5,041 to $65,997 and $22,685, respectively, for NASDAQ-listed targets. Similarly, both the mean and median depths for NYSE-listed targets increase significantly. Thus, the liquidity of target stocks increases tremendously during the acquisition intention announcement window compared to that for the pre-announcement window.

As expected, the enhanced liquidity is accompanied with a marked increase in the trading volumes for the targets during the announcement window. The mean and median numbers of daily trades increase significantly and dramatically from 319 and 66 to 990 and 337, respectively, for the NASDAQ-listed targets. The same conclusion is reached for the NYSE-listed targets.

To rule out the possibility that these increases are caused by a reduction in trade size, the total daily volume and the average volume per trade also are examined. Both the dollar and the number of share measures of volume indicate an increase regardless of the listing venue of the target. For example, the mean and median daily number of shares increase from 241,841 and 77,173 to over 1.5 million and 622,033 shares, respectively, for the NASDAQ-listed targets. A similar pattern is found for the NYSE-listed targets. With regard to daily volume, the mean and median move significantly from 8.4 and 0.3 million dollars to 45.1 and 5.2 million dollars, respectively, for NASDAQ-listed targets, and from 11.8 and 2.9 to 98.0 and 29.5 million dollars, respectively, for NYSE-listed targets. Although the relative increase is higher for NASDAQ-listed targets, these statistics show that the average NYSE-listed target is traded more than the average NASDAQ-listed target for both the pre-announcement and announcement windows.

For both trade venues, the average dollar value per trade increases for the announcement window. The mean and median per trade value increase significantly from \$8,069 and \$5,194 to \$18,640 and \$10,859, respectively, for NASDAQ-listed targets, and from \$29,099 and \$23,981 to \$85,690 and \$62,591, respectively, for NYSE-listed targets. Therefore, the significant increase in the dollar volume is the result of a significant increase in both the traded number of shares and in the average dollar value per transaction. Brennan and Subrahmanyam (1998) argue that average trade size is inversely related to trading cost components, and therefore to total trading costs as measured by the bid-ask spread in a strategic trading framework. Our findings provide empirical support for such a negative relation.

Volume also is classified based on the direction of trades using the classification algorithms discussed earlier. We report and discuss only the results based on the Lee and Ready algorithm based on a two second time lag since the results from other models are similar. Like total volume, buyer- and seller-initiated volume, as measured by number of trades, number of shares or dollar volume, increase dramatically from the pre-announcement to the announcement window for the targets both differentiated and undifferentiated by listing venue. Specifically, the mean and median numbers of buyer-initiated trades increase from around 163 and 29 to 464 and 142 for NASDAQ-listed targets, and from 129 and 69 to 287 and 172 for NYSE-listed targets. The mean and median numbers of seller-initiated trades increase significantly from 156 and 36 to 526 and 195, respectively, for NASDAQ-listed targets, and significantly from 112 and 58 to 379 and 242, respectively, for NYSE-listed targets. The increase in the number of seller-initiated trades is higher than that for buyer-initiated trades for the announcement window. This also is the case for the other trading variables such as the daily dollar volume. The increase in the seller initiated trades is well above that observed for buyer initiated trades for both NYSE and NASDAQ-listed targets.[28]

These results are puzzling at first since they suggest that investors are more inclined to sell their holdings with the announcement of the acquisition. Black (1986) provides two motivations for traders to transact individual assets; namely, private information or noise. Because investors can adjust their portfolios using other instruments, they are unlikely to trade specific assets to rebalance their portfolios based on firm-specific events. O'Hara (2003) argues that informed and uninformed (noise) investors hold different portfolios which may lead them to adjust the component assets in their portfolios differently. Therefore, investors are likely to differ on their choice of whether or not to realize any event-related abnormal gains after such gains materialize. Thus, once the price of the target stock increases after announcement, its relative weight increases in the portfolio of each shareholder, and some investors will adjust their holdings back towards their target weights by selling part of their holdings.

Baker and Svaşoglu (2002) argue that shareholders of the target firm will sell part of their shares, as there is a non-zero probability that the transaction may not materialize. This risk leads the more risk averse of these shareholders to depose of part of their holdings and to park the resulting proceeds in a safer investment. Hence, some selling pressures exist that may restrict the price from fully reflecting the newly released information. As a result, some abnormal profits are possible by buying the shares being sold by these shareholders. Using the limited arbitrage

---

[28] Several signing algorithms are used to test the possibility that our statistical findings are due to mis-signing trades. The first potential source of mis-signing is caused by error in the determination of the relevant prevalent bid-ask quotes, which is addressed herein by using both a two and a five second lag. The second potential source of incorrect signing is with trades that occur inside or outside the quotes. This is addressed by using both the Lee and Ready, and the Ellis et al. algorithms. We observe a cluster of outside quotes on the morning following the announcement of the event when the event is announced overnight. However, these trades always take place at a price higher than the ask quote and the previous day close. Therefore, these are classified consistently as buyer-initiated trades by both algorithms.

argument of Shleifer and Vishny (1997), Baker and Svaşoglu (2002) find that arbitrageurs can realize a positive arbitrage profit of up to 0.9%.[29]

The entire sample of targets is also differentiated by the method of payment; namely, cash, shares, hybrid of cash and shares, and other. In this essay, the analysis and discussion focuses on only the cash and share methods of payment.[30] Globally, the same conclusions are reached for the targets differentiated by method of payment as reported earlier for the targets undifferentiated by method of payment for both listing venues. Both sub-samples differentiated by method of payment experience higher liquidity, as shown by lower trading costs and higher quoted depths, and higher trading activity, as measured by greater numbers of trades, numbers of shares traded and dollar traded value.

The first noteworthy difference is that the targets offered share consideration do not experience significant changes in effective spreads (proportional and weighted) for the intention to acquire announcement window. Second, the change in all the other variables (except buyer-initiated trades) is amplified for the targets offered cash payment versus those offered share payment for both NYSE- and NASDAQ-listed stocks. For example, the mean and median depth ratios are significant 16.69 and 7.35 and 3.26 and 2.27 for NYSE-listed targets offered cash and share payment, respectively. The contrast is even bigger for the NASDAQ-listed targets, where the mean and median depth ratios are significant at 21.60 and 12.42, respectively, for cash payment and 2.71 and 1.96, respectively, for share payment. The mean ratios for the number of buyer-initiated trades for NASDAQ-listed targets are a significant 5.44 and 6.86 for cash and share payment, respectively. Similar results are found for the ratios for NYSE-listed targets but significance is only obtained for the medians. These results indicate that investors sell the target stock more frequently right after the announcement of the tender offer, especially when cash

[29] This arbitrage is different in nature to that reported by Mitchell, Pulvino and Stafford (2004) where arbitrageurs buy targets and short sell acquirers. However, Mitchell et al only investigate selling pressure on acquirers around the pricing date.

[30] The transaction is reclassified as cash payment when the deal is not related to the share price of the acquirer.

payment is offered. Since the literature reports that targets receiving cash payment enjoy higher positive abnormal returns, our findings are consistent with our conjecture that traders lock-in their gains post-announcement by selling some or all of their holdings of the target.

3.3.2 Changes in liquidity and trading activity for the acquirers

The cross-sectional averages for each of the four event windows are reported in table 12 for the acquirers, where panels A and B relate to NASDAQ- and NYSE-listed acquirers, respectively. Based on a preliminary review of table 12, the number of significant results is proportionally lower for acquirers than for the targets. Moreover, while most of the results for the targets were significant at the 1% level, most of the significant results for the acquirers are only significant at the 5% or 10% level.

[Please insert table 12 about here.]

The mean dollar quoted spread does not change significantly while the median dollar quoted spread decreases significantly for NASDAQ-listed acquirers. This behavior also occurs for the two sub-samples differentiated by method of payment. Similar inferences are reached for the percentage quoted spread and the effective spread (both dollar and per dollar). For the weighted effective spread, no significant differences occur between any of the event windows. The decline in the quoted spread is statistically confirmed more robustly for NYSE-listed acquirers. Only the mean posted spread during the benchmark window of 11.2 cents changes (decreases) significantly. Both the mean and median drop to 9.0 and 8.0 cents, respectively, for the effective date window. The downward slide continues during the post-effective window where the mean and median reach 8.3 and 7.2 cents, respectively. The same patterns are also found for the effective dollar and per-dollar spreads.

Unlike the case for the targets, quoted depth is reduced for both NYSE- and NASDAQ-listed acquirers. The mean and median dollar quoted depth of $12,867 and $9,094 during the pre-announcement window for all NASDAQ-listed acquirers fall over the following three event windows. The mean and median depths drop to $12,670 and $8,886 during the announcement window although only the change in the median is significant. The mean and median depths drop further to $11,686 and $8,833, respectively, for the effective date window, with the changes in both being significantly different from their values in the pre-announcement window. The depth decreases further for the post-effective window where the mean and median reach $10,835 and $8,572. The same pattern is also observed for the NYSE-listed acquirers. The results differentiated by method of payment indicate that the downward trend in depth is due mainly to acquisitions involving share payment for NASDAQ-listed acquirers, and to acquisitions involving both methods of payment for NYSE-listed acquirers.

This decline in depth cannot be explained by information flow. Usually, upon the arrival of major news that is ambiguous (as is the case for a tender offer announcement made by the acquirer), market makers reduce depth to facilitate price discovery for themselves and to protect themselves against adverse price moves. Therefore, the expectation is that depth will decrease around the announcement, and then return to its previous level after all information is released. A possible explanation for the decrease in quoted depth may be the decrease in stock price related to the well-documented negative abnormal returns accruing to acquirers following acquisition. To test for that, depth as measured by number of shares also is investigated. The mean and median depth for NYSE-listed targets of 2763.03 and 1762.74 shares for the pre-announcement window change insignificantly to 2654.81 and 1695.61, respectively, for the announcement window. The mean and median depths of 2051.09 and 1332.35 for the effective date window are both statistically lower than the values for the pre-announcement window. The mean and median depths of 2654.81 and 1696.61 for the post-effective day window are even lower, and significantly different than the corresponding values for the pre-announcement window. Tests of differences over the four windows find that the differences are significant (specifically, the p-values are 0.0000 for both the repeated measure ANOVA that corresponds to an F-value of 8.76 and for the Friedman Chi-square statistic of 81.42).

The intertemporal behavior of depth differs for the NASDAQ-listed acquirers. The mean and median depth as measured by number of shares of 740.49 and 625.11 for the pre-announcement window change (increase) not significantly to 757.28 and 627.53, respectively, for the announcement window. Thereafter, the mean (not median) depth increases slightly but significantly. For example, the mean depth becomes 1.12 during the post-effective window. Since the depth measured in terms of number of shares either increases or stays constant after announcement of the tender offer, we conclude that a lower price level due to a decline in value causes the reduction in dollar depth for NASDAQ-listed acquirers. We provide evidence for such negative returns later in the essay.

While marked and significant changes occur in trading activity for targets, such is not the case for the acquirers. To illustrate, the median (and not mean) number of trades and number of shares change (increase) significantly for NASDAQ-listed acquirers. However, since neither the mean nor median dollar volume change significantly post-announcement, the average trade size must have decreased for the dollar volume to stay stable. The results of the univariate Wilcoxon signed rank test confirm this, and the Friedman test results also indicate that average trade size is not constant across the four windows for buyer- and seller-initiated trades and trades not so differentiated. The findings for NYSE-listed acquirers are similar.

The analysis of buyer versus seller initiated trades shows that the sharp contrast in such differentiation that was found for the targets is not extended to the acquirers. In most cases a moderately significant change according to one statistical test is not confirmed by the second statistical test. To illustrate, the number of buyer initiated transactions for NASDAQ-listed acquirers shows no significant change in the mean and a significant increase in the median which is entirely due to cash acquirers. The dollar buyer initiated volume shows no change in the mean and median. The NYSE results show a mild increase, as in the NASDAQ number of buys. For the seller initiated transactions, the same conclusions are reached. Both the number of sales and their dollar value increase upon announcement and effective date for the NYSE-listed acquirers for both cash and share acquirers. Mitchell, Pulvino and Statfford (2004) relate the increase to selling pressure from arbitrageurs that have a short-term impact on the stock price because of a downward sloping demand curve.

3.4. Changes in Limit Orders for Targets and Acquirers

Changes in limit order execution are analyzed in this section to further investigate the change in liquidity. Limit orders can be considered as the competitor of the specialist on the NYSE and of dealers on NASDAQ where limit orders are executed first based on price and time preference. By supplying depth at various price levels, limit orders expand the order book and enhance liquidity through added depth. In contrast, market orders reduce liquidity by matching already submitted orders and thus reducing the market depth where it is needed most, i.e., at the inside spread.

Chung, Van Ness and Van Ness (1999) find that limit orders represent a large proportion of the posted quotes for the NYSE. Glosten (1994) formulates a model where limit order traders gain from temporary price changes caused by liquidity orders and lose from permanent price changes caused by informed traders. Foucault (1999) develops a theoretical model for limit orders and finds that the volatility of the traded asset is the main determinant of the mix between market and limit orders. His conclusions and empirically testable hypotheses are (i) the proportion of limit orders in the order flow is higher with higher volatility, and (ii) the fill rate of the limit orders is lower for higher volatility. Handa and Schwartz (1996) explain that traders find it profitable to place limit orders when transitory order imbalance happens and short run volatility increases. Ahn, Bae and Chan (2001) confirm these findings using data on the Hong Kong Stock Exchange, where limit orders cluster around bids (asks) when the increase in transitory volatility is caused by trading at the bid (ask). Kavajecz (1999) finds that both the specialist and limit order traders reduce the depth around information events to protect themselves against informed traders. They also may adjust the depth on only one side when they believe that informed traders are present.

Given the absence of access to the order book or data on limit orders submitted or cumulated, limit order execution is inferred herein by using the Greene (1997) algorithm.[31] This involves the tracking of successive quotes where the posted bid and ask are the same and only the depth falls. All trades that occur at bid (ask) between the two successive quotes are then tracked. Up to the fall in the depth, the assumption is that the volume traded is exercised against limit buy (sell) orders.[32]

The frequencies of executions against limit orders classified by limit type (i.e., buy or sell), trading venue (i.e., NASDAQ or NYSE) and method of payment (i.e., cash or shares) for the targets are reported in table 13. To control for the surge in trading activity upon announcement of a tender offer reported in the previous section, the execution against limit orders is investigated as a fraction of the total trading volume. Panels A and B report the proportions for the NASDAQ- and NYSE-listed targets in each table. Limit order execution is investigated by two trading activity measures; namely, number of trades and number of shares.[33]

[Please insert table 13 about here.]

---

[31] Biais, Hillion and Spatt (1995) analyze the limit orders on the Paris Bourse, which is a pure limit order market. Sandas (2001) investigates limit orders on the Stockholm Stock Exchange for 10 stocks using the electronic order book. Lo, MacKinlay and Zhang (2002) use data on limit orders from the trading desk at ITG. Ahn et al (2001) investigate the limit orders of the 33 stock of the Hang Seng Index on the Hong Kong Stock Exchange, which is similar to the Paris Bourse in that it is a pure limit order market. Kavajecz (1999), Chung, Van Ness and Van Ness (1999), Kavajecz and Odders-White (2001) and others use the TORQ database, which contains orders handled by the SuperDOT system only for the period November 1990 to January 1991. While the Greene algorithm will not result in the limit order book nor the exact execution against the limit orders, it does to some extent capture trading against limit orders, as noted in Easley, O'Hara and Saar (2001).

[32] For a full description of the algorithm, see Greene (1997). A major difference with the original algorithm is that only successive quotes where both posted bid and ask are the same are considered herein. This isolates any specialist intervention that causes a change in one quote. In contrast, if the second quote has a different bid price, then the assumption in the original Green algorithm is that trades that occur in between the two successive quotes at the first bid quote are executed against bid limit orders. This difference leads to a lower frequency in execution against limit orders.

[33] Dollar value of limit order executions also is examined but not reported herein because the results for this measure are similar to those for number of shares.

Based on table 13, the mean executions against limit orders is 9.91% and 12.35% of total executions for NASDAQ- and NYSE-listed targets, respectively. Limit order executions increase at both the bid and ask for the NASDAQ-listed targets. The mean and median proportions of executions measured by number of trades against bid limit orders increase significantly from 5.35% and 4.83% of total executions pre-announcement to 10.52% and 8.92%, respectively, upon announcement. The mean and median executions against bid limit orders of 5.38% and 4.27% pre-announcement also increase significantly to 10.66% and 8.04%, respectively, upon announcement for NYSE-listed targets.[34]

The results are mixed and more ambiguous for executions against ask limit orders. The increase is small compared to that for bid limit orders for NASDAQ-listed targets. The mean and median executions against ask limit orders increase from 4.56% and 4.26% pre-announcement to 5.87% and 5.41%, respectively, during the announcement window. The change is even smaller for the number of shares. In contrast, the proportions of executions against offer limit orders decrease for NYSE-listed targets. Based on the number of trades, the proportions fall significantly from a mean and median of 6.97% and 6.91% pre-announcement to 5.46% and 5.05%, respectively, on announcement.[35]

To this point, the findings indicate that executions against bid limit orders increase and are inconclusive for ask limit orders for targets during the announcement window. The increase in the former may be due to traders who aggressively want to liquidate part or all of their holdings (the cash parking hypothesis) or to traders who place bids at higher prices in order to attract investors to sell. Both sides conform to the limited arbitrage theory of Baker and Svaşoglu (2002).

The target sample is next differentiated by both listing venue and method of payment. Executions against bid limit orders increase from a mean and median number of shares of 5.12%

[34] The result is similar for both listing venues when the number of shares measures trading.

[35] Based on the number of shares, the increase in the mean and median proportions are even smaller for NASDAQ-listed targets, and only the decrease in the median proportion is significant for NYSE-listed targets.

and 4.83% pre-announcement to 14.92% and 13.56% upon announcement, respectively, for NASDAQ-listed targets for cash payments. The corresponding means and medians for NYSE-listed targets are 5.71% and 4.51% pre-announcement and 14.38% and 12.02% upon announcement. On average, the proportion of executions against bid limit orders triples upon announcement of the tender offer, and this also applies to the use of number of shares or dollar volume as the measure of trading activity. A less pronounced increase occurs for acquisitions involving share payment for both trading venues. The mean and median proportions of executions against bid limit orders increase from a mean and median of 5.25% and 4.83% pre-announcement to 6.98% and 5.86%, respectively, upon announcement for NASDAQ-listed targets. Results for NYSE-listed targets are similar to those of the NASDAQ-listed targets. Thus, the increases are still significant but significantly lower in magnitude for both listing venues when the payment method is shares rather than cash, and this result is robust for alternate trading activity proxies such as number of shares and dollar value. In turn, this leads to the conclusion that the increase in the proportion of executions against bid limit orders for targets is driven primarily by acquisitions involving cash payment. As reported in the literature, target shareholders usually observe a higher increase in the value of their holdings when the method of payment is cash rather than shares. Therefore, there is a higher need to sell part of their holdings to realize the heightened capital gains associated with such tender offers in order to rebalance their portfolio holdings.

The proportion of executions against ask limit orders has a small and significant increase upon announcement for cash tender offers and no significant change upon announcement for share tender offers for NASDAQ-listed targets. The results indicate that no significant changes occur for cash tender offers, and a significant decline in limit order executions occurs for share tender offers for NYSE-listed targets.[36]

[Please insert table 14 about here.]

[36] This occurs when the number of trades and number of shares are used.

The frequencies of executions against limit orders classified by trade type (i.e., buy or sell), trading venue (i.e., NASDAQ or NYSE) and method of payment (i.e., cash or shares) for the acquirers are reported in table 14. The bid limit order executions drop upon announcement for both listing venues, and these results are robust to the proxy used for trading activity. For example, the mean and median proportions of execution bid orders to the total number of trades change significantly from 4.30% and 3.81% pre-announcement to 3.61% and 3.06%, respectively, upon announcement for the NASDAQ-listed acquirers. The same mean and median variable change from 4.30% and 3.82% pre-announcement to 3.80% and 3.63%, respectively, upon announcement for NYSE-listed acquirers. While most of the decline is realized at the announcement date for NASDAQ-listed acquirers, the decline is steady over the four windows for NYSE-listed acquirers. Furthermore, the change for acquirers is of a lower magnitude and in the opposite direction to that reported earlier for the targets.

A decline in the average number of trades also is observed for the acquirers differentiated by tender offer consideration. However, the evidence of decline based on the number of shares is weak. For example, only the decline in the mean (not median) number of shares post-effective window is significant for cash tender offers.

The average proportions of executions against ask limit orders drop post-effective date for both listing venues and for both volume proxies. For example, the mean and median proportions of executed sell limit orders in terms of number of trades change significantly from 6.39% and 5.99% pre-announcement to 6.04% and 5.86%, respectively, post-effective date for NYSE-listed acquirers. Only the fall in the mean (not median) proportion is significant for both volume proxies for the NASDAQ-listed acquirers. Furthermore, both multivariate tests support the change over the four windows. No significant changes are identified for the average proportions for the acquirers differentiated by method of payment.

In summary, the execution rate declines upon announcement for buy limit orders for acquirers but this drop is of a lower magnitude than the increase for targets. This evidence suggests that traders are not selling the acquirers at the announcement or effective dates as aggressively as they are selling targets. Similarly, the proportion of executions for sell limit orders falls marginally post-effective date for acquirers. No discernible change occurs in the proportion of executions against ask limit orders for acquirers.[37]

3.5. Changes in the Spread Components

In this section, the reasons for the drop in trading costs for the targets upon announcement are addressed. In the microstructure literature, bid-ask spreads are decomposed into several components; namely, order processing cost (Tinic, 1972), inventory holding cost (Garman, 1976; Stoll, 1978; and Ho and Stoll, 1981);[38] and information asymmetry (Bagehot, 1971; Copeland and Galai, 1983; Glosten and Milgrom, 1985; Kyle, 1985; and Easley and O'Hara, 1987). Following the literature, only two components of the bid-ask spread are estimated herein. The adverse information component is called the permanent or variable cost component due to its permanent impact on prices. The ordering processing and inventory cost component is usually referred to as the transitory, temporary or fixed cost component in the literature.

Van Ness et al. (2001) argue that measures of adverse selection from spread decomposition models weakly measure adverse selection. They also show that different models can produce different results. However, Clarke and Shastri (2000) find that these measures are related to other variables that proxy for information asymmetry, although these measures are not perfectly correlated. As result, several spread decomposition models are used to check the robustness of our results. The specifics for the five models used herein are presented in the appendix to this thesis. The models of Neal and Wheatley (NW) (1998), Masson (1994), Glosten and Harris (GH) (1988), Lin, Sangher and Booth (LSB) (1995), and Madhavan, Richardson and Rooman (MRR) (1997) are used herein.

---

[37] This does not prevent intensified buying activity since volume is increasing. Instead, the constancy is in the proportion of market buys against sell limit orders.
[38] Stoll (1989) reports that the inventory cost component is small compared to the other components.

3.5.1 Changes in the spread components for targets

The spread decomposition results for the NASDAQ-listed targets are reported in table 15. The table reports mean and median estimates of dollar temporary cost, dollar permanent cost, their proportional or per dollar counterparts, and the parameter π, which represents the proportion that temporary costs represents of total spread cost. Under each parameter, the left and right columns relate to the pre-announcement and announcement windows, respectively. The mean and median cross-sectional ratios of the dollar cost components for the two windows are tested if they differ from 1 using t- and Wilcoxon signed rank tests, respectively. The significance levels for these tests are noted in the announcement columns. For the remaining three parameters, the cross-sectional mean and median matched differences are tested to determine if they differ from zero using the same two tests.

[Please insert table 15 about here.]

The dollar temporary cost component declines upon announcement for the NASDAQ-listed targets. The LSB model gives the maximum mean dollar temporary cost component of 14.7 cents for the pre-announcement window. This component drops to 8.7 cents upon announcement, which represents a cross-sectional drop of 35.50%. The lowest drop of 26.69% (11.9 cents to 8.3 cents) is associated with the NW model. The decline is strongly significant for all models, except for the median for the Masson model. This general result also holds for both the cash and share method of payment sub-samples.

The decline in the temporary cost also occurs when method of payment is shares but is less pronounced. For instance, the estimate from the LSB model has the sharpest fall. Its mean and median dollar temporary costs drop from 14.7 and 12.4 cents pre-announcement to 9.7 and 8.5 cents upon announcement, respectively.

As reported in Table 16, the behavior of the dollar temporary component behaves differently for NYSE-listed targets. The change in the dollar temporary component upon announcement is not significant for the NW, GH and MRR model. The change is significant for the mean (8.5 to

7.4 cents) and not median for the LSB model, and is significant for the mean and median for the Masson model. The dollar temporary component changes significantly only for the Masson and MRR models when the targets are differentiated by method of payment. It decreases and increases for the cash and share methods of payment, respectively.

[Please insert table 16 about here.]

The permanent dollar component tends to drop upon announcement for NASDAQ-listed targets. The mean and median estimates from the NW and MRR models show significant decline, and only the median estimates from the other three models show significant decline. As an illustration of magnitude, the mean and median permanent cost decrease from 3.7 and 2.7 cents pre-announcement to 2.8 and 1.2 cents upon announcement for the MRR model.

The findings differentiated by method of payment for NASDAQ-listed targets are somewhat similar to those for the entire sample. For example, the mean and median permanent cost estimates from the NW model decline significantly from 4.8 and 3.1 cents pre-announcement to 2.0 and 1.0 cents upon announcement for cash methods of payment, which corresponds to a significant mean decrease of 45.76%. The corresponding decreases in the means and medians for the share method of payment are from 4.8 and 3.0 cents pre-announcement to 2.4 and 1.1 cents upon announcement. The decrease in the mean of 51.73% is significant.

The findings for NYSE-listed targets for all five decomposition models provide additional support for the decrease in the permanent trading cost component upon announcement. In some cases, the results are even stronger than reported earlier for the NASDAQ-listed targets. For example, the mean permanent cost estimate from the Masson model falls significantly from 5.8 cents to 3.3 cents. Similar conclusions are reached based on the NYSE-listed targets differentiated by method of payment. No evidence is found that the permanent cost increases upon announcement for all five models. With one exception, the evidence indicates very strongly that this measure declines upon announcement.

Therefore, the general conclusion from this set of findings is that the permanent cost remains unchanged or drops, and that the evidence for a drop is stronger for cash versus the share method of payment. This is consistent with our hypothesis that an acquisition announcement lowers the adverse selection problem by revealing the event. Since we do not capture to what extent the announcement is a surprise to the investing public,[39] we do not know whether the impact of the announcement on asymmetric information is already impounded in the bid-ask spread pre-announcement. Clearly, if the announcement is totally (un)anticipated, then it should have no (much) impact on the permanent component of the spread. Thus, our mixed results under some of the models are consistent with the belief that the average acquisition conveys some surprise.

The proportional trading cost components also are analyzed since the expectation is that the level of per-share price is likely to change upon announcement. Proportional trading costs are the relevant costs for traders as they relate the cost to the traded value. Based on an examination of tables 15 and 16, the decreases in both percentage cost components are significant. This result is robust for all five decomposition models, both listing venues and both methods of payment. The maximum and minimum mean percentage temporary cost estimates pre-announcement for NASDAQ-listed targets of 2.57% and 1.49%, respectively, are for the LSB and MRR models. These values decline to 1.39% and 0.81%, respectively, upon announcement. The highest and lowest decreases in the mean percentage temporary costs of 117.41 and 22.16 basis points (bps) occur for estimates from the LSB and Masson models, respectively. The declines in the percentage temporary cost estimates upon announcement from all five models are systematically higher for acquisitions involving cash versus the share method of payment. For example, for the Masson model, which yields the smallest percentage temporary cost estimates for all samples, the

[39] As noted in a previous section, the identification of announcement dates involved a backward search in time to find the first public notification of such. Therefore, all second announcements related to changes in the bid structure are ruled out. The purpose is to minimize prior market expectations, and thus, maximize any pure surprise to the market. Of course, this limits but does not eliminate the prior market expectations of the event.

decline of 33.14 bps upon announcement for the cash method of payment is significantly higher than the 14.67 bps decline for the share method of payment.[40]

The percentage temporary cost estimates from all five decomposition models drop upon announcement for NYSE-listed targets. Furthermore, the proportional temporary cost estimate is lower for each decomposition model for NYSE- versus NASDAQ-listed targets. This could suggest that the NYSE trading mechanism is more efficient in terms of order processing costs for acquisition targets. However, this also could be caused by the smaller average size of the NASDAQ-listed targets.

The highest (lowest) mean and median estimates of the per-dollar temporary costs pre-announcement are 0.77% (0.45%) and 0.39% (0.15%) for the LSB (MRR) models for NYSE-listed targets. Both decline upon announcement to 0.50% (0.27%) and 0.30% (0.13%), respectively. The drop upon announcement is again more pronounced for cash versus share tender offers. The decreases in the mean per dollar temporary cost estimates for cash and share methods of payment are 13.16 bps and 6.05 bps for the NW model, 29.45 and 7.12 bps for the Masson model, 14.68 and 4.42 bps for the GH model, 38.07 and 10.97 bps for the LSB model, and 16.82 and (non significantly different from zero) 1.59 bps for the MRR model.

As is the case for the percentage temporary cost, the decline in the proportional permanent cost exhibits greater significance and magnitude compared to the dollar permanent cost for the NASDAQ-listed targets. All five models document the drop in this proportional cost component. The largest drop in the mean and median proportional permanent cost from 0.78% and 0.53% to 0.33% and 0.17%, respectively, occurs for the NW model. The smallest average decline of 10.58 bps (2.57% to 1.39%) upon announcement is for the LSB model. As for the percentage temporary cost, the decline in the percentage permanent cost is greater for cash versus share tender offers. To illustrate, the NW model estimates that the proportional adverse information cost fall from a

[40] This result may be induced by the higher percentage temporary cost pre-announcement for cash tender offer targets.

mean and median of 0.80% and 0.66% to 0.26% and 0.17%, respectively, upon announcement for the cash method of payment, and from a mean and median of 0.75% and 0.44% to 0.38% and 0.19%, respectively, upon announcement for the share method of payment. The drops for the share payment method of 36.96 and 25.40 bps, respectively, are significantly lower than those for the cash payment method for all five decomposition models. The first instance of a drop in the per-dollar permanent cost being not significant occurs for NASDAQ-listed targets for the share payment method for the LSB decomposition model.

Table 16 shows that the fall in the percentage permanent trading cost for NYSE-listed targets using all five spread decomposition models is similar to that for the NASDAQ-listed targets reported earlier. Because of this similarity, we do not report the figures and leave it to the reader to verify our observation by examining table 16.

The temporary cost component as a proportion of total trading cost, or π, is examined next. The contribution of the permanent information cost component to total trading cost is given by $(1-\pi)$. An increase in π upon announcement indicates that the temporary cost component has decreased relatively less than the permanent cost component. As shown in tables 15 and 16, the change in π depends on the spread decomposition model used. For example, the pre-announcement mean and median π estimates for the NW model of 74.8% and 76.9% increase to 82.8% and 83.8%, respectively, upon announcement for NASDAQ-listed targets. In contrast, the π estimates decrease upon announcement for the other four decomposition models. For example, the mean and median π estimates from the Masson model fall significantly from 79.1% and 78.3% to 75.5% and 74.7%, respectively, upon announcement. In general, this implies that temporary costs fall faster than permanent costs upon announcement for NASDAQ-listed targets.

However, with one exception, π increases significantly upon announcement for NYSE-listed targets. The only exception is the insignificant change in the mean upon announcement for the MRR model. For example, the mean and median contribution of the temporary to total cost estimates from the LSB model increase from 67.8% and 68.6% to 81.8% and 83.0%, respectively, upon announcement.

Differences in firm-specific characteristics may be an explanation for the differences in the directional changes of the π estimates upon announcement for NASDAQ- and NYSE-listed targets. Since the former are smaller and less liquid, the order processing costs for the former are higher, as shown by their pre-announcement π estimates. For example, the temporary cost represents on average 70.1% and 46.3% of the total spread using the MRR model for NASDAQ- and NYSE-listed stocks, respectively. With the relatively greater increase in trade volume observed upon announcement on the NASDAQ, the gap between NYSE- and NASDAQ-listed targets shrinks in terms of relative order processing costs due to heightened trading. Thus, the fall of the temporary cost component has a higher impact even if the permanent cost component declines due to the release of news upon the announcement of the tender offer.

3.5.2 Changes in spread components for acquirers

The estimates for five parameters for the five spread decomposition models for NASDAQ- and NYSE-listed acquirers are summarized in tables 17 and 18, respectively. The first four columns refer to the pre-announcement window (left most), post-effective window, the announcement window, and the effective window (right most). The dollar temporary cost component declines after the tender offer announcement for NASDAQ-listed acquirers. To illustrate, the mean and median temporary trading cost estimates from the NW model fall from 13.4 and 10.8 cents pre-announcement to 11.9 and 9.3 cents upon announcement to 10.6 and 8.3 cents upon the effective date to 9.1 and 7.5 cents post-effective date. The change is significant over the four windows, and a similar change pattern occurs for the estimates from the other four models. The highest mean and median estimates of 15.4 and 11.5 cents pre-announcement are for the LSB model. The mean and median for the LSB models drop significantly over the three subsequent windows; namely, to 13.3 and 10.2 cents upon announcement, to 12.0 and 9.4 cents upon the effective date, and to 10.5 and 8.1 cents post-effective date.

[Please insert Tables 17 and 18 about here.]

Based on table 18, a similar but more ambiguous drop occurs in the temporary cost for NYSE-listed acquirers. The changes (drops) in the median estimates compared to the pre-announcement window are significant for all subsequent windows for the five models. For example, the median temporary dollar cost estimate from the NW model of 4.1 cents pre-announcement becomes 3.8 cents upon announcement, 3.1 cents upon effective date, and 3.0 cents post-effective date. The mean estimates are significantly lower for each of the three post-announcement windows compared to the pre-announcement window for only the LSB model, significantly lower for the announcement and effective windows for the Masson model, and significantly lower for the announcement and post-effective windows for the GH and MRR models. Most of the fall in the temporary cost component occurs during the effective and not announcement window.

The results are similar for the acquirers differentiated by method of payment. Based on table 17, the temporary component estimates for all five models fall after the acquisition for NASDAQ-listed acquirers. To illustrate, the median temporary costs for cash and share payment methods for the NW model fall significantly from 11.0 and 9.0 cents pre-announcement to 9.7 and 9.2 cents upon announcement to 9.3 and 7.6 cents effective date to 8.6 and 6.2 cents post-effective date. The change in the mean benchmarked to the pre-announcement date is significant only for the effective date for the share payment method, and only for the post-effective date for the cash payment method. The temporary cost mean estimates for cash and share payment methods for the Masson model fall from a mean of 18.8 and 12.1 cents pre-announcement to 17.7 and 10.1 cents announcement to 16.3 and 8.3 cents effective date to 13.8 and 7.4 cents post-effective date. Based on unreported univariate tests, most of the decline occurs in the post-effective window. The remaining three models yield similar results for the NASDAQ-listed acquirers.

The results are weaker for the permanent versus temporary cost component for NYSE-listed acquirers, which in general tend to decline as the tender offer acquisition cycle unfolds. The mean and median permanent cost estimates for the NW model drop from 4.1 and 2.5 cents pre-announcement to 3.1 and 1.7 cents post-effective date, respectively. The mean and median estimates from the GH model of 1.9 and 1.5 cents pre-announcement drop significantly to 1.5 and 1.2 cents post-effective date, respectively. The same conclusion occurs using the MRR model. Only the median estimates from the LSB and Masson models exhibit a significant decrease from the pre-announcement to the post-effective date window. Unlike the results presented earlier for targets, the permanent cost changes only after the realization and not the announcement of the acquisition. This is unexpected since this cost should be related to information. A possible explanation for this result is that we are only investigating tender offers, where the probability of deal completion is lower than for friendly board offers. For instance, there is a non-zero probability that a different bidder may counter offer at a higher bid price for tender offers, which, in turn lowers the probability that the first potential acquirer will ultimately be successful in acquiring the target.[41] Of course, this does not change the probability that a bidder will acquire the target ultimately. Therefore, only after the acceptance of the tender offer and the completion of the transaction is the news widely accepted.

The declines in the permanent cost estimates also are observed for the NYSE-listed acquirers, as can be see from table 18. The mean and median permanent cost estimates for the MRR model fall from 3.5 and 2.9 cents pre-announcement to 2.7 and 2.1 cents, respectively, post-effective date, and most of this fall occurs during the effective date window. Most of the decrease in the permanent cost component from the Masson and GH models also occurs during the effective date

[41] Although our sample includes the ultimate winning bidders, this should not influence the outcome, since the identity of the ultimate bidder is not known pre-announcement or upon announcement of the tender offer.

window. In contrast, the estimate for the NW model declines primarily during the announcement window. Thus, the inference drawn from this evidence is that the permanent trading cost component adjusts faster for NYSE- versus NASDAQ-listed acquirers.

The behavior of the permanent cost component for acquirers differentiated by method of payment is examined next. The evidence for a decline in the permanent cost component is weak for cash tender offers for NASDAQ-listed acquirers. While the mean and median estimates from the GH and NW models decline significantly, those from the Masson, LSB and MRR models exhibit no significant change. In contrast, the declines in the estimates for all models are significant for share tender offers. For example, the mean and median permanent cost component estimates for the NW model decrease from 2.5 and 1.5 cents to 1.5 and 1.2 cents, and most of the decline is observed during the effective date window.

The decline in the permanent cost identified for cash tender offers for NYSE-listed acquirers is smaller in magnitude than the decline for share tender offers. For example, the mean and median permanent cost estimates for the NW model for cash tender offers drops from 6.5 and 5.9 cents pre-announcement to 4.9 and 5.3 cents post-effective date, while the corresponding values for share tender offers are 7.6 and 7.6 cents pre-announcement to 5.3 and 4.4 cents post-effective date. Thus, the mean and median declines of 13.75% and 16.69% for cash tender offers are smaller than the mean and median declines of 28.05% and 38.27% for share tender offers. Similar comparative results are found for the estimates from the Masson, GH and MRR models. In contrast, the mean and median estimates from the LSB model increase from 3.0 and 2.3 cents pre-announcement to 3.4 and 2.5 cents post-effective date.

To summarize, the dollar permanent cost declines for acquirers, primarily on and after the acquisition effective date, and is higher for share versus cash tender offers. A possible explanation is that the announcement of a tender offer is not considered as bad nor good news for acquirers because if the acquisition is consummated it is likely to be value neutral for the acquirer. However, since accepted share tender offers are associated with negative abnormal returns in the empirical literature, the cost of the adverse information component drops upon offer acceptance. This is because the market interprets the share payment as a signal that the shares of the bidder are overvalued (Myers and Majluf, 1984).

The proportional cost components, which are adjusted to account for changes in the price level, also are reported for the NASDAQ- and NYSE-listed acquirers in tables 17 and 18, respectively. The decline in the temporary cost component is significant even after controlling for the per share price for both NASDAQ- and NYSE-listed acquirers. For example, the mean and median proportional temporary cost estimates from the NW model fall significantly from 1.07% and 0.72% pre-announcement to 0.95% and 0.57%, respectively, post-effective date for NASDAQ-listed acquirers. Except for the estimates from the LSB model, most of the decreases occur during the effective or post-effective date windows for NASDAQ-listed acquirers, and during the announcement date window for NYSE-listed acquirers. As noted earlier, the proportional temporary component adjusts faster for the NYSE- versus NASDAQ-listed acquirers, and is significant for both cash and share tender offers.

The proportional permanent cost component estimates from the LSB, GH and MRR models exhibit no significant change from the pre-announcement window for the NASDAQ-listed acquirers. The estimates from the NW and Masson models are mixed in that changes in the means are not significant while changes in the medians are significant. Therefore, there is some very weak evidence to support the notion that the decline in the dollar permanent cost is at least partially explained by a drop in the price level. If this is true, the expectation is that the impact is higher for share tender offers. The evidence supports this expectation. For example, the proportional permanent cost estimate from the GH model even increases upon announcement of the share tender offer. This is a puzzling result given that the dollar permanent cost decreases for the same model, which can only be reconciled by a decline in the per share price.

The time-series behavior of the proportional permanent cost differs for NYSE- versus NASDAQ-listed acquirers in that it falls for all five models and for both methods of payment.

However, as for NASDAQ-listed acquirers, NYSE-listed acquirers using share tender offers experience the most dramatic change in this cost measure. For example, the mean and median drop in the proportional permanent cost estimates from the MRR model are 2.88 and 2.60 bps from the pre-announcement to post-effective windows. The mean and median fall rates for share tender offers of 5.29 and 4.91 bps, respectively, are significantly higher than those for the corresponding cash tender offer sample. The mean and median declines in the estimates from the LSB model for the proportional permanent cost of 3.96 and 2.35 bps for cash tender offers and 5.49 and 6.22 bps for share tender offers are all significantly different from zero. Only the differences in the mean proportional cost estimates from the NW model for cash and share tender offers (7.42 bps and 7.34 bps, respectively) are not significant. This reinforces our prior conclusion that share tender offers are more informative about the bidder in that it conveys negative news. In turn, this reduces the adverse selection trading cost for acquirers using share tender offers.

3.6. Trading Intensity and Changes in Information Trading

To further test the robustness of our results about noise and informed trading obtained in the previous section from the five bid-ask spread decomposition models, the EKOP model of Easley, Kiefer, O'Hara and Paperman (EKOP 1996) is now estimated. In this trading model, which is developed in full in the appendix, the spread is due to information asymmetry between informed traders and the market maker. The arrival intensity parameters and the probability of informed trading are obtained by maximizing the logarithm of the likelihood function given by:

$$L\langle (B,S) | \Theta \rangle = \prod_{i}^{I} \left[L\langle (B_i, S_i) | \Theta \rangle \right] \tag{7}$$

where B_i and S_i are the number of buyer- and seller- initiated trades on day i, respectively, and

$L\langle (B_i, S_i) | \Theta \rangle$ is the likelihood of observing B_i buys and S_i sells on day i conditional on the information set Θ.

This likelihood includes the probability α that an event occurs at the beginning of day i, that δ is the probability conditional on this occurrence that the event has a negative impact, and that μ and ε are the intensities of trading by informed and uninformed traders, respectively. These last four trading parameters are estimated for each target and acquirer for pre-announcement and for post-effective periods of 60 trading days each.

3.6.1 Trading intensity and changes in information trading for targets

The EKOP parameter estimates for the NASDAQ- and NYSE-listed targets are reported in panels A and B of table 19, respectively.[42] A cautionary note before we analyze these findings. Since the parameters are inferred from the observed number of trades classified as buyer- and seller-initiated, misleading inferences can occur if the number of one trade type is not related to information. Earlier it was documented that seller-initiated trades increase upon announcement. We offered two explanations that are unrelated to the future cash flows or risk level of the targets. The first explanation, which is based on the behavioral finance literature, states that positive quasi-arbitrage profits are available to dealers because investors only sell part of their shares and the market under-reacts to the announcement because of selling pressure. The second explanation is that investors may decide to sell some of their shares to re-balance their portfolios due to the unexpected increase in the value of their holdings in the target.

[Please insert table 19 about here.]

[42] EKOP and Easley, O'Hara and Saar (2001) estimate and fit models similar to the one used here using NYSE data. They argue that the NYSE trading mechanism better conforms to the assumptions of the model since the model is based on changes in quotes by a specialist who sets bid and ask prices based on the order flow. Thus, care must be exercised when the model is used for NASDAQ-listed targets and acquirers. However, after the opening, both markets are somewhat similar in terms of handling order flow since the NYSE specialist faces competition from limit orders. Also, like all microstructure models, the EKOP model does not capture all of the complexities of price formation and order handling mechanisms. For example, depth plays no role in the EKOP model while depth adjustment is an important tool used by both dealers and specialists to better align prices and quotes to reflect the "true" market price.

The results are in complete accordance with our expectations. First, α or the probability of event arrival increases upon announcement. This probability increases from a mean and median of 44.5% and 36.2% pre-announcement to 61.4% and 66.7%, respectively, upon announcement for NASDAQ-listed targets. The mean and median probabilities for NYSE-listed targets change significantly from 38.6% and 35.7% pre-announcement to 53.2% and 33.3%, respectively, upon announcement. Furthermore, for NASDAQ-listed targets, the change due to announcement is more pronounced for cash tender offers, and is only significant for the median change for share tender offers.

The average δ parameter (particularly, the median) increases dramatically upon announcement.[43] The mean probability that the event is "bad" increases from 53.3% and 38.6% pre-announcement to 68.6% and 66.1% upon announcement for the NASDAQ- and NYSE-listed targets, respectively. This parameter increases from 54.6% and 45.6% pre-announcement to 87.1% and 78.0% upon announcement for cash tender offers by NASDAQ- and NYSE-listed targets, respectively. The corresponding changes in this parameter for share tender offers by NASDAQ- and NYSE-listed acquirers are more modest; namely, from 50.3% and 22.6% pre-announcement to 53.3% and 52.1%, respectively, upon announcement. As noted earlier, we believe that this parameter is only capturing changes in trade direction intensity.

The trading intensity parameters μ and ε (i.e., the trading intensities of informed and uninformed investors as measured by number of trades) are of primary interest herein. Both parameters increase dramatically upon announcement for NASDAQ-listed targets. Conditional on

[43] The median δ parameter around the announcement window is almost one for the announcement window for cash tender offers. This means that, conditional on the arrival of an event, we are sure that the event is negative. Several potential rationales are offered to explain this result. The first is the limited number of days (3) used in estimating the parameters for the announcement window. As noted by EKOP, since the estimate for each day is either zero or one, a clustering of the estimates at either of these two values can be observed. The same critique applies to the α parameter. Using a time frame of five days gives the same results and increasing the window's length leads to the loss of focus on the event. The second possible rationale is that δ equals one for many targets because of the disproportionate number of seller-initiated trades that biases the median towards one. Since the mean is much lower, we place greater reliance on the mean even if the median yields the same inferences.

information arrival, the informed trading intensity significantly increases from a daily 57.24 trades pre-announcement to 139.47 trades upon announcement. The corresponding numbers for the uninformed are significant and are a daily 149.56 and 465.55 trades, respectively. Thus, trading intensity increases relatively more for the uninformed versus the informed. As is evident from panel B of table 19, the results are similar for NYSE-listed targets, since both the mean μ and ε increase from 95.53 to 560.85 and from 107.93 to 294.87 daily trades, respectively, upon announcement. A few outliers cause the higher increase in uninformed trading. Thus, the median ratios for the increases in μ and ε are almost identical at 2.51 and 2.85, respectively, for the informed and the uninformed trading intensities, respectively. The increase in informed trading intensity is lower for share versus cash tender offers for NYSE-listed targets. Specifically, the mean and median ratios of the changes in informed trading intensity are 11.88 and 3.03 for cash tender offers, and only 2.74 and 1.88 for share tender offers. Since no significant differences exist in the ratios of the trading intensities of the uninformed, cash tender offers are more informative than share tender offers for targets.

The last parameter of interest is the probability of informed trading, which is given by:

$$\text{PIN} = \frac{\alpha\mu}{\alpha\mu + 2\varepsilon} \tag{8}$$

The numerator of equation (8) measures the expected number of trades by the informed, and is equal to the probability of event occurrence multiplied by trading intensity, as measured by the number of trades conditioned on event occurrence. The denominator is total trading activity (informed and uninformed). In the denominator, the trading intensity of the uninformed is equal to two times the parameter ε, since the uninformed are equally likely to buy or sell at a rate of ε at all times. Once again, the estimates for PIN need to be interpreted with caution since they are dependent on other estimates.

Previously, we reported increases in both α and μ, which imply that the expected trading volume of the informed should increase after announcement. Whether the observed increase in ε

offsets or even exceeds the increase in informed trading volume is of interest. If it does not, then the expectation is that PIN will increase. Otherwise, the expectation is that PIN will decrease.

The results for the change in PIN for the targets are mixed. The probability of trading against an informed trader declines from a mean and median of 23.8% and 25.0% pre-announcement to 19.8% and 20.4% upon announcement, respectively, for NASDAQ-listed targets. The decline is due mainly to share tender offers where the PIN declines from a mean and median of 21.7% and 21.5% to 17.3% and 18.1%, respectively, over the same event windows. The opposite change is found for NYSE-listed targets where the probability of informed trading actually increases from a mean and median of 15.4% and 15.1% pre-announcement to 18.9% and 17.3% upon announcement, respectively. In this case, the increase is caused by cash (and not share) tender offers, where the mean and median PIN increase significantly from 18.4% and 17.8% pre-announcement to 24.3% and 27.5%, respectively, upon announcement.[44]

3.6.2 Trading intensity and changes in information trading for acquirers

The EKOP parameters estimates for the NASDAQ- and NYSE-listed acquirers are reported in panels A and B of table 20, respectively. The α estimates change significantly for the effective (not announcement) window for NASDAQ-listed acquirers. The mean α estimate increases from 54.1% pre-announcement to 61.5% effective date. The increase is due to the share tender offers since the change for the cash tender offers is not significant. The mean and median α estimates also increase from 43.8% and 40.0% pre-announcement to 48.5% and 45.7%, respectively, post-effective date for the NYSE-listed acquirers. The increases in the α estimates are significant for both types of tender offers for the NYSE-listed acquirers. However, the increase in α is only temporary upon announcement since it reverts back to its pre-announcement value post-effective date. The mean and median probabilities of event occurrence move from 45.9% and 43.7% pre-

[44] The corresponding changes for share tender offers are not significant.

announcement to 67.1% and 66.7% upon announcement to 65.4% and 66.7% effective date to 47.1% and 45.2%, respectively, post-effective date.

[Please insert table 20 about here.]

The δ estimates, which relate to the probability that the event is unfavorable news, behave differently for NASDAQ- and NYSE-listed acquirers. While δ falls significantly for NYSE-listed acquirers, no significant change occurs for NASDAQ-listed acquirers. The mean and median δ fall from 28.6% and 21.3% pre-announcement to 21.4% and 15.7%, respectively, post-effective date for the NYSE-listed acquirers. A similar decline occurs for both payment types of tender offers for the NYSE-listed acquirers.

Based on the μ estimates reported in table 20, informed trading activity intensifies after the announcement, and the increase is more pronounced for NYSE-listed acquirers. The mean (not median) informed trade intensities increase for both the announcement and effective dates relative to their pre-announcement values for NASDAQ-listed acquirers. The mean number of daily transactions by informed traders moves significantly from 69.88 pre-announcement to 146.45 and 143.11 for the announcement and effective dates, respectively. The increase in these μ estimates is temporary since the values revert back to their pre-announcement levels thereafter. Both types of tender offers display a similar behavior for the NASDAQ-listed acquirers. Specifically, the daily mean number of informed trades moves from 68.12 pre-announcement to 113.41 on the announcement date to 57.86 on the effective date for cash tender offers, and from 77.64 to 197.90 to 61.69 for the same windows for the share tender offers.

In contrast, the average μ increases for NYSE-listed acquirers. The mean and median number of daily informed trades increases significantly from 106.22 and 74.13 pre-announcement to 113.63 and 92.55, respectively, on the effective date. The mean and median increase rates are a significant 27.0% and 12.3%, respectively. The results upon announcement and completion are mixed. The mean increases to 114.33 and 118.34 on the announcement and effective dates, respectively, while the median decreases significantly to 67.33 and 62.80 for the same two dates. A similar time-series behavior occurs for both types of tender offers for the NYSE-listed acquirers.

The second intensity term ε, which is related to uninformed trading, increases on the announcement and effective dates. The mean and median ε increase from 736.76 and 101.70 daily trades pre-announcement to 842.15 and 136.00 daily trades on the announcement date to 914.20 and 127.99 daily trades on the effective date to 794.92 and 144.37 daily trades post-effective date, respectively, for NASDAQ-listed acquirers. Similarly, the mean and median ε move from 282.54 and 115.35 daily trades pre-announcement to 342.95 and 137.33 daily trades on the announcement date to 370.23 and 147.40 daily trades on the effective date to 359.70 and 156.53 daily trades post-effective date, respectively, for the NYSE-listed acquirers. Both multivariate tests strongly show that the estimates are different across the four event windows. A significant difference between uninformed trading intensity exists based on the type of tender offer for NASDAQ- and not NYSE-listed acquirers. The average trading intensity is almost 100 percent higher for share versus cash tender offers for NASDAQ-listed acquirers.

The last parameter of interest is PIN or the probability of trading against an informed trader. For the reasons discussed earlier, the expectation is that PIN will decline as the acquisition process advances. The mean and median PIN decline significantly from 16.1% and 18.2% pre-announcement to 13.5% and 14.5%, respectively, on the announcement date for NASDAQ-listed acquirers. The decline is driven mainly by the significant decline in cash (not share) tender offers, whose mean and median PIN fall from 17.8% and 18.4% pre-announcement to 15.5% and 15.9% post-effective date, respectively. Neither the mean nor median PIN changes significantly over the various event windows for NYSE-listed acquirers. The mean PIN of NASDAQ- and NYSE-listed acquirers of 13.5% and 13.1%, respectively, are not significantly different after the effective date. However, during the pre-announcement period, the mean PINs of 16.1% and 12.8% for NASDAQ- and NYSE-listed acquirers pre-announcement are significantly different.

3.7. Relation Between Abnormal Returns and Changes in Information Asymmetry

In this section, we assess if the abnormal returns associated with acquisition can be explained by changes in private information content, as derived from the order flow and inferred from the trading cost components. Abnormal returns should reflect any previously private information revealed through public announcement. If most of the information is a surprise, then a positive relation should exist between the sudden decline in information asymmetry through public dissemination of the acquisition event and abnormal returns. If information leakage occurs, then the decline in information asymmetry should be gradual, and its impact on prices should also be gradual.

Two measures of information asymmetry are used in this section of the essay; namely, the proportional permanent cost from the LSB spread decomposition model, and the PIN measure as estimated by the EKOP model. Abnormal returns are obtained from a dual beta market model. Wiggins (1992) finds that stocks with high (low) historical betas have higher (lower) betas during up than down markets. Bhardwaj and Brooks (1993) use a dual bull and bear beta model to explain the size effect. Howton and Peterson (1998) find a strong beta-return relation even in the presence of Fama and French (1993) factors. Pettengill, Sundaram and Mathur (1995) find that conditioning the realized returns version of the CAPM on the risk premium sign improves model performance. When the excess return on the market is negative (positive), a negative (positive) relation between beta and return should exist. In this section, we use a dual beta market model for the return equation.[45] Unlike Howton and Peterson who define bull and bear markets by comparing the market return to its unconditional mean over the period under study, we classify up and down market as in Pettengill, Sundaram and Mathur (1995, 2002), given that the model is being used in an event-study setting.

The market model used herein is given by:

[45] Pettengill et al (2002) argue that the market premium categorization is sufficient, and that using up and down market betas is not a necessary condition.

$$R_{i,t} = \alpha_i + \beta_i^{UP} \times R_{m,t}^{UP} + \beta_i^{DOWN} \times R_{m,t}^{DOWN} + \beta_i^{UP*} \times R_{m,t}^{UP} \times I_{a,t} + \beta_i^{DOWN*} \times R_{m,t}^{DOWN} \times I_{a,t} + \kappa_1 \times I_{announc,t} + \kappa_2 \times I_{effectiv,t} + \varepsilon_{i,t} \tag{9}$$

where $R_{i,t}$ is the excess return of stock i during day t, where the risk-free rate is proxied by the daily rate for three month treasury bills as published by the US Department of Treasury and the daily stock returns are from the CRSP database;

$R_{m,t}^{up}$ is the market excess return if positive, and is zero otherwise, where the value-weighted CRSP index which contains stocks from the NYSE/NASDAQ/AMEX exchanges is used;

$R_{m,t}^{down}$ is the market excess return if negative, and is zero otherwise;

$I_{a,t}$ is a dummy variable equal to 1 if post-announcement date, and is zero otherwise;

$I_{announc,t}$ is a dummy variable equal to 1 for the day preceding, the day of and the day after the share tender offer announcement, and is zero otherwise;

$I_{effectiv,t}$ is a dummy variable equal to 1 for the day preceding, the day of and the day after the acquisition effective date, and is zero otherwise; and

$\varepsilon_{i,t}$ is an error term with the usual assumed properties.

The approach of Scholes and Williams (1977) is used to correct for any nonsynchronous trading problem by estimating betas on lagged, lead and contemporaneous market returns. All excess returns are computed as nominal daily compounded returns less the daily three-month Treasury bill rate for 100 trading days before the announcement date and up to the next effective date for acquirers. The parameters κ_1 and κ_2 capture any abnormal returns that may occur on the announcement and effective dates, respectively.

Volatility is modeled using the common GARCH(1, 1) model with an asymmetric effect on volatility for shocks to returns, as in Glosten, Jagannathan and Runkle (1993). Let $h_{i,t}$ denote the conditional variance of $R_{i,t}$. Then $h_{i,t} = E\left(\varepsilon_{i,t}^2 \mid F_{t-1}\right)$ where F_{t-1} is the information set available for prediction at time t, so that:

$$h_{i,t} = \varpi_i + \phi \times \varepsilon_{i,t-1}^2 + \gamma \times \varepsilon_{i,t-1}^2 \times I_{\varepsilon_{i,t-1}} + \psi \times h_{i,t-1} + \theta \times I_{a,t} \tag{10}$$

The parameter θ captures any impact from the tender offer announcement on return volatility, and $I_{\varepsilon_{i,t-1}}$ is a dummy variable that is equal to 1 if $\varepsilon_{i,t-1} > 0$, and is zero otherwise.

[Please insert table 21 about here.]

The results for the GARCH estimation are reported in table 21 for the four possible combinations of listing venue and tender offer party. Both the up and down market betas for both targets and acquirers are higher for NASDAQ- versus NYSE-listed stocks. While our expectation is that up market betas will be higher than down market betas (especially for acquirers who enjoy high growth during bull markets), the Wald test results only support this expectation for NASDAQ-listed acquirers. The up market betas decrease significantly for targets after the acquisition announcement for both listing venues. The down market betas only decline for NASDAQ-listed targets. Daily abnormal returns of 6.74% and 5.07% are associated with the announcements for NASDAQ- and NYSE-listed targets, respectively. These correspond to compound average abnormal returns of 21.61% and 15.99% over the 3-day announcement window. Consistent with the literature, the abnormal returns are considerably higher for cash versus share tender offers. For example, significant daily average abnormal returns of 12.35% and 3.56% are found for cash and share tender offers, respectively, for NASDAQ-listed targets. These correspond to compound average abnormal returns of 41.81% and 11.06%, respectively, for the 3-day announcement window. The leverage effect is significant for all four samples. Counter to a priori expectations, volatility decreases after announcement for only NASDAQ-listed bidders and targets. Since trading volume, especially for targets rises after the announcement, we expected at least that the transitory component would increase given that mainly noise and liquidity traders drive this volatility component.[46] We have no plausible explanation for this puzzling result, and we leave it to future research.

We now move to the measurement of the relation between abnormal returns and the extent of information asymmetry. First, consider the case of a successful cash tender bid for a given target. This type of news usually is announced during market closure or during a trading halt requested by the target. Early morning or other firm quotes are used to determine price direction. Orders cumulate and the implicit price jumps to reflect the good news for the bidder shareholders. When the market opens or resumes for the target shares, the quotes have already moved away from their previous levels. This also is accompanied by a reduction in information asymmetry with the public dissemination of information. For an acquirer making a share tender offer, the literature reports that the market on average perceives it as being bad news. Hence, price will decline, and the associated negative abnormal return should also be accompanied by a decrease in information asymmetry. For an acquirer making a cash tender offer, the literature reports that the bidder, on average, earns no abnormal return. In the absence of a formal model of price discovery for the evolution of the tender offer process, we simply test if a direct relation exists between abnormal returns and changes in information asymmetry.

For this purpose, our tests use a binary (dummy variable) version of the abnormal returns from the fitted GARCH model estimated above as the dependent variable in a logit model. This dummy variable is set to one when significant abnormal returns are observed, and is set to zero otherwise. While the change in the probability of informed trading (PIN) as estimated from the EKOP model is a potential candidate for the change in information asymmetry, it is not a "true" measure of information asymmetry as was discussed earlier. For example, assume for simplicity

[46] The relation between volatility and trading activity as measured by volume or more specifically number of trades is well documented in the literature, see Karpoff (1987), Gallant, Rossi and Tauchen (1992), Jones, Kaul and Lipson (1994) and Anderson (1996).

that one trader exactly knows the true final liquidation value of the stock, and all remaining traders only have a very diffuse estimate of this final liquidation value. While the level of adverse information is high, PIN is low since the proportion of informed traders is very low compared to the total number of traders. This is the reason why we also use several alternative proxies from the bid-ask spread decomposition models estimated earlier.

Several control variables are used. For instance, size may be important for several reasons. First, there is a possibility that our market model does not capture the well-documented size effect. Secondly, our expectation is that small targets enjoy higher abnormal returns because of a greater surprise effect because small companies in general do not capture the attention of the investing public nor of financial professionals. According to Merton (1987), small firms that show up in the news attract new investors which reduces their required return, which in turn causes their prices to increase due to a reduced discount factor effect. The method of payment offered in a tender offer is a second variable of interest. As noted earlier, the literature reports a strong link between method of payment and abnormal returns. An information link is present here since the method of payment can be interpreted as a signal. For example, Travlos (1987) argues that managers use shares as a method of payment when their own shares are overvalued. Finally, the listing venue is also used as a control variable to account for institutional and clientele differences between the two listing venues under study.

The full logit regression can be expressed as:

$$F(ABN_i = 1 \mid X_i, \theta) = \frac{\exp(X_i'\theta)}{1 + \exp(X_i'\theta)} \qquad (11)$$

where ABN_i is the abnormal return for stock i, which is equal to one for significant abnormal returns and is zero otherwise;[47]

X_i is a vector of the independent variables; and

[47] This is given by the significance of the parameter κ_1 in the dual beta market model with GARCH(1,1).

θ is the vector of parameters to estimate.

The various independent variables used are:[48]

L(assets): the logarithm of the total assets from Compustat (Data item 6) as of the end of the year preceding the announcement;

ΔPIN: the change in the probability of trading against informed traders, which is computed as the difference in the PINs from the EKOP model between the announcement and pre-announcement windows;

GH and LSB: the change in the adverse selection cost as measured by the difference between the proportional permanent cost between the announcement and pre-announcement windows for the GH and the LSB models, respectively;

Nature: a dummy variable that differentiates between bidders (zero) and targets (one); and

Cash and Shares: dummy variables related to the method of payment, where cash (shares) is equal to one if cash (shares) is used as the method of payment and is zero otherwise, and its use is facilitated herein by the use of hybrid and other methods of payment.

After adjusting for missing values, the logit regression is run for a sample of 679 stocks for four models where each model uses each of the changes in the three information asymmetry measures. The findings are summarized in table 22. Interpreting the coefficients in such limited dependent estimations is not easy because the coefficient estimates do not represent the marginal contribution of each variable independently of the others. Therefore, we focus only on the significance and sign of the estimated parameters. The power of the fit for the 12 estimations is not high given the low levels of the log likelihood function. The LR ratio tests, where the model coefficients are restricted to zero, does not strongly reject the null for all models. Moreover, the

[48] Several other variations of these variables also are used. For example, size also is measured by market capitalization, which is obtained by multiplying data items 24 and 25, and by the number of employees, which is taken to be data items 29 and 146 from the Compustat database. Volume from CRSP also is used. Only two of the changes in per dollar costs from the five decomposition models are reported because of the similarity of their results.

estimated intercept is always very significant. Size plays almost no role as it marginally explains the abnormal return only when it is associated with the change in PIN in model (2).

[Please insert table 22 about here.]

The changes in informed trading (PIN) are not as significant as those for the intercept, and lose power when additional variables are added to the regression, as is evident from a comparison of estimations (1) and (2) in table 22. The negative coefficient estimate for PIN of -0.493 in estimation (1) implies that the likelihood of achieving abnormal returns is higher if the probability of informed trading decreases. The intuition behind this relation is that the impact on prices is expected to be considerably significant if the announcement is so highly informative that it decreases information asymmetry. The impact on price is not to compensate investors for an increase in the adverse selection risk about the company. Since adverse selection risk is lower, the abnormal return is simply a manifestation of the lower discount rate effect. This explanatory power disappears completely when other factors, particularly the tender offer party, are considered. The positive coefficient for the party to the tender offer means that being a target increases the probability of achieving positive abnormal returns. The reduced informativeness of changes in the PIN estimates is not that puzzling since most of the information of relevance to the setting of a target's price is revealed irrespective of the method of payment, and this suggests that its price would change. Thus, the reduction in PIN provides no additional information of relevance for setting prices. The positive and significant coefficient estimate of 0.191 for the cash dummy variable in estimation (4) implies that cash payment increases the probability of positive abnormal returns, although share payment generates negative abnormal returns for acquirers.

Estimations (5) to (8) and (9) to (12) replicate estimations (1) to (4) using different measures for the change in information asymmetry. The results for these estimations show that the previously discussed results are robust to the measure of the change in information asymmetry. The relation between the abnormal returns and changes in adverse selection is still negative, and expanding the set of independent variables weakens this relation, especially when the added variable identifies the firm as being a target or acquirer. The final observation of interest is that listing venue is not an abnormal return determinant, as is evident from the results for estimations (3), (4), (7), (8), (11) and (12).

3.8. Concluding Remarks

In this essay, we investigated the microstructure impact of successful acquisitions by tender offer on both targets and acquirers that were listed on NASDAQ and the NYSE. Our findings contribute greatly to our understanding of how price reacts to news announcements. We find that trading activity for targets, whether measured by number of trades, number of shares or dollar value, intensifies upon the announcement of the tender offer, irrespective of the targets listing venue. We also find that liquidity is improved upon announcement as both quoted and effective spreads fall, and quoted depth and average trading value increase.

Although both buyer- and seller-initiated trades increase, the use of two different methodologies finds that seller-initiated trades increase relatively more for targets than for acquirers upon announcement of the tender offer. The two methodologies are the use of signed trades, as determined by several trade indicator algorithms (Lee and Ready, 1991; and Ellis, Michaely and O'Hara, 2000b), and the inferred execution against limit orders using the Greene (1997) algorithm. We find that investors intensify trading against bid limit orders, which indicates that investors more often use market sell orders against these bid limit orders. The increase in seller-initiated orders relative to buyer-initiated orders is unexpected. Although the expectation is that the bid will raise the interest of uninformed investors who are previously unaware of the target, the result is consistent with two explanations, including a behavioral explanation. First, since the weight of the target in the portfolio of a shareholder increases (especially for cash tender bids) upon announcement, the shareholder may feel a need to sell part of the holding in the target to rebalance her portfolio. Second, according to the parking the cash hypothesis, an existing target shareholder may decide to sell part or all of her holding to realize or lock in the unexpected capital gain. In turn, the heightened selling pressure may lead to a market under-reaction to the tender offer announcement and to potential near arbitrage, as is documented by Baker and Svaşoglu (2002).

The bid-ask spread components and their relation to their sources were studied for the targets. The temporary component is related to volume and trading activity, while the permanent component is linked to information asymmetry. Both cost components decrease in dollar and proportional terms for targets as the tender process unfolds. While the increase in the dollar components are related to increased trading, the increase in the proportional components means that information asymmetry is reduced upon announcement of the tender offer. This is an anticipated result since the intention of the public announcement is to level the information playing field. Stronger results are obtained for the targets when cash is used as the method of payment. Permanent trading costs decrease more for targets of cash tender offers, because such offers are more informative about the value of the target than share tender offers. The abnormal returns are the manifestation of the newly revealed information about the target, which based on the literature, is expected to be positive for cash tender offers and neutral for share tender offers.

On average, trading activity also increases for acquirers, but to a lesser extent than that for targets. The evidence for a decline in the spread measures (including depth) is mixed and much weaker for acquirers. The average trade size decreases for acquirers, which indicates that dealers use depth and volume to discover the value of the acquirer. Unlike the evidence reported for targets, investors do not relatively increase their selling using market orders for acquirers upon announcement of the tender offer. The decrease in temporary costs is explained by the increase in trading volume, and the change in the permanent cost component is mixed. While the permanent cost appears to fall, this conclusion differs by both listing venue and method of payment. Specifically, the permanent cost clearly declines only for share tender offers. We explain these results for both targets and acquirers by the informativeness of the transaction, where the choice of payment method is very informative for targets and acquirers. Cash and share tender offers are interpreted as good and bad signals, respectively, for targets. In contrast, cash and share tender offers generally are interpreted as neutral and bad signals for acquirers.

The degree of association between abnormal returns and either the decline in permanent trading cost is studied further when this cost is derived from one of the spread decomposition models or is proxied by the probability of informed trading, as inferred using the Easley, Kiefer, O'Hara and Paperman methodology. The relation between these two variables is weak, especially when additional explanatory variables are added. When significant, the sign for the probability of informed trading is negative. This implies that as the probability of informed trading and information asymmetry decrease, the likelihood of observing abnormal returns increases. This result corresponds to our expectations. With the decline in information asymmetry, much information is imbedded in the price and reflected upon announcement in the form of abnormal returns. However, the relation between abnormal returns and permanent trading costs is more complex and multi-directional than would appear a priori and needs to be investigated further in future research.

CHAPTER 4

Where Do Informed Traders Trade Canadian Shares Cross-Listed on US Trading Venues?

4.1 Introduction

Cross-listed shares have been investigated from various perspectives such as the motivations for a company to cross-list its shares on a second market. Foerster and Karolyi (1999) find that companies that cross-list their shares on US markets incur positive abnormal returns upon listing. They link these returns to the expanded shareholder base and the funds raised on the US market. They explain the reduction in required returns or cost of capital using the Merton (1987) model, which states that investors invest in stocks they know about and require an added premium for stocks unfamiliar to them. Baker, Nofsinger and Weaver (2002) investigate firms cross-listed between the NYSE and the London Stock Exchange. They document an increase in the number of analysts following UK stocks and in the number of citations in the financial press with cross-listing. Using a two-factor asset-pricing model,[49] they report a lower cost of capital for the cross-listed stocks.

Miller (1999) reports a return reaction with cross listing in the US market for several Depositary Receipts programs. He finds that the magnitude depends on the cross-listing exchange (with the largest returns achieved on the major US exchanges as opposed to the smallest and over the counter exchanges), the nature of the Depositary Receipt program, the geographical location of the listing company (with those from emerging markets achieving higher returns), and the avenues for raising funds (with public placements achieving positive returns as opposed to private placements). Coppejans and Domowitz (2000) find that the variance of Mexican stocks is higher for higher proportions of foreign ownership when their ADRs are cross-listed. Doukas and Switzer (2000) examine Canadian companies interlisted between the TSX and US venues and show that the mild segmentation hypothesis is supported. They show that Canadian stocks

[49] The two factors are the usual domestic and international market risks.

experience positive abnormal returns upon listing on US markets even after controlling for the change in the disclosure system for Canadian companies.

Several papers examine the price formation and discovery process, and the role of specialist participation for cross-listed shares. Eun and Sabherwal (2003) use an error correction model to quantify the reciprocal influences on mid-quotes from US and Canadian trade venues, respectively, for Canadian firms cross-listed in the US. Since they find that US prices also adjust to Canadian prices, they conclude that prices in the US contribute to the formation of Canadian prices. Xu and Fung (2002) find similar results for Chinese shares inter-listed on the NYSE and the Stock Exchange of Hong Kong. Based on an examination of stocks cross-listed on the NYSE and on the TSX, the London Stock Exchange, the Xtera system of the Deutsche Borse and the Paris Bourse, Grammig, Melvin and Schlag (2004) find that most of the price discovery occurs in the home market. The US market plays a role in forming prices for the small sample of five Canadian companies in their sample, as was found earlier by Eun and Sabherwal (2003). Using proprietary data on specialist trading, Bacidore and Sofianos (2002) find that specialist participation and price stabilization of cross-listed stocks on the NYSE for shares from foreign developed markets is higher than that for US stocks, which, in turn, exceeds that for stocks from emerging markets.

The impact of cross-listings on trading activity is also a central topic in the interlisting literature. For example, Bailey, Karolyi and Salva (2002) investigate changes in volume and volatility around earnings announcements for various cross-listed foreign shares on US markets. They argue that the firm chooses to disclose more information to reduce informational asymmetry when the firm is cross-listed. However, they find that both volume and trading volatility increase upon cross-listing for firms making earnings announcements.

Several papers examine the impact on share liquidity from cross-listings. Noronha, Sarin and Saudagaran (1996) analyze liquidity upon the decision by US firms to cross-list on the London Stock Exchange and the Tokyo Stock Exchange. They find that the quoted spreads on the US market do not decrease initially as the increased competition hypothesis would suggest. They attribute this to an increase in information based trading which increases the market making costs of liquidity providers. In contrast, Foerster and Karolyi (1998) find that both quoted and effective spreads decrease upon cross-listing of Canadian stocks on the three major US exchanges, and that the decrease increases with an increase in the relative share of trading activity that migrates to the US markets. Domowitz, Glen and Madhavan (1998) investigate inter-listings of Mexican companies on US markets. They argue that the impact of inter-listing depends on the openness of the original domestic market to foreign investors. They show that foreign investors may migrate to the non-home market in the case of open securities, and that this leads to a reduction in liquidity as measured by a Kyle type of depth measure.[50]

Kryzanowski and Zhang (2002) show that execution cost depends on the trading venue for Canadian stocks cross-listed on the US market. They establish a pecking order for execution for these stocks where traders should consider first the TSX market, then the US listing venue, and lastly other US markets including the regional exchanges. The authors show that the midspread is different and helps to explain differences in execution cost.[51] Ahn, Cao and Choe (1998) find that decimalization on the Toronto Stock Exchange (TSX) has no impact on bid-ask spreads of Canadian stocks cross-listed on the NYSE and AMEX. For the stocks cross-listed on the NASDAQ, the decline in spreads is small compared to that on the TSX. If the midspread is equivalent across markets, then order flow should migrate to the TSX where the bid-ask spread and hence trading cost is lower. Ahn et al find that traders do not switch trading venues, which they explain by the higher benefits of trading on the US markets. The practice of preferencing and

[50] Although the authors mention the fragmentation issue, they do not analyze the impact of splitting the order flow on the price discovery process.

[51] This is related to a branch in the literature that deals with arbitrage. Differences in prices of cross-listed stocks should be arbitraged out. Usually, this is not a perfect arbitrage since the cross-listed securities in the US are ADRs that are not fully fungible at zero cost due to differential trading costs and barriers. This is however not the case for the Canadian cross-listed shares. For more on this, see Gagnon and Karolyi (2003), Froot and Dabora (1999), Rosenthal and Young (1990), among others. On the limits to arbitrage, see Shleifer and Vishny (1997).

the payment for order flow on the US markets is a second reason. Kryzanowski and Zhang (2002) find that the advantage of the Canadian market over the US markets is reduced after the reduction in the tick size on the US markets in 1997. Kryzanowski and Rubalcava (2004) identify a clientele effect for the shares cross-listed on the US and the Canadian markets in accordance with the Amihud and Mendelson (1986) holding period assumption, except for shares cross-listed on the NASDAQ. Our finding that the effective spreads are no longer different between the US and the Canadian trading venues weakens the evidence for the clientele effect, particularly around information events.

The choice of interlisting venue is also of interest in the literature. Pagano, Roell and Zechner (2002) report that European companies that cross-list in the US tend to be bigger and are in the high tech and high growth sectors, while the European firms who choose to cross-list in Europe exhibit lower growth. Sarkissian and Schill (2004) find that the interlisting market is a key issue. They relate this finding to the home bias of investors who overweight their portfolios in domestic assets. Companies seem unconcerned about the diversification aspects of interlisting which reduces their cost of capital. This is evidence against the notion that firms interlist to increase the awareness of investors about the interlisting company in the foreign market.

The primary purpose of this essay is to analyze trading (including the probability of information trading) on the various trading venues for Canadian firms that are already cross-listed. Based on trading patterns, we can identify where the informed traders trade first and how the price innovation is propagated and impounded into the price. To emphasize the informational content of trades, we analyze trades around earnings announcement dates, i.e., periods known for information flow. Our expectation is that most of the information is discovered in the Canadian trading venue. However, the US trading venue should play a role in price discovery because if it did not it would be totally redundant and should disappear as a trading venue. We are not interested in the event itself, but rather in the fact that it corresponds to a period that occurs at a regular frequency and is characterized by high trading activity and (possibly) with a change in private information trading activity. From this perspective, a possible extension of our conclusions to other similar events can be considered.

The contribution of the essay to the literature is four-fold. The first contribution is to show that the Canadian market no longer presents a cost advantage over the US markets for traders of Canadian shares cross-listed on the US markets, at least for the period and the data under study. We show that both the proportional quoted and effective spreads are at best the same. We also show that for the Canadian shares that are cross-listed on the US trading venues, that there is no preference ordering based on transaction cost as measured by spreads. In other words, it does not make any difference from a trading (spread) cost perspective whether to list on the NYSE, the NASDAQ or the AMEX.

The second contribution is the finding that the Canadian market still offers higher depth and thickness compared to the US market. This mitigates the conclusion in the previous paragraph, which targets one dimension of liquidity, namely, the spread trading cost. This depth attracts both liquidity and privately informed traders to trade on the Canadian market. In turn, this leads to a small differential in terms of the probability of informed trading in favor of the US market place. This is partially expected since in fragmented markets, it is anticipated that one market will prevail.

The third contribution is to show that the services of market makers are required to a greater extent on the US market than on the domestic Canadian market. This is the case for all three US listing venues analyzed in this chapter, and even for the NYSE where specialists are generally less involved in trades compared to a purely dealer market like the NASDAQ. This is related to market depth. On the domestic Canadian market, more limit orders are outstanding at and away from the best bid and offer quotes so that the book is wider. Thus, incoming orders are more likely to execute against limit orders, especially after event occurrence when investors are in need of liquidity to adjust and react to the announcement and to rebalance their portfolios.

The last contribution is related to changes in (private) information structures and the asymmetric reaction to information between the two markets. We show that the change in the probability of trading against informed traders is not large, and is asymmetric between the US and the Canadian markets. The small change in the probability of trading against informed trading hides several contradicting effects. First, the information disclosure eliminates the usefulness of previously private information, which reduces the probability of informed trading. This impact is quick and common to both markets. However, the presence of a larger pool of uninformed traders renders the market more attractive for other privately informed traders. These informed traders may simply decide to acquire new private information. This behaviour is rational and profitable since the informed traders can take advantage of the increasing number of uninformed traders. However, the informed traders do not split their trades relatively equal on both markets. They trade more frequently in the domestic market compared to their pre-announcement trading patterns on both markets. As a consequence, we observe a decline in the probability of trading against informed investors in the US market, while the tendency is less clear in the Canadian market. We even find that the permanent trading cost which is closely related to private information trading increases upon announcement on the Canadian market.

The remainder of the chapter is organized as follows. Section 2 describes the data set. Section 3 reports and discusses the results for the liquidity and trading activity comparisons between the Canadian and the US markets for the Canadian cross-listed shares. Section 4 investigates executions against limit orders on both markets. Section 5 reports the estimates of the probability of informed trading using different methodologies. Section 6 infers the level of information asymmetry using a regime-switching model and estimates the differential in the spread components. Section 7 concludes the chapter.

4.2. Data

Data on quarterly earnings announcements for the calendar year 2002 are collected from different sources for 172 Canadian firms cross-listed on the US exchanges. For each company, we search its press releases in SEDAR and on its website to identify the day of the announcement. In some cases, we use the CBCA and Lexis Nexis and Bloomberg databases to identify the announcement date. All announcement dates with any announcement window overlap for the same company are deleted, where each announcement window covers the 41 trading days centered on the announcement date. For example, the earnings announcements of February 19 and April 16 for Aeterna Laboratories, which is cross-listed on the TSX and NASDAQ, are deleted. Announcement windows during which the stock switched US listing venue also are deleted. To illustrate, the earnings announcement of July 30 by Cott Corporation is deleted because its window includes its switch from the NASDAQ to the NYSE. Observations with trading prices that are below one dollar are deleted.[52] As a result, our final sample contains a total of 493 observations representing 135 companies (specifically, 58 observations on the AMEX, 187 on the NASDAQ and 248 on the NYSE).[53] The descriptive statistics on these companies, which are reported in Table 23, suggests that these firms span almost all economic activities.

[Please insert table 23 about here.]

The distribution of the firms based on the first two digits of the North American Industry Classification System (NAICS) is presented in table 24.[54] As expected, the major portion of these firms is in manufacturing, and sizeable representations are in pharmaceuticals and biotechnology. The natural resource sector (oil exploration and gold and silver ore mining) also is well-represented in the sample.

[Please insert Table 24 about here.]

[52] These so-called "penny stock" trades are deleted because their microstructure will differ because of the change in the minimum trading price increment for stock trades of one dollar or more and those less than one dollar. For example, on the TSX, board lot definition depends on whether the per-share price is above or below one dollar.

[53] Each "observation" in our sample corresponds to a combination of earnings period and stock. Since up to four windows are possible for the same firm, we subsequently need to deal with the fact that some of our observations are not independent.

[54] The NAICS was introduced in 1997 to replace the Standard Industrial Classification (SIC) system and was updated in 2002. It aims to harmonize classifications between the US, Canada and Mexico.

Closer examination of the distribution of the earnings announcements dates show that these announcements occur mostly during the mid-week (80% on Tuesday through Thursday). The 493 announcements are distributed as follows: 63 on Mondays, 120 on Tuesdays, 121 on Wednesdays, 151 on Thursdays and 38 on Fridays. No announcement was made over a week-end day.

The trading data are obtained from the Equity Trades and Quotes History (ETQH) database that is available from the Toronto Stock Exchange (TSX). This data set contains information on all trades and quotes on the TSX, such as trade prices, number of shares traded, quotes, depth, date and time stamps, conditions and broker identifiers. Some filters are applied to clean the data. First, any quote or trade outside of the regular trading hours (9:30 to 16:00 eastern time) is deleted. Second, trades are deleted if they are open trades, report zero number of shares traded, are cancelled or corrected trades, are delayed delivery trades or trades with special settlement conditions, or are trades for which the price change over the last reported price exceeds 50%. Third, quotes are deleted if the bid price is higher than the ask price or if either is equal to zero, if the relative spread exceeds 30%, or if the quote is posted during a trading halt.[55]

We also construct a consolidated database of Trades and Quotes (TAQ) that contains all trades and quotes that satisfy the above filters on the main US trade venues, including the regional exchanges and the Chicago Board Options Exchange (CBOE). To avoid any problems associated with autoquotes from inactive dealers, we use only the quotes posted on the US listing venue, as in Chordia, Roll and Subrahmanyam (2001).

4.3. Trading Activity and Liquidity of Canadian Shares Inter-Listed on US Exchanges

The statistics on the cross-sectional distribution of various trading activity measures for the cross-listed shares, such as dollar and share volumes, number of transactions and clustering by

[55] These filters eliminated 2.2067% and 0.4585% of the quotes and trades, respectively, on the Canadian exchange. The corresponding statistics are 0.6121% and 0.0023% for the US market.

trade sign, are reported in table 25. The trading activity statistics also are reported by trade initiator, where the Lee and Ready (LR) algorithm is used to sign trades as buyer or seller initiated.[56] Direct comparisons of the dollar-associated values are not problem free since they are reported in local currencies and contribute little to our understanding beyond a comparison of proportional trading costs.

[Please insert table 25 about here.]

Various statistics on the cross-sectional distribution of the liquidity measures (quoted and effective spreads and the depth offered at the best bid and ask quotes) of the Canadian stocks cross-listed on the US market are reported in table 26 for the Canadian and US exchanges, and by listing and trade venue. For spreads, both dollar and proportional values are reported. Again, direct comparisons of the dollar-associated values between the Canadian and US markets are not possible since they are reported in local currencies.

[Please insert table 26 about here.]

The average posted spread for the cross-listed shares is 9.95 US cents on the three US exchanges and 15.53 Canadian cents on the Canadian exchange. The corresponding effective spreads are naturally lower at 7.61 US cents and 12.59 Canadian cents. For the inter-country comparison, we rely only on the proportional trading cost. The mean proportional quoted spread is 1.41% and 1.43% for the US and Canadian quotes, respectively. For the proportional effective spreads, the corresponding costs are 1.08% and 1.14%. To test for any differences inter-country, we use the matched sample where we compute the difference for each observation between the cost for the US and the Canadian based legs. We then compute the usual t-statistics to test if the mean is statistically different from zero or compute the Wilcoxon statistic to test if the median is zero. To deal with the lack of independence problem caused by some companies being represented up to four times in the sample, bootstrapped p-values are computed.

---

[56] A trade is signed if a quote precedes a trade by at least five seconds.

The bootstrapping procedure used is as follows. We run a regression of the appropriate differential trading cost on a vector of ones to get an estimate of the mean differential cost and its associated t-statistic. To generate the empirical distribution of this t-statistic under the null hypothesis, the residuals (mean deviations) are first computed from this regression. Then, N samples of pseudo-random residuals are generated by drawing with replacement from the computed residuals. Each sample corresponds to a bootstrapped sample of the dependent variable (the cost differential) under the null since the latter corresponds to the mean being zero. By running each of these N samples on a vector of ones and computing the t-statistic of each intercept, which is the only explanatory variable, we obtain a vector of N t-statistics simulated under the null hypothesis. We then simply insert our original t-statistic into this empirical distribution and determine the corresponding p-value from the cumulative empirical distribution.[57] For the choice of N (i.e., the number of replications), two possibilities are used. The first is to use a fixed 999 repetitions, and the second is to use the three-step procedure suggested by Andrews and Bushinsky (2000). The results are not materially different. Table 27 summarizes the results of these statistical tests using the Andrews and Bushinsky approach.

[Please insert table 27 about here.]

The results show that no difference in trading costs exists for the Canadian shares cross-listed in the US between the US and Canadian trade venues around earnings announcements. Kryzanowski and Zhang (2002) show that the trading advantage of the Canadian trade venue compared to the US venues for the Canadian cross-listed shares weakened after the reductions in the minimum quotation increment in the markets of both countries. We show that the cost advantage not only vanished but that the effective proportional cost is now significantly lower in the US.[58] However, these results hide some dissimilarities depending on the US listing venue. For

---

[57] For more details, please see Davidson and MacKinnon (2004) and Greene (2003).

[58] We compare trading cost implied from all trades regardless of their order size, trade-side initiator or time of the day. Naturally, smaller trade size can lead to a lower trading cost since it can be executed at the best bid or ask while larger transactions may need to go deeper in the book. However, pre-arranged larger block

the shares cross-listed on the NASDAQ, no significant difference exists in the proportional costs between the US and the Canadian based trades and quotes. For the shares cross-listed on the NYSE, the mean proportional quoted spreads are not significantly different at 0.38% on the US venue and 0.36% on the Canadian trade venue. In contrast, the proportional effective spread is significantly higher at 0.46% on the TSX than on US venues (0.41%). For the shares cross-listed on the AMEX, both the quoted and effective proportional spreads are significantly higher at 2.89% and 2.28%, respectively, on the TSX. The corresponding mean values for the AMEX are 2.45% and 1.76%, respectively.

Differences in trade costs also exist between listing venues in the same country. To illustrate, the mean posted spread is 7.77, 7.33 and 14.09 US cents on the AMEX, the NYSE and NASDAQ, respectively. This is not merely due to passive quote posting by dealers. The effective spread which corrects for any trading at the inside quotes shows that the mean costs on the AMEX and NYSE markets are respectively 5.80 and 5.45 US cents, which is approximately half the corresponding cost of 11.04 US cents on the NASDAQ.[59] One possible explanation might be that this is simply a manifestation of higher general trading costs on the NASDAQ. However, since the well-publicized paper by Christie and Schultz (1994), which documented avoidance of eighth quotes by NASDAQ dealers,[60] several reforms have occurred on NASDAQ, including the introduction of new order handling rules in 1997. Barclay, Christie, Harris, Kandel and Schultz (1999) and Chung, Van Ness and Van Ness (2002) report that the cost on NASDAQ has dropped after these reforms. Although their findings still document slightly but statistically significant higher trading costs on the NASDAQ, these differences are too small to explain the magnitude of the differences that we document herein.

---

trades can also be negotiated at the inside of the BBO. Our conclusion is not conditional on any of the controlling variables.

[59] The medians for both types of spread measures exhibit similar patterns to their means.

[60] Several papers investigate the differential in trading costs between the NYSE and the NASDAQ, including Huang and Stoll (1996), Barclay (1997) and Bessembinder and Kaufman (1997).

Thus, our contention is that these differences are not exchange-specific for our sample but rather are share-specific. If we consider the Canadian-based trades for these stocks and split them by US cross-listing venue, we still have a similar pattern. For instance, the TSX shares cross-listed on AMEX and NYSE have posted spreads of respectively 15.25 CDN cents and 11.25 CDN cents, and both of these values are significantly lower than the 20.97 CDN cents for TSX shares cross-listed on NASDAQ. The comparisons are similar for effective costs, where the means are 11.75, 9.91 and 16.39 CDN cents for TSX shares cross-listed on AMEX, NYSE and NASDAQ, respectively.

The difference can be explained by the per-share price level. Since trading cost should be related to the price level, it is more suitable to investigate the proportional trading cost, which measures spreads per dollar traded. As table 26 reports, the shares cross-listed on the NYSE still exhibit the lowest mean spreads. However, the costs for this measure on the AMEX now are even higher than those on the NASDAQ. On the US markets, the mean quoted proportional spread is at 0.56%, 2.20% and 2.45% on the NYSE, NASDAQ and AMEX, respectively. For the proportional effective spread, the costs are respectively 0.42% for the NYSE and 1.76% for both the AMEX and the NASDAQ. As for the Canadian based trades, the costs still are much lower for the NYSE cross-listed shares than for the other two US exchanges. To illustrate, the mean effective proportional spread is 0.46%, 1.69% and 2.28% for TSX shares cross-listed on NYSE, NASDAQ and AMEX, respectively.

To examine the determinants of these differences, cross-sectional regressions are run to test if these differences are explained by share characteristics or exchange differences. To this end, the following regressions are run:

$$spread_i = \alpha_1 + \alpha_2 \times AX_i + \alpha_3 \times NSQ_i + \beta_1 \times size + \beta_2 \times volat_i + \beta_3 \times vol_i + \varepsilon_i \qquad (12)$$

In equation (12), spread corresponds to either the proportional posted (or effective) spread. Size, which is a proxy for adverse information, measures the size of the company as the natural logarithm of its total assets or its total market capitalization. Bigger companies are more likely to be followed by more financial analysts and the investing public usually knows more about these firms. Therefore, the β_1 coefficient estimate is expected to be negative. Volat is the volatility as measured by the standard deviation of daily stock returns over the same period over which the spread is measured. The volatility captures the risk of carrying excess or low inventories by market makers who are subject to prices moving against them. Therefore, we expect a positive β_2 coefficient estimate. Vol is the average daily dollar trading volume or the average daily number of trades over the same period. Volume is inversely related to the order processing cost, where the latter is mainly fixed per transaction. Therefore, the higher the volume, the lower the processing cost per share or per traded dollar. Therefore, we expect a negative relation between volume and spread as suggested by the literature. The coefficients of interests are the α_2 and α_3 estimates which measure the specific additional cost of the AMEX and NASDAQ markets over the NYSE. AX and NSQ are dummy variables taking the value of one if share i is cross-listed on AMEX and NASDAQ, respectively, and is zero otherwise.

The results for regression (12) are reported in table 28. Models {1} through {4} and models {5} through {8} use the proportional quoted spread and the effective quoted spread, respectively, on the TSX as the dependent variable. Models from {9} through {12} and models {13} through {16} use the same two spread measures, respectively, on the US trade venues as the dependent variable. Each block of four regressions uses a mix between two size variables (namely total assets and total market capitalization) and two volume explanatory variables (i.e., average daily dollar volume and average daily number of trades). In order to reduce the dependence problem, only the shares that appear at the fourth quarter for each listing venue are used. Therefore, each company appears only once in our regressions.[61]

[Please insert table 28 about here.]

Globally, the R-square values of all 16 specifications are high ranging from 66.7% to 75.1%. For the Canadian trades, the β_1 coefficient estimate on the size variable is not significantly different from zero whether total assets or market cap are used. However, for the US trades, this coefficient estimate is significant in all eight specifications and has the negative predicted sign. The estimated β_2 coefficient is significant in all 16 specifications at the 10% level, and in 14 specifications at the 5% level. It also has the right predicted positive sign confirming the conjecture that market makers widen spreads to protect themselves when volatility is higher. The results are even stronger for the estimated β_3 coefficients. In all specifications and for all dependent variables, this estimate is significantly different from zero and has the predicted negative sign with all p-values below 0.1%. This suggests that spreads are closely related to trading volume and that the order processing cost which is partly linked to trading volume is an important component of trading costs.

As for any exchange-specific effect, the coefficient estimates of α_2 and α_3 on the dummy variables AX and NSQ show mixed evidence. First, there appears to be a strong AMEX impact on the posted proportional spreads on the US markets. For the four specifications, the α_2 coefficient estimate is significantly positive ranging from 4.96 basis points to 5.45 basis points for the quoted proportional spread. This represents the excess trading cost in comparison to the NYSE after controlling for the share-specific factors. However, this extra cost disappears when the effective proportional cost is considered. In contrast, Canadian shares cross-listed on AMEX do not have different trading costs for the Canadian based trades and quotes. The same applies to

[61] The size variables are measured at the end of the calendar year 2002 and the data are obtained from the S&P Compustat database, as in table 1.

the shares cross-listed on the NASDAQ for both Canadian and US based trades and quotes. We conclude that the higher overall trading costs for the shares cross-listed on the NASDAQ (and to a lesser extent the AMEX) is due primarily to smaller firms that are subject to higher adverse selection, less liquid companies with higher per trade order processing costs, and riskier companies leading to higher inventory risk for market makers.

Depth represents a second dimension of liquidity. As is shown in table 26, the Canadian trade venue offers a deeper market for traders. The mean depth at both quotes is 2,314 shares on the US exchanges compared to a significantly higher 2,588 shares on the Canadian venue.[62] For cross-listed shares on both the NASDAQ and NYSE, which account for more than 85% of our sample, depth is lower than on the Canadian trade venue. The depths on the US trade venues exhibit much variability with a standard deviation of almost 8,000 shares. The AMEX accounts for much of the cross-sectional variability in depths for the US trade venues.[63]

The relative dominance of the Canadian market as the trade venue of choice for the Canadian cross-listed shares is apparent from table 25. The average cross-listed share in our sample trades 385,703 shares per day on the US exchanges compared to a statistically higher 537,350 shares on the Canadian exchange. The mean (median) ratio of Canadian to US share volume is 9.61 (2.01), which suggests that trading on the Canadian market represents up to 90% (67%) of total trading. A similar conclusion follows from the number of trades where the average daily cross-listed share has 303 trades daily on the US exchanges compared to 419 trades on the Canadian trade venue. The mean and median ratios from table 28 are 4.02 and 1.58, which suggests that the share of Canadian based trading is 80.08% and 61.24%, respectively.

As a conclusion to this section of the essay, we can infer that the Canadian market dominates but its dominance does not lead to the elimination of the US market for Canadian cross-listed

---

[62] These inferences are based on the bootstrapped p-values reported in table 26.
[63] Outliers do exist on the other two US trade venues. For example, the average depth for Nortel Networks is 162,276 shares during the third quarter of 2002 on the NYSE.

shares. However, this dominance is less pronounced for shares cross-listed on the NYSE, which accounts for half of our sample.

4.4 Executions Against Limit Orders

Limit orders are orders submitted such that their execution is triggered if the price hits a pre-determined value within a given period of time. Limit orders are the biggest liquidity providers for several markets before specialists or registered traders.[64] In contrast, market orders reduce liquidity by matching already submitted orders and reducing the outstanding demand or supply for shares (i.e., reducing market depth at the inside spread).

Changes in limit order execution now are analyzed to further investigate changes in liquidity. Limit orders are competition for the specialists on the NYSE and for dealers on NASDAQ where limit orders are executed first based on price and then by time preference. By supplying depth at various price levels, limit orders expand the order book and enhance liquidity.

Glosten (1994) formulates a model where limit order traders gain from temporary price changes caused by liquidity orders and lose from permanent price changes caused by informed traders. Foucault (1999) develops a theoretical model for limit orders and finds that the volatility of the traded asset is the main determinant of the mix between market and limit orders. His conclusions and empirically testable hypotheses are (i) the proportion of limit orders in the order flow is higher with higher volatility, and (ii) the fill rate of the limit orders is lower for higher volatility. Handa and Schwartz (1996) argue that traders find it profitable to place limit orders when transitory order imbalances occur and short-run volatility increases. Ahn, Bae and Chan (2001) confirm these findings using data on the Hong Kong Stock Exchange, where limit orders cluster around bids (asks) when the increase in transitory volatility is caused by trading at the bid

[64] For example, Chung, Van Ness and Van Ness (1999) find that limit orders represent 75% of all quotes in the NYSE TORQ database. They also report that adding limit orders to the quotes of dealers can reduce quoted spreads by 25%. Sofianos and Werner (2000) report that specialists are involved only in 11% of the trades on the NYSE while the floor brokers participate in 44% of such trades.

(ask). Kavajecz (1999) finds that both specialists and limit order traders reduce depth around information events to protect themselves against informed traders.

These findings lead to the following testable hypothesis:

Executions against limit orders as a proportion of total order executions will increase after an earnings announcement.

The logic behind this testable hypothesis is that earnings announcements, which are material events, will impact the price level and contain an element of surprise, and thus, will increase volatility. In turn, this should increase the number of limit versus market orders submitted. However, since these limit orders are executed against market orders, executions against limit orders as a proportion of total order executions should increase.

A modified version of the Greene (1997) algorithm is used to infer executions against limit orders. First, successive quotes are identified such that both their bids and asks are unchanged but the depth on either side of the market is reduced. To illustrate, assume that the depth on the ask quote is reduced. Then all trades that take place between the two successive quotes at the constant ask price are investigated. These trades, up to a cumulative total volume equal to the depth at the ask, are considered as executed against selling limit orders. The idea is that the decline in depth is due simply to executions against outstanding limit orders, and that the market maker simply reduces the depth since the additional liquidity to his own is absorbed first. This is based on the notion that the market maker trades only if orders cannot be matched or in order to smooth prices.

Secondly, successive quotes are examined where one of the posted bid and ask quotes or both move in the same direction. As an illustration, consider the case where both bids and asks increase or the bid stays constant while the ask increases or the reverse. Then all trades that take place between the two successive quotes at the ask price are considered. All these trades, up to the depth at the ask of the first quote, are considered as executed against limit selling orders. In this case, the total liquidity provided by limit orders is exhausted and the market maker is obliged to trade from his own account to face the excess demand for the asset beyond the limit selling orders. As a response, the market maker moves up either or both of the quotes for two reasons. The first reason is that, according to the inventory theory of the bid-ask spread as proposed by Ho and Stoll (1978, 1981), this upward movement increases the likelihood that the next trade takes place at the bid and reduces excess inventory. The second reason is the positive probability that the excess demand originates from privately informed investors and that the value of the security should be revalued upwards.

Executions (both in terms of number of trades and share volume) against selling and buying limit orders as proportions of total executions for the entire period of 41 trading days centered on the earnings announcement dates are reported in table 29. Globally, executions against both types of limit orders are more likely in the Canadian than in the US markets for the cross-listed companies (77% and 41%, respectively, for number of trades).[65]

[Please insert table 29 about here.]

This result can be explained by a greater requirement for market maker services on US compared to Canadian markets since Canadian companies cross-listed on the US markets are more likely to be better known to Canadian market participants. Thus, in the Canadian market where trading activity also is relatively greater, traders provide most of the liquidity themselves. Furthermore, since trading on the US market is conducted on different markets with different trading mechanisms, the results are expected to be exchange dependent.

Table 29 also presents the proportion of executions against limit orders as fractions of total executions by different listing and trading US venues. As expected for the Canadian market, the US listing venue does not make a difference using number of trades as a measure of trading volume. Specifically, for the AMEX, NYSE and NASDAQ markets, the proportions are respectively 79%, 78% and 75%, which are not significantly different based on pair-wise t-tests. In contrast, the average executions based on dollar volume of 58% and 56% for NASDAQ and

[65] The respective percentages using share volume are 58% and 34%.

NYSE, respectively, are significantly lower than the 68% for the AMEX.[66] In general, executions against limit orders are higher in proportion for number of trades (a measure that favors less liquid and often small companies) compared to share volume. For US market trades, the lowest proportions of executions against both selling and buying limit orders occur on NASDAQ. To illustrate, executions against limit orders represent 44% and 43% of total executions, respectively, for the AMEX and NYSE, and a significantly lower 39% for the NASDAQ. This result is expected since dealers are more active on the NASDAQ than specialists on the NYSE.

The results for the three-days announcement window are presented in table 30. The results based on the number of trades are not statistically different from those for the entire period. For example, the average proportion of executions against limit orders for the total sample on the Canadian exchange is 77%. Their ratio of 1.007 is not statistically different from one using bootstrapped p-values for t- and Wilcoxon tests. In contrast, weak evidence exists for the US exchanges that executions against limit orders fall around the announcement date. The significant mean ratio of 1.0260 implies that investors submit less market orders or limit orders that are equivalent to market orders and replace them with limit orders. This outcome is expected since earnings announcements are typically accompanied by an increase in volatility, and the number of trades is strongly related to volatility (Handa and Schwartz, 1996; Foucault, 1999). [67] However, these undifferentiated results mask that this outcome is mainly due to the NASDAQ, and to a lesser extent the AMEX.

[Please insert table 30 about here.]

The ratios based on share volumes for the TSX are below one regardless of the US cross-listing venue and trade direction. For example, the mean (median) ratio of executions against limit orders for the entire sample during the entire period compared to the announcement period

---

[66] Similar results are obtained for the medians based on Wilcoxon-Mann-Whitney non parametric tests.

[67] The relation between volume and volatility is well documented. For examples, see Karpoff (1987), Gallant, Rossi and Tauchen (1992) and Anderson (1996). However, Jones, Kaul and Lipson (1994) and Jiang and Kryzanowski (1997) report empirical evidence that the number of trades and not the size of the trades or trading volume is related to price volatility.

is a significant 0.971 (0.946), which indicates a lower proportion of executions against limit orders around the announcement date This mitigates our previous conclusion. In contrast, the ratios are not significantly different from one for the US trade venues.

4.5. Probability of Informed Trading for Cross-Listed Shares

4.5.1 Basic results

In this section of the essay, our first objective is to measure the probability of informed trading (PIN) on a daily basis on both the Canadian and US markets for each stock. Easley, Kiefer, O'Hara and Paperman or EKOP (1996) assume that, if an event takes place, the event occurs before trading starts for that trading day. Using maximum likelihood, these authors are able to estimate the probability of an event occurring over a given number of days based on the argument that this probability is either one or zero for each day and can not be inferred directly. Since we need a time–varying daily measure of the PIN, we split each day into several exclusive intervals and apply the EKOP methodology to each day.

Specifically, we divide each trading day into 78 successive intervals of five-minutes length, and treat the trades in each interval as a single block. Ten samples are constructed where each sample contains eight trading blocks except for the ninth and the tenth that contain seven trading blocks each. Block assignment is conducted systematically on a rolling basis. The first block that covers the time period of 9:30 to 9:35 a.m. is assigned to the first sample. The second block that follows immediately is assigned to the second sample and so on. This design suffers from fewer problems than other alternatives in that not only are blocks of trades kept together but every sample contains blocks spread throughout the trading day.[68] Assigning individual trades randomly to samples would ignore the fact that the market maker may be able to infer potential private

[68] Samples formed successively during the trading day also are used. The trade clustering phenomenon well documented in the literature with periods of high trading volume like the morning session and the end of the trading day and periods of low trading volume like the midday cause the samples from this sampling design to be quite different, which leads to erroneous inferences from its use.

information from the time-series behavior of buy and sell orders and adjust his quotes accordingly. Furthermore, the interval needs to be long enough to capture divided orders. To illustrate, consider one large selling order that is executed against several outstanding limit orders. If the sample includes only these trades, we can infer that it is more likely that a negative event happened. An examination of successive trades with the same sign and trader ID from our sample of the ETQH shows that these trades are executed within 15 seconds in over 97% of the cases.

The arrival of informed and uninformed traders to the market place on day t follows a Poisson process with intensity parameters of μ_t and ε_t, respectively. For every sample, the probability of event occurrence is α_t and the conditional probability that the event has a negative impact on the stock is δ_t for day t. For every sample i on day t, we observe $B_{i,t}$ buyer-initiated trades and $S_{i,t}$ seller-initiated trades. Dropping the t subscript for convenience, the likelihood of observing B_i and S_i conditional on information set Θ is given by:

$$\begin{aligned} L\left\langle (B_i, S_i) \middle| \Theta \right\rangle &= (1-\alpha) e^{-\varepsilon} \frac{\varepsilon^{B_i}}{B_i!} e^{-\varepsilon} \frac{\varepsilon^{S_i}}{S_i!} + \alpha\delta e^{-\varepsilon} \frac{\varepsilon^{B_i}}{B_i!} e^{-(\mu+\varepsilon)} \frac{(\mu+\varepsilon)^{S_i}}{S_i!} \\ &\quad + \alpha(1-\delta) e^{-(\mu+\varepsilon)} \frac{(\mu+\varepsilon)^{B_i}}{B_i!} e^{-\varepsilon} \frac{\varepsilon^{S_i}}{S_i!} \end{aligned} \tag{13}$$

The first term in (13) corresponds to the case of a sample with no news events (i.e., the case where all traders are uninformed). The second term is linked to a bad event sample, and the third to a good event sample. The parameter vector to be estimated is $\Theta = (\alpha, \delta, \varepsilon, \mu)$ using a data set consisting of the numbers of buys and sells. In EKOP, α and δ are constrained to be inside the interval $[0,1]$ through a logit transformation. In addition, ε and μ are restricted to be positive by a logarithmic transformation.

Over the ten daily samples that are assumed to be independent, the likelihood function is:

$$L\langle (B,S) | \Theta \rangle = \prod_{i=1}^{10} \left[L\langle (B_i ; S_i) | \Theta \rangle \right] \tag{14}$$

This function is maximized using several numerical methods; namely, the Newton and Quasi-Newton algorithms (as developed by Broyden, Fletcher, Goldfarb, and Shanno, and by Davidon, Fletcher, and Powell), a combined Quasi-Newton with a Line search with analytic derivation of the gradient and the Hessian, and the Hill-Climbing algorithm of Quandt as used by EKOP. To reduce the probability of being trapped in a local maximum, several starting points are used for the various algorithms.

The parameter of interest is the probability of informed (PIN) trade, which is given by:

$$\mathrm{PIN}_t = \frac{\alpha_t \mu_t}{\alpha_t \mu_t + 2\varepsilon_t} \tag{15}$$

Its standard error using the delta method is equal to:

$$VAR(PI) = \begin{bmatrix} \frac{2\mu\varepsilon}{(\alpha\mu + 2\varepsilon)^2} & 0 & \frac{2\alpha\varepsilon}{(\alpha\mu + 2\varepsilon)^2} & -\frac{2\alpha\mu}{(\alpha\mu + 2\varepsilon)^2} \end{bmatrix} COV(\alpha, \delta, \mu, \varepsilon) \begin{bmatrix} \frac{2\mu\varepsilon}{(\alpha\mu + 2\varepsilon)^2} \\ 0 \\ \frac{2\alpha\varepsilon}{(\alpha\mu + 2\varepsilon)^2} \\ -\frac{2\alpha\mu}{(\alpha\mu + 2\varepsilon)^2} \end{bmatrix} \tag{16}$$

Before discussing the results, an important empirical issue needs to be addressed. Our estimates will be poor if a stock is thinly traded. To illustrate, assume that a single daily trade occurs that is buyer initiated so that all the five minute intervals but one contains an observed pair of (0,0) and the sole exception contains the entry (1,0). Maximizing the logarithm of (14) in this case is trivial, and will force the delta parameter to a value of zero. Therefore to obtain valid results, firms need to experience some minimum number of admissible trades per day. The choice of the minimum number of trades is discussed in the next section.

The empirical estimates for the intra-daily EKOP model and a more standard inter-daily version are reported in Table 31. The first parameter of interest is α which measures the probability of event occurrence. For the entire sample, the median probability of an event occurring is 34.58% and 34.87% based on trades on the US and Canadian trade venues, respectively. These values are not statistically different based on the bootstrapped p-values reported in table 32. This result conforms to a priori expectations since no differences in event occurrence or their probabilities of occurrence should exist for the same stocks over the same time periods. The significant difference in the mean α for the shares cross-listed on the AMEX, which suggests that the probability of event occurrence is higher based on the Canadian trades, is caused by a few outliers, especially for Bema Gold during the fourth quarter of the year 2002. Thus, the median α s of 31.86% and 33.01% based on the Canadian- and US-based trades, respectively, are not significantly different.

[Please insert tables 31 and 32 about here.]

The estimated δ parameter from the US-based trades that measures the probability of a negative event is lower than that from the Canadian-based trades by a significant 3.65% (see table 32). Furthermore, the estimate is significantly lower based on trades from NASDAQ and NYSE, and not significantly different based on trades from the AMEX.

While investors trade more intensively on the Canadian venue than on the US venues, no significant differences exist in the estimates of the trading intensity parameters for shares cross-listed on the TSX and the AMEX, NASDAQ or NYSE. The mean number of trades initiated by uninformed or liquidity traders is a daily 28.98 on the US trading venues and 60.50 on the Canadian trade venue. However, the mean ratio of 4.45 given in table 32 suggests that cases exist where practically all informed trading takes place domestically on the Canadian market. To illustrate, the ratio is 45.49 for Noranda Inc, which is cross-listed on the NYSE. This means that the Canadian market attracts 98% of the uninformed trading for this stock. The mean ratio for

Canadian uninformed trades over those for the AMEX, NASDAQ and NYSE are 1.40, 3.05 and 6.37, respectively. The corresponding median ratios are substantially lower at 1.34, 1.16 and 3.25. These findings lead to the inference that the uninformed trade more frequently on the Canadian than on the US market.

The same conclusion is reached for informed trading intensity. Based on table 31, the mean number of daily informed trades conditional on event occurrence is 29.40 on the US markets and a significantly higher 47.36 on the Canadian trade venue. As reported in table 32, their mean and median ratios of 2.60 and 1.15 are significantly different from one, due primarily to such activity on the NASDAQ and NYSE. However, the results are opposite and less conclusive for the AMEX cross-listed stocks, where the mean (median) trading intensity by informed traders is 45.26 (27.44) on the US trade venue. This value is higher than the mean (median) of 44.27 (24.48) on the Canadian trade venue. However, as shown in table 32, the mean matched ratio of 1.46 is significantly higher than one while the median ratio of 0.80 supports higher intensity on the US trade venues. The low t-statistic of 1.44 indicates that the results are driven by high heterogeneity in the sample. Globally and according to expectations, informed traders trade more intensively on the Canadian trade venue.

Given that the probability of event occurrence is the same for the US and Canadian markets and that both liquidity and informed trading activity are higher on the Canadian trade venue and that the Canadian-US market difference is wider for liquidity-based trades, we expect that the probability of trading against an informed trader is lower on the Canadian market according to expression (4). Based on table 31, a small but statistically significant difference in the PIN parameters of 263 basis points exists between the Canadian and the US trading venues (18.27% versus 20.90%) as expected. Furthermore, listing venue-specific differences occur for this metric. For example, the probability of trading against an informed trader is higher on the Canadian market than the AMEX (mean PINs of 27.20% and 20.75%, respectively), which can be explained by greater market thinness on the AMEX. This greater market thinness reduces the ability of the informed to hide their trades.

4.5.2 Impact of market fragmentation

The extent of information asymmetry can be related to the degree of market fragmentation between each pair of trade venues for each of the Canadian cross-listed shares. Consolidation versus market fragmentation is an important issue and its implications are of primary concern for traders, dealers, brokers and exchanges since it affects the price discovery mechanism, and thus the "public interest" (O'Hara, 1995).[69] Market fragmentation potentially can improve trading operational efficiency through inter-market or venue competition. The trading process evolves and the most competitive trade venue or platform should prevail. There is no incentive for the members of an over-the-counter or an organized exchange to achieve a better trading mechanism and to pass the benefit to traders if they are not threatened by competition. From this perspective, fragmentation can lower transaction costs, as measured by the spread.

However, fragmentation also can have a negative impact on market efficiency and the price discovery mechanism.[70] Trading can be revealing in that it can be a second component of information, as in Blume, Easley and O'Hara (1994), since privately informed traders initiate a portion of all trades. If trading is not concentrated, then its information content is split or even lost. If orders are not exposed to the "floor" (i.e., all outstanding limit orders), then the trader is not guaranteed to get the best execution. Time precedence for limit orders may not be respected since an equivalent limit order that is submitted later on a different venue may be executed earlier. These issues are related to the literature on market transparency. A consolidated order

[69] For this reason, the SEC adopted several rules to deal with the issue. As an example, the SEC introduced rule 19c-3 which eliminated trading off the NYSE of stocks listed after April 26, 1979. Davis and Lightfoot (1998) provide an excellent review of this rule. Rule 19c-3 also calls for inter-market competition. The SEC introduced the National Market System (NMS) which links all markets to provide the opportunity to trade against better orders from different locations. Quotes are posted on the Consolidated Quotation System (CQS) and orders are routed and executed on the Intermarket Trading System (ITS).

[70] Hamilton (1979) argues that trading off the main trading venue has both effects with small and opposite impacts. Competition among market makers is increased while trade fragmentation leads to inefficiency.

book available to the specialist gives the specialist the monopolistic power needed to face informed traders. Having access to the entire book confers better information than viewing partial fragments linked to separate trading platforms.

Amihud, Lauterbach and Mendelson (2003) manage a "clean" test of consolidation value by investigating the exercise of warrants. Unlike options, warrants lead to the creation of new shares. Therefore, deep-in-the-money warrants are considered substitutes for the shares and upon exercise there is consolidation of both markets. Amihud, Lauterbach and Mendelson report an increase in trading volume, a decline in the implicit spread, and positive abnormal returns upon consolidation. The abnormal return is not information related since the exercise is totally expected, and hence linked to enhanced liquidity. These findings are related to the degree of fragmentation in that the effects are greater for higher levels of fragmentation.

Pagano (1989) develops a model with multi-trading venues where traders transact only for liquidity purposes (i.e., privately informed investors are absent). He shows that the most likely outcome is that one market will eventually dominate the other and attract all trades. Chowdhry and Nanda (1991) develop an equivalent model in the presence of asymmetric information and show that one venue again will dominate the other in terms of trading volume for a short-lived information case. The privately informed trader will split his order strategically to hide but will trade aggressively to take advantage of the fragmentation. However, the existence of discretionary liquidity traders will lead to an Admati and Pfleiderer (1988) concentrated market. In a multi-period case, the release of information on order flow by trading venue is critical. If the market maker on a specific market commits to the release of order-flow information, then the privately informed trader avoids trading on that venue. Chowdhry and Nanda show that the only equilibrium in this case is the one where all market makers report information on their respective order flows. The market quality is even enhanced by implementing insider trading controls and supervisory mechanisms. However, as the authors clearly note, they do not consider the exchanges as strategic competitors to each other.

Using a model based on Glosten and Milgrom (1985), Madhavan (1995) shows that fragmented markets are exploited by large liquidity traders and by dealers given reduced price competition. Fragmentation is related to the degree of information disclosure about the order flow in each market. If the dealers publicly announce their respective order flows, then the market is unified.. The intuition behind the Madhavan result is straightforward. Due to the presence of informed traders and the behavior of large traders to trade usually on the same side of the market, the impact of their trades is higher on prices and so is the execution cost higher.

Davis and Lightfoot (1998) find that stocks trading under rule 19c-3 that permitted off the board trading (i.e., market fragmentation) had higher spreads than stocks under rule 390 that prohibited off the board trading. Similarly, Bennett and Wei (2003) report that stocks that switched listing from NASDAQ to NYSE had higher reductions in variances and lower execution costs if their pre-switch market was more fragmented.

Dual listings also present an opportunity to test for the liquidity trading versus the noise trading hypothesis. As summarized in the literature review by Karolyi (1998),[71] the main issue is the relation between volume and volatility. Since the increase in volatility also is associated with higher volume, then variance is induced by information and not by noise trading.

Isolating the importance of information based trading by examining regular trading hours now extends this literature.[72] From the results reported earlier in sections 3 and 4, we found that the Canadian market dominance over the US trading venues for Canadian cross-listed shares is not total and that the US markets still capture a material portion of the trading activity for these shares. In order for both markets to survive, they should be able to attract both types of traders, namely, liquidity and privately informed traders. We find that both markets do retain trades from both trader types as was shown by the EKOP inter-daily results. The probability of trading against

[71] This includes Barclay, Litzenberger and Warner (1990), Makhija and Nachmann (1990), Werner and Kleidon (1996), Forster and George (1994) and Chan, Fong, Kho and Stulz (1996).
[72] The US and the Canadian trade venues share the same trading hours. Therefore, we do not have the extended trading hours problem and the associated potential confounding effects that affect many other cross-country market pairings.

an informed trader is the same between the two trading venues. Uninformed traders, as Admati and Pfleiderer (1988) and Chowdhry and Nanda (1991) argue, tend to trade together on the same venue at the same time. Strategically, this reduces the impact of trading on the price and diminishes the probability of getting bagged by the privately informed traders. Uninformed investors will then pick the trading venue that is more convenient for trade. For instance, they will consider the trade venue with the lowest quoted trading cost giving rise to the inter-market competition argument. Given their beliefs about the trading behavior of the uninformed, the informed traders also will strategically trade in the active trade venue to hide their trades in order to delay the informational impact of their cumulative trades on prices and to prolong their informational advantage over the uninformed traders. In turn, this leads to a Chowdhry and Nanda (1991) type of equilibrium where the Canadian market should completely dominate the US market.

However, what we observe differs from this stylized prediction. While the Canadian market is still deeper than the US market, its spread cost advantage has essentially disappeared. The greater depth should attract both types of traders since uninformed traders can be less concerned about submitting larger size orders with the risk of price movement against them, and privately informed traders can use the depth that absorbs their trades before the market realizes that it is moving on one side. Nevertheless, the US market continues to be deep enough to attract both types of investors for Canadian cross-listed shares.

To further investigate the trading patterns of both trader types, we first investigate where the informed trade. Based on the informativeness issue, we expect the informed to start trading on the main market, which is usually the Canadian trade venue, and to then split their trades between the fragmented markets to extend their advantage. We expect the Canadian market to be more informative but also that the US market contributes to price discovery since the privately informed also trade there. Using an error correction model, Eun and Sabherwal (2003) find that the prices of Canadian cross-listed shares on either market are influenced by price changes on the other market. They document that this feedback effect is more important from the Canadian to the US market than in the opposite direction.

By analyzing the intra-daily EKOP estimates, we find evidence that corroborates this and explains the origins of the mechanism. Figure 1 shows the time trend of the EKOP parameter estimates around earnings announcement dates. Since the expectation is that days before the announcement are characterized by trading based on private information, we can identify where informed trade first begins and how the pattern moves between the two competing trade venues. Panel A of figure 1 shows the mean and median estimates and their 95% confidence interval for α for both the US and Canadian trades. All the x-axes are centered on day zero or the earnings announcement date.

[Please insert figure 1 about here.]

The graph for the US trades documents a clear increase in the probability of event occurrence on day zero to a mean (median) peak value of 60.55% (60.20%). However, no discernable peak is evident around day 0 for the Canadian trades. Instead, there is a steady decline in this probability that begins about four days prior to the announcement. As expected, the cross-sectional time series average alpha parameters over the entire time period are 58.92% and 54.70% for the US and Canadian markets. Compared to the inter-daily version where the parameter estimates were the same for the two groups, we now have a lower value on the Canadian market compared to the US market. The intra-daily mean also is significantly higher in value than the mean inter-day estimate essentially due to the added noise caused by greater data frequency.

Based on panel B in figure 1, a very short-lived decline is observed at the announcement date for the delta parameter. This decline takes place simultaneously on both the Canadian and US markets. Furthermore, no difference exists between the estimate from the inter-daily and that of the intra-daily versions.

The most dramatic impact occurs for the trading intensity parameters. Based on Panel C, informed trading intensity increases but by different magnitudes on both US and Canadian trade venues around the earnings announcement days. The increase in the US market is quite muted compared to that observed for the Canadian market, which peaks on day 1. The increase in the trading intensity of informed traders can be dated to three days prior to the announcement for the Canadian market.

Based on panel D, no differences exist in the time series pattern of the liquidity trading intensity parameters between the US and Canadian markets. Both markets experience a clear and sudden jump in such trading that corresponds with the release of news about earnings. Privately informed trades peak at 18.70 on day 1 after the announcement on the US market, and peak at 24.12 on the Canadian market. These correspond to daily values of 187.0 and 241.2, respectively.[73] If the values for the peak periods are excluded, the mean μ estimates for the US and Canadian markets are 12.69 and 17.44, respectively. The increase in liquidity trades includes trades by investors who rebalance their portfolios after the release of the information, traders who trade on the information based on the belief that it has not been completed reflected in prices, traders who trade because they observe higher trading volumes, and traders who trade on noise as if it was information (Black, 1986).

The final parameter of interest is the probability of informed trading (PIN). Given that the alpha parameter slightly increases upon earnings announcement, that the uninformed liquidity traders intensify their activity and that the informed modestly increase their trading activity, the expectation is for a lower probability of trading against an informed trader because of the dilution in the trader pool created by more uninformed traders. Based on Panel E of figure 1, this conjecture is confirmed as the mean PIN on the US market drops from 41.05% two days before the earnings announcement to 37.25% on the day after the earnings announcement date. A similar pattern is observed on the Canadian market although informed traders intensify their trading activity. The PIN for the Canadian leg of the total market falls from 37.20% to 34.96% for the

[73] This occurs because ten samples are used to estimate the intra-daily model for each day. The daily figures are higher than those estimated from the inter-daily version of 141 and 198 liquidity motivated trades per day for US and Canadian market venues, respectively, which were presented earlier in table 31.

same dates. As for the inter-daily estimation, the PIN estimates for the intra-daily EKOP are lower on the Canadian versus US markets. This means that, even if the number of informed traders or their trading activity is more intense on the Canadian market, the mere presence of more uninformed traders or the fact that they trade more frequently reduces the probability that the counterpart is indeed a privately informed trader for a specific trade initiated by an uninformed trader.

The decline in the PIN parameter can be traced to the day just preceding the earnings announcement for both competing markets. Therefore, we cannot conclude that either market is preceding the other in terms of price discovery.

4.6. Changes in the Probability of Informed Trading Using a Regime Switching Approach

In this section, the daily probability of informed trading is inferred from US and Canadian based trades for Canadian shares cross-listed on the main US exchanges using an alternate estimation method. The implied quoted spread also is decomposed into its temporary and permanent components to obtain a better understanding of the information differential between the two trade venues.

4.6.1 Model and methodology

Our approach is similar to that used by Nyholm (2003) for 20 NYSE-listed shares over the month of August 1995 in that we use a model based on Glosten and Harris (1988). However, unlike Nyholm, we allow the trading cost to be directly dependent on trading volume. We first classify all trades based on their size into three categories. Then within each category, we let the relation be dependent on the size itself. To develop our model, we first assume that the "true" price of the asset follows the motion equation given by:

$$m_t = m_{t-1} + I_t \times Z_t \times s_t + e_t \tag{17}$$

where m_t is the "true" price at time t,

I_t is the trade indicator at time t (-1 for seller initiated, and +1 for buyer initiated),

Z_t is the adverse information cost given that the trade is information based, which has a permanent impact on the "true" price of the asset,

s_t is an unobserved state variable related to the nature of the trade, which is equal to 1 if the trade is information based and 0 if not (i.e., the case of a purely liquidity based trade), and

e_t is related to the public news released during the interval between t-1 and t.

In (17), the state variable s_t is unobserved for the econometrician only. The market maker is assumed to perfectly identify the origin of the trade. Of course, it is unlikely that the market maker can infer this with total precision.

Once the "true price" is set, the market maker sets transaction prices to recover her own order processing fees using the following pricing mechanism:

$$P_t = m_t + I_t \times C_t \tag{18}$$

where I_t is defined as above, and C_t is the order processing cost and corresponds to the temporary component of the bid-ask spread.

Given the true price motion (17) and the pricing function (18), the change in price between time t-1 and t is computed using:

$$dp_t = I_t \times Z_t \times s_t + I_t \times C_t - I_{t-1} \times C_{t-1} + e_t \tag{19}$$

In (19), dp_t depends on the state variable s_t. The change in the transaction price is $dp_t = I_t \times Z_t + I_t \times C_t - I_{t-1} \times C_{t-1} + e_t$ if an informed trader initiates the transaction, otherwise the market maker changes the transaction price by $dp_t = I_t \times C_t - I_{t-1} \times C_{t-1} + e_t$ only if a liquidity trader initiates the trade. Glosten and Harris (1988) assume that both C_t and Z_t are related to the size of the transaction at time t. Therefore, we use size as a determinant of the trading cost as is found in the literature.[74] Barclay and Warner (1993) find that medium size trades have the largest impact on the price and conclude that these trades contain more private information than small or large size trades. Chakravarty (2001) not only confirms this stealth trading hypothesis but refines it by reporting that medium size trades initiated by institutional investors are those with the largest price impact. Keim and Madhavan (1996) develop a model for block trades where the price impact is a concave function of the trade size.

Based on these findings, we separate our trades into three categories that are expected to have different marginal price impacts. We define small trades as those with 500 shares or less as in Barclay and Warner (1993), Chakravarty (2001), Koski and Michaely (2000). Medium size trades are transactions of 501 to 5000 shares, and large trades are transactions of 5001 shares and more. Since block trades on the NYSE and NASDAQ are defined as trades of 10,000 shares and more, this would be a natural definition of a large trade. We choose not to use this break point between medium and large trades for the following reasons. First, as noted by Bessembinder and Venkataraman (2005), "...the definition of a block trade should vary depending on share price and trading activity in the stock". If a stock has a high per share price, then a transaction of 5,000 shares can be considered as a large trade. Also, if the stock is thinly traded, 5,000 shares is a very large trade. For the sample under investigation, there are cases where no transactions of more than 10,000 shares are registered. This is especially true for the US based trades of the Canadian shares cross-listed on the NASDAQ. Following Bessembinder (2003) and others,[75] we thus use 5,000 shares as the cut-off point.

Hence, we have:

$$C_t = c_0 + c_1.V_t.DS_t + c_2.V_t.DM_t + c_3.V_t.DL_t \tag{20a}$$

---

[74] Nyholm uses a fixed cost per size category. We argue that since the cut off points are arbitrary, allowing size variability within each class can alleviate the classification problem especially for the medium size trades that are considered as the ones with the highest proportion of informed trading.

[75] Koski and Michaely (2000) define medium trades as those at 5,000 shares. Moreover, SEC rule 11Ac 1-5, which requires exchanges to disclose information on average execution costs for different order types and sizes, uses the threshold of 5,000 shares as the cutoff between medium and large transactions.

$$Z_t = z_0 + z_1.V_t.DS_t + z_2.V_t.DM_t + z_3.V_t.DL_t \qquad (20b)$$

where DS_t is a dummy variable equal to one when the trade size is below 500 shares and zero otherwise,

DM_t is a dummy variable equal to one when the trade size is between 501 and 5,000 shares and zero otherwise, and

DS_t is a dummy variable equal to one when the trade size is strictly higher than 5,000 shares and zero otherwise.

Therefore, the change in the trading price is:

If state 1:

$$\begin{aligned} dp_t &= \alpha_1 + c_0 \times dI_t + c_1 \times d(I_t.V_t.DS_t) + c_2 \times d(I_t.V_t.DM_t) \\ &\quad + c_3 \times d(I_t.V_t.DL_t) + e_t \end{aligned} \qquad (21a)$$

If state 2:

$$\begin{aligned} dp_t &= \alpha_2 + c_0 \times dI_t + c_1 \times d(I_t.V_t.DS_t) + c_2 \times d(I_t.V_t.DM_t) + c_3 \times d(I_t.V_t.DL_t) \\ &\quad + z_0 \times I_t + z_1 \times I_t.V_t.DS_t + z_2 \times I_t.V_t.DM_t + z_3 \times I_t.V_t.DL_t + e_t \end{aligned} \qquad (21b)$$

where d(x) is the first order difference of the variable x.

Following Nyholm (2003) and assuming that the state of nature follows a Markov chain, the parameters of interest are estimated using a Hamilton type filter similar to the Kalman filter. Maximum Likelihood Estimation is used for this purpose. First, the density vectors of the residuals are formed assuming that they are normally distributed. Using the notation in Hamilton, this vector is named η where:

$$\eta_t = \begin{pmatrix} \eta_1 \\ \eta_2 \end{pmatrix} = \begin{pmatrix} \dfrac{1}{\sqrt{2\pi\sigma_1^2}} \exp\left(-\begin{pmatrix} dp_t - \alpha_1 - c_0 \times dI_t - c_1 \times d(I_t.V_t.DS_t) - c_2 \times d(I_t.V_t.DM_t) \\ - c_3 \times d(I_t.V_t.DL_t) \end{pmatrix} \right) \\ \dfrac{1}{\sqrt{2\pi\sigma_2^2}} \exp\left(-\begin{pmatrix} dp_t - \alpha_2 - c_0 \times dI_t - c_1 \times d(I_t.V_t.DS_t) - c_2 \times d(I_t.V_t.DM_t) \\ - c_3 \times d(I_t.V_t.DL_t) - z_0 \times I_t - z_1 \times I_t.V_t.DS_t \\ - z_2 \times I_t.V_t.DM_t \quad - z_3 \times I_t.V_t.DL_t \end{pmatrix} \right) \end{pmatrix} \qquad (22)$$

In (22), we allow for two different intercepts to account for the differences not explained by the regressors. Secondly, (22) is an unrestricted model with unequal variances, although a restricted model with $\sigma_1^2 = \sigma_2^2$ also is estimated. Allowing the variance to be state dependent is appealing and has interesting implications but limits the ability to draw inferences because it reduces the number of cases where convergence is achieved. For this reason, only the restricted model results are reported herein.

The state vector ξ_t is updated according to the motion equation:

$$\xi_{t+1|t} = \mathrm{P}\xi_{t|t} \tag{23}$$

where P is the transition matrix that is given by:

$$\mathrm{P} = \begin{pmatrix} P_{11} & 1-P_{22} \\ 1-P_{11} & P_{22} \end{pmatrix} \tag{24}$$

In (24), P_{11} and P_{22} correspond to the probability that the state variable remains at states 1 and 2, respectively. $\xi_{t|t}$ is the conditional probability of the state vector based on the data up to time t. $\xi_{t+1|t}$ is the conditional expectation of the one-step-ahead state vector, which is a posterior update on the state vector given data up to time t.

By the conditional probability definition, $\xi_{t|t}$ can be inferred from:

$$\xi_{t|t} = \frac{\xi_{t|t-1} * \eta_t}{1'(\xi_{t|t-1} * \eta_t)} \tag{25}$$

where $*$ denotes the element-by-element multiplication. The model is estimated using a quasi maximum likelihood approach where the likelihood function to be maximized is the intertemporal sum of the natural logarithms of the numerator in equation (19)[76]. Specifically, the estimation is based on:

[76] The same optimization techniques and algorithms are used here as were used earlier for the EKOP estimations. Specifically, the BFGS, DFP and Hill Climbing with different starting points are used to reduce the risk of getting trapped in a local optimum.

$$\underset{\theta}{Max}\sum_{t=1}^{T} Log\left[1'(\xi_{t|t-1} * \eta_t)\right] \tag{26}$$

where the vector of parameters is $\theta = (\alpha_1, c_0, c_1, c_2, c_3, z_0, z_1, z_2, z_3, \alpha_2, \sigma^2, p_{11}, p_{22})$.[77] The model is first estimated using all the filtered microstructure data. For many companies, this is very cumbersome and time consuming and the maximization algorithm fails for several reasons. The model also is estimated using equally time-spaced data that are sampled every 30 minutes to yield 14 observations per trading day.

The smoothed estimates of the state vectors using the Kim (1993) algorithm also are generated. These inferences are not one-step-ahead "forecasts" but rather use all the data up to time T. Technically, these smoothed estimates are computed as backward iterations starting from t = T-1 and based on the expression:

$$\xi_{t|T} = \xi_{t|t} * \left(\mathrm{P}' \cdot \left[\xi_{t+1|T} (\div) \xi_{t+1|t}\right]\right) \tag{27}$$

The notation $\xi_{t|T}$ emphasizes the fact that the smoothed fitted values use all the data.

4.6.2 Results on informed trading

The results from estimating system (17) to (26) are reported in table 33. For each stock-observation, we run separate estimations using trades on the US and the Canadian markets. The estimation covers the 41 trading days centered on the earnings announcement. Out of the entire sample of 493 earnings announcements, convergence is achieved for 234 and 261 cases for the US and the Canadian markets, respectively. Out of these, 144 cases correspond to the common sample whose results are reported in table 33 and in the remainder of the chapter.

[Please insert table 33 about here]

Glosten and Harris (1988) argue that only the parameters c_0 and the z's should be significant. Since c_0 corresponds to the temporary cost, it should not be related to volume but rather to the per-transaction fixed order processing cost. The expectation is that this parameter estimate should

[77] To use a free maximization procedure and to avoid the constraints, an exponential transformation is made for σ and a logistic transformation is made for both probability parameters p_{11} and p_{22}.

be positive. As for the permanent cost, the argument is that the higher the trading volume the more likely the trader is informed who acts aggressively. Thus, since the permanent trading cost is predominantly a variable per share cost, the estimated z parameters are expected to be positive and significant. However, Barclay and Warner (1993), amongst others, argue that the z estimates depend on trade size. Thus, our expectation is that z_2 will be significantly positive indicating that average size trades are hiding orders from privately informed traders, while z_3 is probably of smaller magnitude and insignificant as large trades are normally not information motivated but arranged before execution.

Based on table 33, all c_0 estimates are positive for the Canadian based trades and most are positive for the US trades. Since the trading cost captured by c is fixed, we expect that the cost per share falls for higher trade volumes. However, the mean c estimates are negative for the Canadian trades, which indicates that trading costs decrease with higher trading volumes. For the US trades, the estimated c_3 coefficients are positive (i.e., for large trades), which indicates that the order processing cost is higher for large transactions. The reason is that dealers usually need to manually allocate trades and spend more research effort to fill large trades.

The estimates of z_1 and z_2 are positive. Thus, for small and medium sized trades on both markets, the information asymmetry cost increases with higher trade sizes. However, the mean and median z_3 parameters are negative for Canadian trades, which indicate that the information asymmetry cost decreases with larger trade size for large trades. This finding is consistent with the results reported in the literature that large trades are not usually motivated by private information. However, for the US trades, the average z_3 coefficient estimate is positive. Although this is inconsistent with expectations, it can be explained as follows. From the perspective of a large trader who is liquidity motivated, he is more likely to submit his order to the deeper (Canadian) market since his order is large and is likely to work down the book to less attractive limit orders. If such traders submit their orders to the thinner US market, there is a higher probability that the order is information motivated.

The continuation probabilities of states one and two are reported in table 33. P_{11} (P_{22}) is the probability that the next trade by the dealer will be against an informed (uninformed) trader given that the present trade is against an informed (uninformed) trader. Based on table 33, the continuation of state 1 is the more likely based on its higher means and medians for both Canadian and US trades. The cut-off points of the cross-sectional distribution at the first and the third quartiles also confirm this finding. The distribution of the P_{11} parameter for the US trades dominates that from the Canadian trades, and its mean of 82.58% is significantly higher than the corresponding mean for Canadian trades of 77.98%. The P_{22} parameter estimate exhibits a similar but less pronounced pattern for the two trading venues. While the parameter estimate for the US trades dominates that for Canadian trades in terms of the first quartile, the median and the third quartile, it has a wider distribution given its smaller minimum and larger maximum values than for the Canadian trades. This is supported by the matched-sample t-test but not the Wilcoxon test. The mean of P_{22} of 30% for the Canadian trades indicates that dealers expect an informed trade to be followed by an uninformed trade with a probability of 70%, almost 2.5 times the likelihood of trading again with an informed trader. This contrasts with the likelihood of trading with an informed trader after dealing with an uninformed trader of 17.42% and 22.02% for the US and Canadian trade venues, respectively. The corresponding odds ratios are respectively 4.74 and 3.54 times. These odds ratios provide some initial information on informed trading activity in that it is less likely on the US market.

To investigate this issue further, the unconditional estimates of trading against informed and uninformed traders (i.e., the probabilities that states 1 and 2 continue) are computed for both trading venues. The unconditional probabilities that the dealer is trading against an informed trader are reported in table 33. The unconditional probabilities are given by the limit of the transition matrix, whose first element is equal to:

$$P_1 = \frac{1 - P_{22}}{2 - P_{11} - P_{22}} \tag{28}$$

The results reported in table 33 provide weak support for our hypothesis that informed traders are more likely to trade on the domestic Canadian market. While the mean unconditional state 1 probability of 82.34% for US trades is significantly higher than the 77.61% mean estimate for Canadian trades, the medians are not significantly different.

The above methodology can only compute the unconditional states probabilities for the entire period since it uses all observed trades for that period. It can not be used to examine changes around the earnings announcements dates, and whether any change are symmetrical between trading venues.

To compute a probability of trading against (un)informed traders for both markets at both announcement and non announcement dates, an inference on the realization of the state vector s_t is required. To that end, the vector $\xi_{t|T}$, which corresponds to the conditional probability of the state vector for each trade based on smoothing using all the data available, is build. The trades that correspond to the three-day announcement periods are then isolated, and a sub-vector from $\xi_{t|T}$ that corresponds to these trades is build. The probability of state 2 over the earnings announcement period is the sum of the second column of the sub-vector $\xi_{t|T}$ divided by the corresponding number of trades. By analogy, the probability for the days that exclude the earnings announcement uses the $\xi_{t|T}$ components that do not correspond to trades that occur during the earnings announcement window.[78]

The resulting estimates for both trading venues are reported in table 34 for the probability of trading against an informed investor on the Canadian (US) market at the announcement (non-

[78] The probability of state 1 (i.e., trading against the uninformed) is obtained using the same methodology used in obtaining the values reported in the first column of the vector $\xi_{t|T}$.

announcement dates). The results of various statistical tests that compare these four groupings are reported in the second panel of this table.

[Please insert table 34 about here]

Based on table 34, the probability of informed trading is not significantly different between announcement and non-announcement periods for the Canadian market based on both the t- and Wilcoxon tests. In contrast, the probability of information trading declines for US-based trades. The mean probability of informed trading falls significantly from 19.64% to 14.18% in the earnings announcement window. Consistent with the results reported in section five, the probability of trading against the informed declines only for US-based trades during the earnings announcement window. Furthermore, the magnitude of informed trading estimates is approximately 19% for both the regime-switching and EKOP models.

Based on the first column in Table 34, no significant difference exists in the likelihood of information trading for the earnings (non)announcement windows between the two trading venues. Combining the findings reported in tables 33 and 34, although informed traders are more likely to trade in the domestic Canadian than foreign US market, the probability of trading against the informed is similar between the two trading venues. Both trader types maintain a relatively constant presence so as not to change the equilibrium of either markets. As long as both markets preserve similar proportional characteristics in terms of informed-to-uninformed trading, both can survive in a fragmented market.

4.6.3 Trading cost and spread components

An implied bid-ask spread and its permanent and transitory components can be computed from the regime-switching estimates. Based on equations (20a) and (20b), the half quoted spread can be estimated by:

$$\begin{aligned}\hat{S}_t = \hat{C}_t + \hat{Z}_t = \hat{c}_0 + \hat{z}_0 + \left(\hat{c}_1 + \hat{z}_1\right) \times V_t \times DS_t + \left(\hat{c}_2 + \hat{z}_2\right) \times V_t \times DM_t \\ + \left(\hat{c}_3 + \hat{z}_3\right) \times V_t \times DL_t\end{aligned} \tag{29}$$

where the hat over the variables indicates the estimated value from the regime-switching model. The half permanent variable and half temporary fixed costs are given respectively by:

$$\hat{Z}_t = \hat{c}_0 + \hat{z}_0 + \hat{z}_1 \times V_t \times DS_t + \hat{z}_2 \times V_t \times DM_t + \hat{z}_3 \times V_t \times DL_t \tag{30}$$

$$\hat{C}_t = \hat{c}_0 + \hat{c}_1 \times V_t \times DS_t + \hat{c}_2 \times V_t \times DM_t + \hat{c}_3 \times V_t \times DL_t . \tag{31}$$

One drawback of a Glosten-Harris like approach is that it can yield negative estimates of the implied spread or its components. This result is usually caused by one dominant component (usually the permanent component)[79] being negatively related to volume. However, by relating the z parameter to the trade size itself in a piecewise linear manner, this problem is greatly alleviated.

The cross-sectional distribution of the half spreads and their components for both the Canadian and the US trades and for the (non) event windows are reported in table 35, and tests of their significance are reported in table 36. The total implied half spread is on average 0.30% for the earnings announcement window. As expected, this value is well below the posted half spread of .71% and is closer to the effective half spread of 0.31% (both of the latter values are reported in table 36). The reason is that the implied spreads are driven by transaction prices and account for trades that occasionally occur inside the posted quotes. The estimates from the US trades are similar with a mean implied half spread of 0.25%. Thus, both the quoted and implied spreads are lower on the US compared to Canadian trade venues as was reported in section 3.

[Please insert tables 35 and 36 about here]

The statistical significance of the spread differential between Canadian and US implied trades in the announcement window are reported in Panel A of table 36. Total half spread and half

[79] This is more common for small trades. Theoretically, when the estimated z_0 parameter is negative and the z_1 parameter is a small positive value, the permanent component is dominated by the negative intercept. In turn, this results in a negative estimate of the permanent trading cost.

permanent costs are higher on the Canadian versus US market.[80] The change in the proportional temporary component is not significant based on the t-test and significant and higher for the Canadian trading venue based on the Wilcoxon test. However, both tests agree that the proportional permanent cost component is higher for Canadian- versus US-based trades. The mean (median) differentials for the half spread and the half permanent cost are a significant 8 (5) basis points above the US estimates. This supports our earlier conclusion that more informed trades occur on the domestic Canadian market. Based on panel B of Table 36, the reverse occurs during the non-event windows. This further supports our earlier conclusion that the impact of the announcement is mostly on the US permanent cost component.

With regard to the announcement-induced change, the permanent cost component increases and the temporary component exhibits no change on the Canadian market, as is shown in panel C of table 36. While the temporary component also exhibits no change on the US market so does the permanent cost component. As a result, the overall implied spread increases significantly on average (by 4 basis points) only on the Canadian market. The increase in the permanent cost for Canadian-based trades is a reaction by the dealers to the intensified presence of informed traders, primarily on the Canadian trade venue. Therefore, most informed traders shift their trades to the Canadian domestic market during the announcement window. This also explains the more marked decline in the PIN measure on the US market that was reported in section five. The informed investors take advantage of the higher uninformed trading intensity of impatient traders who are rebalancing or are reacting to the news announcement. Since these investors are more likely to be present on the same side of the market, the depth that the Canadian market offers is very valuable. This provides ation on why the uninformed do not massively shift their trades to the US market.

[80] Even though statistics based on a comparison of the dollar trading cost between the US- and Canadian-based trades are reported, we do not analyze them because, as expected, the dollar cost in Canada is higher than the dollar cost in US given the exchange rate differential.

4.7. Concluding Remarks

The liquidity of the Canadian shares that are cross-listed on the major US markets was investigated in this chapter. Cross-listing is an example of market fragmentation where several trading platforms survive together. For this market situation to hold, minimum trading conditions must be met so that one market does not become dominant and force the others to close. The dynamics of the trading game between the informed and uninformed traders and the market makers allows the survival of all markets only if all market participants are present to some extent on all of the markets. For example, if uninformed traders concentrated on only one market, the resulting equilibrium is not stable in that only the market with the concentration would survive, since all informed traders would move away from the market where the uninformed are absent. The reason is that the privately informed traders need the uninformed to hide their trades.

To better examine information-based trading, we analyzed trading across periods with changing information structures. Since material corporate announcement events are a typical example of a changing intertemporal private information structure, this chapter examined earnings announcements. The expectation was that such announcements are information revealing, and thus, would reduce information related trades.

The domestic Canadian market no longer offers a spread cost discount for trades. The cost advantage argument for trading on the Canadian market plays a lesser role in attracting trades since all markets offer similar spread cost structures. However, the domestic Canadian market still offers a deeper market compared to the US market for Canadian cross-listed shares. Therefore, the Canadian market is more appealing for medium and large trades because it can absorb these trades with almost no price impact.

We also find that more informed traders intensify their trades on the domestic compared to the foreign market after an earnings announcement as manifested in the probability of informed trading and behavior of the bid-ask spread components. Several papers argue that both markets participate in making the price of a stock through feed back effects since investors infer the price and update their beliefs by observing both markets simultaneously. This chapter presents an argument for mainly following the Canadian market for earnings announcements. Since this is the market where most investors trade, its aggregation power is stronger. Secondly and more importantly, the Canadian market is the locale for most informed trades. Further investigations on the (very) short-term feedback effects between the two markets, namely the US and the Canadian markets for cross-listed shares, need to be conducted in future research to support or refute this conjecture.

CHAPTER 5

CONCLUSION

Managers use corporate announcements to inform outsiders about various events that can influence the firm's value. Some investors may already be in possession of such information before its public release and hence take advantage of it. The public announcement should reduce information asymmetry by spreading the news to the wider investing public. This thesis focused on the liquidity and information asymmetry impacts of such announcements. More specifically, we studied stock splits, mergers and acquisitions, and earnings announcements. For the latter event, we were more interested in comparing liquidity differences between trading venues for the Canadian shares cross-listed on the US main stock exchanges around a corporate disclosure, such as an earnings announcement, that involves a time-varying asymmetric information regime.

The first essay dealt with stock splits and found that both liquidity and trading activity change for stock splits. Consistent with the literature, we found that proportional trading costs increase and market depth declines after splits. However, this deterioration in liquidity is offset somewhat by a small improvement in trading activity. We found that both dollar and share volumes increase. In order to identify the causes of the increase in trading activity, we decomposed the quoted bid-ask spread into its temporary and permanent components. The permanent component corresponds to the compensation that market makers receive for trading against privately informed traders while the temporary component is the cost of processing orders and is usually fixed per trade. The strong increase in both components implies that informed traders intensify their trading activity around the split announcement. However, we found that the permanent component did not increase for high per-share priced stocks, and that this component decreased for low per-share priced stocks. This implies that the split had no impact on information asymmetry for high per-share priced stocks, and is mainly a tool to reduce the per-share price for these stocks back to its normal range, as in Angel (1997).

The second essay investigated the change in liquidity and trading activity of both targets and bidders around acquisition events. A dramatic increase in trading volume for targets around the acquisition announcements (and to a lesser extent for bidders) is accompanied by a reduction in the bid-ask spread as expected but also by a decrease in quoted depth. We also documented selling pressure around the announcements where seller-initiated transactions increase more than buyer-initiated transactions. Selling pressure is stronger for targets acquired with cash transactions. The stronger appetite by shareholders to submit orders that hit the best outstanding buy orders further supports these results. This is equivalent to submitting a market order, which indicates that investors are impatient to sell all or part of their holdings.

This finding is linked to portfolio rebalancing activity and limited arbitrage transactions. To further investigate the motivations of traders around acquisitions, we investigated both the temporary and permanent components of bid-ask spreads. Both components decline for targets. Higher trading activity reduces the per-dollar cost to process orders. Cash payment signals that the target is either undervalued, or that the bidder thinks so and is willing to pay a premium to acquire the target. The consequence in either case is a reduction in information asymmetry and a decline in the cost component that compensates for this risk. The permanent bid-ask spread component for bidders who use shares to acquire targets also declined. This empirical result is related to the literature that considers that share acquisition is a negative signal about the value of an acquirer. Our results show that the decline in information asymmetry is linked to abnormal returns for both cash targets and share bidders. In an apparent contradiction to the reduction in information asymmetry, we found that the trading intensity of informed traders increases post-announcement. The news announcement attracts more informed investors. However, this is caused by the relatively higher increase in uninformed trading activity. Traders with no private information who react to the acquisitions for various reasons by trading create an opportunity for (potentially) informed investors who can better hide their transactions among a bigger trading pool. As was found for stock splits, uninformed traders who act strategically continue to trade knowing that they are less likely to trade against informed traders. The reason is again that both groups trade simultaneously so that the probability that the counterparty in a particular trade is informed is reduced.

The third essay analyzed trading activity and liquidity on the various trading venues for Canadian firms that are already cross-listed. From the trading patterns, we identified where the informed traders trade first and how price innovations are propagated and impounded into the price. The analysis was conducted around earnings announcement dates because the periods around such dates are supposedly characterized by high information asymmetry. Specifically, information asymmetry should dramatically decrease right after the announcement since information is no longer private if it is widely disseminated among the investing public. Therefore, the choice of earnings announcements as the studied event is purely determined by the fact that such announcements are characterized by informational flow.

We found that most of the information is discovered in the Canadian trading venue, although the US trading venue is neither totally passive nor redundant. This helps to explain why Canadian firms maintain interlistings on US markets. The main findings of the third essay relate first to a comparison of liquidity. Bid-ask spreads, which are one dimension of market liquidity, are not materially different between the Canadian and the US markets for the announcement periods. The Canadian spread cost advantage has vanished over time and may now favor the US market, although the Canadian market still exhibits the higher depth. Based solely on the bid-ask trading cost, a Canadian company is indifferent between the three main US listing venues (namely, the NYSE, the AMEX and the NASDAQ). In other words, for a Canadian company considering cross-listing in the US, the trading cost that its investor will carry is irrelevant in terms of choosing the optimal US venue. We also found that market makers are solicited more on the US market than on the Canadian market for the Canadian cross-listed shares on US trade venues. The domestic Canadian market is deeper because of a higher number of limit orders submitted by traders who compete against the market makers. Therefore, the Canadian market attracts more informed traders since they can more easily hide their transactions. However, the differential is small but widens during earnings announcements (i.e., a period of high market uncertainty). An earnings announcement has two effects. First, it reduces information asymmetry by reducing or eliminating trading by privately informed traders. Uninformed traders react to the news announcement by trading in the market with the lowest adverse price movement. Therefore, the uninformed trade mostly on the deeper domestic Canadian market. However, this larger pool of uninformed traders attracts other privately informed traders. Since the uninformed do not split their trades proportionally between the two competing trade venues but overtrade on the domestic market, the Canadian market becomes more informative in terms of pricing.

One central issue common to the three essays is the change in the composition of the trading pool of investors. Grossman and Stiglitz (1980) showed that both the privately informed and the uninformed must be present in a market for the market to survive. While informed traders add information into prices, pricing would not be fully informative if it does not pay to acquire information and trade upon it since information can be obtained without cost by observing prices. The latter requires the presence of uninformed traders in a sufficiently large proportion to attract the informed who will pay to acquire the costly information. The informed earn profits by trading against less informed traders while simultaneously contributing to market efficiency, since part of the information is imbedded into the price for every trade they make. If the market consisted of only informed traders, prices would be fully revealing and the market would shut down. If the market consisted only of uninformed traders, prices would deviate from their fundamental true values and would become so noisy that trading would be uninteresting.

Black (1986) summarizes this situation by highlighting the contradicting role of noise in financial markets. While noise trading adds noise to prices, noise is needed for information to arrive into the market place. Thus, the decomposition of trading between informed and uninformed traders and the trading behaviour of each group is of interest. Each group is familiar with its own interest and is aware of the behaviour of the opposing group. Informed investors know that they are better off when dealing with larger groups of uninformed traders and try to time their trades to take the most advantage of their private information by limiting the speed of the adjustment of prices to incorporate private information. In turn, strategic uninformed traders try to limit the possibility of being taken advantage of by trading simultaneously. This creates the trading patterns reported by Admati and Pfleiderer (1988) and Foster and Viswanathan (1990) for short- and long-lived information, respectively.

We confirmed this theory in this thesis using the three corporate events. We observed an increase in the trading activity of both informed and uninformed traders even after an assumed reduction in information asymmetry due to the news announcement itself. Since uninformed traders intensify their trades,[81] the informed decide to take advantage of the bigger pool of uninformed traders. As a result, the uninformed decide to trade simultaneously over a shorter period of time instead of spreading their trades over a longer period. This is the reason why the uninformed exhibit impatient trade behavior by submitting market orders.

These results have practical implications for various bodies concerned with trading mechanisms, which include the traders who are the direct participants in the trading process (such as informed and uninformed traders, and the dealers or market makers), listed companies and the regulatory authorities. Informed traders are interested in making profits by trading upon their private information by balancing the cost of acquiring new information with the profit from its exploitation. Therefore, informed traders should not view any public news announcement as a mechanism that destroys their advantage by revealing one specific information event but rather as an opportunity to seek new information since more of the uninformed traders are attracted to the market place. Uninformed traders should consider trading more frequently around news

[81] Reasons why the uninformed trade just after the announcement can range from pure liquidity to rational portfolio rebalancing to irrational pure noise trading based on the assumption that prices do not adjust quickly to the public news announcement.

announcements since such trading behavior reduces the probability of being bagged by an informed trader. The reason is that the probability of trading against an uninformed trader is higher with a bigger pool of uninformed traders. However, the uninformed must remain mindful that the extent of information asymmetry widens around such events. As liquidity providers, dealers and market makers are primarily concerning with trading against informed traders. By knowing that news announcements trigger a search and trade based on new private information, they can adjust their exposure to informed traders by changing their control variables; namely, their quotes (the bid-ask spread) and their associated depths.

Managements of listed firms are interested in knowing the impact of the news announcements on the liquidity and trading activity of the shares of their companies. Higher liquidity is linked to a lower cost of capital since investors require a premium to compensate for market illiquidity. Management can reduce illiquidity using news announcements through two separate mechanisms that affect the bid-ask spread components. Firstly, by bringing the stock to the attention of the market, and hence increasing trading activity following the Merton (1987) argument, management can increase the demand for the stock. Higher trading volumes mean that the proportional cost is reduced since it is considered to be a fixed cost per trade. Secondly, management can attempt to minimize the information asymmetry differential between the informed and the uninformed by issuing press releases in addition to that dictated by timely disclosure policies. Reducing the information differential reduces the compensation required for the cost of trading against privately informed investors. This corresponds to the permanent bid-ask spread component. Therefore, the total impact of both actions is to reduce the total bid-ask spread or the total trading cost. In turn, such a trading cost reduction improves stock liquidity, reduces the cost of capital, and increases the value of the firm. However, we argue that the news announcement is not systematically related to a reduction in information asymmetry since it attracts more informed traders. Management should announce as much information as possible if it aims to reduce information asymmetry. This is related to the role of stock markets as an allocation tool. The closer prices are to true value, the more efficient markets are and the better is the allocation of scare funds between firms since price is a signal about the value of a company.

Regulatory authorities are interested in protecting the investing public, mainly uninformed traders, by fostering a fair and efficient pricing mechanism. Therefore, regulators are interested in a better information system, which means transparency and equal access to information. Transparency implies that information should be made available as soon as possible since providing only pieces of information can actually widen information asymmetry and may reduce market efficiency temporarily. Fortunately, the reduction in market efficiency is limited since the attraction of more informed traders makes pricing more informative since a part of private information is always dissipated to the market through trading.

References

Admati, A.R. and P. Pfleiderer, 1988. A theory of intraday patterns: Volume and price variability, *The Review of Financial Studies* 1:1, 3-40.

Agrawal, A., J.F. Jaffe and G.N. Mandelker, 1992. The post-merger performance of acquiring firms: A re-examination of an anomaly, *The Journal of Finance* 47:4; 1605-1621.

Ahn, H.J., K.H. Bae, and K. Chan, 2001. Limit orders, depth, and volatility: Evidence from the stock exchange of Hong Kong, *The Journal of Finance* 56:2, 767-788.

Ahn, H.-J., C.Q. Cao, and H. Choe 1998. Decimalization and competition among stock markets: Evidence from the Toronto Stock Exchange cross-listed securities, *The Journal of Financial Markets* 1:1, 51-87.

Ahn, H.J., C.Q. Cao, and H. Choe. 1996. Tick size, spread and volume, *The Journal of Financial Intermediation* 5:1, 2-22.

Aït-Sahalia, S., P.A. Mykland and L. Zhang, 2003. How often to sample a continuous-time process in the presence of market microstructure noise? Working paper.

Amihud, A., and H., Mendelson, 1986. Asset pricing and the bid–ask spread, *The Journal of Financial Economics* 17:2, 223–249.

Anderson, T.G., 1996. Return volatility and trading volume: An information flow evidence, *The Journal of Finance* 51:1, 169-204.

Andersen, T.G., T. Bollerslev and F.X. Diebold, 2004. Parametric and nonparametric volatility measurement, Forthcoming in the Handbook of Financial Econometrics, edited by Ait-Sahalia and Hansen. Amsterdam: Elsevier Science B.V.

Andersen, T.G., T. Bollerslev and F.X. Diebold, 2003. Some like it smooth, and some like it rough: Untangling continuous and jump components in measuring, modeling, and forecasting asset return volatility, The Financial Institutions Center, Working paper 03-33.

Andersen, T.G., T. Bollerslev, F.X. Diebold and P. Labys, 2003. Modeling and forecasting realized volatility, *Econometrica* 71:2, 579-625.

Andrews, D.W.K., and M., Buchinsky, 2000. A three-step method for choosing the number of bootstrap repetitions, *Econometrica* 68:1, 23-51.

Angel, J.J. 1997. Tick size, share prices, and stock splits, *The Journal of Finance* 52:2, 655-681

Bacidore, J. M. 1997. The impact of decimalization on market quality: an empirical investigation of the Toronto Stock Exchange, *The Journal of Financial Intermediation* 6:2 , 92-120.

Bacidore, J.M., and G., Sofianos, 2002. Liquidity provision and specialist trading in NYSE-listed non-US stocks, *The Journal of Financial Markets*, 63:1, 133-158.

Bagehot, W., 1971. The only game in town. *Financial Analysis Journal,* 27, 12-14.

Bailey, W., Y.P. Chung, and J.K. Kang. 1999. Foreign ownership restrictions and equity price premiums: what drives the demand for cross-border investments, *The Journal of Financial and Quantitative Analysis* 34:4, 489-511.

Bailey, W.G., G.A. Karolyi, and C., Salva, 2002. The economic consequences of increased disclosure: evidence from international cross-listing, Working paper, Cornell University.

Baker M., and S. Savasoglu, 2002. Limited arbitrage in mergers and acquisitions, *The Journal of Financial Economics* 64:1, 91-116.

Baker, H.K., J.R., Nofsinger, and D.G., Weaver, 2002. International cross-listing and visibility, *The Journal of Financial and Quantitative Analysis* 37:3, 495-521.

Bandi, F.M. and J.R. Russell, 2003a. Microstructure noise, realized volatility, and optimal sampling, Working paper, Graduate school of business, University of Chicago.

Bandi, F.M. and J.R. Russell, 2003b. Volatility or microstructure noise?, Working paper, Graduate school of business, University of Chicago.

Barndorff-Nielsen, O.E. and N. Shephard (2002a), Econometric analysis of realized volatility and its use in estimating stochastic volatility models, *The Journal of the Royal Statistical Society* 64:2, 253-280.

Barndorff-Nielsen, O.E. and N. Shephard (2002b), Estimating quadratic variation using realized variance, *The Journal of Applied Econometrics* 17:5, 457-478.

Barclay, M., 1997, Bid-ask spreads and the avoidance of odd-eighth quotes on Nasdaq: An examination of exchange listings, *The Journal of Financial Economics* 45:1, 35–60.

Barclay, M.J., R.H., Litzenberger and J.B., Warner, 1990. Private information, trading volume, and stock-return variances, *The Review of Financial Studies* 3:2, 233-253.

Barclay, M.J., W.G. Christie, J.H. Harris, E., Kandel and P.H. Schultz. 1999. Effects of market reform on the trading costs and depths of Nasdaq stocks, *The Journal of Finance* 54:1, 1-34.

Barclay, M.J., Dunbar, C.G. and Warner, J.B., 1993. Stealth and volatility: Which trades move prices?, *The Journal of Financial Economics* 34:3, 281–306.

Battalio, R., and C.W. Holden., 1997. Why doesn't decimal trading eliminate payment for order flow and internalization? Working Paper, University of Notre Dame and Indiana University.

Bessembinder, H., 1998. Trading costs and return volatility: Evidence from exchange listings, Working Paper, Arizona State University.

Bessembinder, H., 1999. Trade execution costs on Nasdaq and the NYSE: A post-reform comparison, *The Journal of Financial and Quantitative Analysis* 34:3, 387-407.

Bessembinder, H., 2003. Quote-based competition and trade execution costs in NYSE-listed stocks, *The Journal of Financial Economics* 70:3, 385–422.

Bessembinder, H. and K. Venkataraman, 2005. Does an electronic stock exchange need an upstairs market? Forthcoming in *The Journal of Financial Economics*.

Bessembinder, H., and H. Kaufman. 1997. A comparison of trade execution costs for NYSE and Nasdaq listed stocks, *The Journal of Financial and Quantitative Analysis* 32:3, 287-310.

Bhardwaj, R., and L. Brooks, 1993. Dual betas from bull and bear markets: Reversal of the size effect, *The Journal of Financial Research* 16:4, 269-83.

Biais B., P., Hillion, and C., Spatt, 1995. An empirical analysis of the limit order book and the order flow in the Paris Bourse, *The Journal of Finance* 50:5, 1655-1689.

Black, F., 1986. Noise, Presidential Address, *The Journal of Finance* 41:3, 529-543.

Bradley, M., A. Desai, and E.H. Kim, 1988. Synergistic gains from corporate acquisitions and their division between the stockholders of target and acquiring firms, *The Journal of Financial Economics* 21:1, 3-40.

Brennan, M. J., and A. Subrahmanyam., 1996. Market microstructure and asset pricing: On the compensation for illiquidity in stock returns, *The Journal of Financial Economics* 41:3, 441-464.

Brennan, M. J., and P. Hughes, 1991. Stock prices and the supply of information, *The Journal of Finance* 46:5, 1665-1691.

Brennan, M.J., and A. Subrahmanyam, 1998. The determinants of average trade size, *The Journal of Business* 71:1, 1-25.

Brennan, M.J., and T.E. Copeland, 1988. Beta changes around stock split: A note, *The Journal of Finance* 43:4, 1009-1013.

Brock, W., and A. Kleidon, 1992. Periodic market closure and trading volume: A model of intraday bids and asks, *The Journal of Economic Dynamics and Control* 16:3-4, 489.

Broyden, C.G., 1970. The convergence of a class of double-rank minimization algorithms, *Journal of the Institute of Mathematics and its Applications* 6, 76-90.

Byun, J. and M. Rozeff, 2003. Long-run performance after stock splits: 1927 to 1996, *The Journal of Finance* 58:3, 1063-1085.

Calvet, A.L. and J. Lefoll, 1987. Information asymmetry and wealth effect of Canadian corporate acquisitions, *The Financial Review* 22:4, 415-431.

Chan, K.C., W. Fong, B. Kho, and R. Stulz, 1996. Information, trading and stock returns: Lessons from dually-listed shares, *The Journal of Banking and Finance* 20:7, 1161-1187.

Chan, K., W. Christie, and P. Schultz, 1995. Market structure and the intraday pattern of bid-ask spreads for Nasdaq securities, *The Journal of Business* 68:1, 35-60.

Chakravarty, S., 2001. Stealth-trading: Which traders' trades move stock prices? *The Journal of Financial Economics* 61:2, 289–307.

Choi, J.Y., D. Salandro, and K. Shastri, 1991. On the estimation of bid-ask spreads: Theory and evidence, *The Journal of Financial and Quantitative Analysis* 23:2, 219-230.

Chordia, T., R. Roll, and A. Subrahmanyam, 2001. Market liquidity and trading activity, *The Journal of Finance* 56:2, 501-530

Christie, W.G., J. H. Harris, and P.S. Schultz. 1994. Why did NASDAQ market makers stop avoiding odd-eighth quotes?, *The Journal of Finance* 49:5, 1841-1860.

Christie, W., and R. Huang. 1994. Market structure and liquidity: A transactions data study of exchange listings, *The Journal of Financial Intermediation* 3:3, 300-326.

Christie, W.G., and P.H. Schultz. 1994. Why do Nasdaq market makers avoid odd-eighth quotes? *The Journal of Finance* 49:5 1813-1840.

Chung, K., B., Van Ness, and R., Van Ness, 2002. Spreads, depths, and quote clustering on the NYSE and Nasdaq: Evidence after the 1997 SEC's rules changes, *The Financial Review* 34:4, 481-505.

Chung, K.H., Van Ness, B.F. and Van Ness, R.A., 1999. Limit orders and the bid-ask spread, *The Journal of Financial Economics* 53:2, 255-287.

Clarke, J., and K. Shastri, 2000. On information asymmetry metrics, University of Pittsburgh, Working Paper.

Conrad, J.S., and R.M. Conroy, 1994. Market microstructure and the ex-date return, *The Journal of Finance* 49:4, 1507-1519.

Copeland, T., and D. Galai, 1983. Information effects on the bid-ask spread, *The Journal of Finance* 38:5, 1457-1469.

Coppejans M. and I. Domowitz, 2000. The impact of foreign equity ownership on emerging market share price volatility, *International Finance* 3:1, 95-122.

Davidon, W.C., 1959. Variable metric method for minimization, *A.E.C. Research and Development Report* ANL-5990.

Davidson, R., and J.G., Mackinnon, 2004. Econometric theory and methods. Oxford University Press.

Davis, Jeffry L. and L.E. Lightfoot, 1998, Fragmentation versus Consolidation of Securities Trading: Evidence from the Operation of Rule 19c-3, *Journal of Law and Economics* 41:1, 209-238.

De Jong, A., L. Rosenthal and M. van Dijk, 2004. The limits of arbitrage: Evidence from dual-listed companies, Working paper, Erasmus University

Desai, A.S., M. Nimalendran, and S. Venkataraman, 1998. Changes in trading activity following stock splits and their effect on volatility and the adverse information component of the bid-ask spread, *Journal of Financial Research* 21:2, 159-183.

Desai, H., and P. Jain, 1997. Long-run common stock returns following stock splits and reverse splits, *The Journal of Business* 70:3, 409-433.

Domowitz, I., J. Glen, and A. Madhavan. 1997. Market segmentation and stock prices: Evidence from an emerging market, *The Journal of Finance* 52:3, 1059-1086.

Doukas, J. and L.N. Switzer, 2000. Common stock returns and international listing announcements: Conditional tests of the mild segmentation hypothesis, *The Journal of Banking and Finance* 24:3, 471–502

Dravid, A., 1987. A note on the behavior of stock returns around ex-dates of stock distributions, *The Journal of Finance* 42:1, 163-168.

Dubofsky, D.A., 1991. Volatility increases subsequent to NYSE and AMEX stock splits, *The Journal of Finance* 46:1, 421-431.

Eades, K.M., P.J. Hess, and P.J., Kim, E. H., 1984. On interpreting security returns during the exdividend period, *The Journal of Financial Economics* 13, 3-34.

Easley, D., and M. O'Hara, 1987. Price, trade size, and information in securities markets, *The Journal of Financial Economics* 19:1, 69-90.

Easley, D., and M. O'Hara. 1992. Time and the process of security price adjustment, *The Journal of Finance* 47:2, 577-606.

Easley, D., M. O'Hara, and G. Saar, 2001. How stock splits affect trading: A microstructure approach, *The Journal of Financial and Quantitative Analysis* 36:1, 25-51.

Easley, D., N. Kiefer, M. O'Hara, and J. Paperman, 1996. Liquidity, information, and infrequently traded stocks, *The Journal of Finance* 51:4, 1405-1436.

Ellis, K., R. Michaely, and M. O'Hara, 2000a. When the underwriter is the market maker: An examination of trading in the IPO after-market, *The Journal of Finance* 55:3, 1039-1074.

Ellis, K., R. Michaely, and M. O'Hara, 2000b. The accuracy of trade classification rules: Evidence from Nasdaq, *The Journal of Financial and Quantitative Analysis* 35:4, 529-551.

Engle, R., and G. Lee, 1999. A long-run and short-run component model of stock return volatility, In: *Cointegration, Causality, and Forecasting A Festschrift in Honour of Clive W.J. Granger*, edited by Robert F. Engle and Halbert White. Oxford University Press.

Engle, R.F. and G. Lee, 1993. Long run volatility forecasting for individual stocks in a one factor model, unpublished manuscript, Department of Economics, UCSD.

Eun, C.S. and S. Sabherwal, 2003. Cross-border listings and price discovery: Evidence from US-listed Canadian stocks, *The Journal of Finance* 58:2, 549-575.

Fama, E.F. and K.R. French, 1993. Common risk factors in the returns on stocks and bonds, *The Journal of Financial Economics* 33:1, 3-56.

Fama, E.F., L. Fisher, Jensen M.C., and R. Roll, 1969. The adjustment of stock prices to new information, *International Economic Review* 10, 1-21.

Ferland, R., and S. Lalancette, 2001. Dynamics of realized volatility and correlations: an empirical study using interest rate spread options, Working paper University of Montreal and HEC.

Fletcher, R., 1970. A new approach to variable metric algorithms, *Computer Journal* 13:3, 317-322.

Fletcher, R. and M.J.D. Powell, 1963. A rapidly convergent descent method for minimization, *Computer Journal* 6:2, 163-168.

Foerster, S. R. and G.A. Karolyi, 1993. International listing of stocks: The case of Canada and the U.S., *The Journal of International Business Studies* 24:4, 763-784.

Foerster, S. R. and G.A. Karolyi, 1998. Market trading and liquidity: A transactions data analysis of Canada-U.S. interlistings, *The Journal of International Financial Markets, Institutions and Money* 8:3-4, 393-412.

Foerster, S. R. and G.A. Karolyi, 1999. The effects of market segmentation and investor recognition on asset prices: Evidence from foreign stocks listing in the United States, *The Journal of Finance* 54:3, 981-1013.

Forster, M.M. and T.J. George, 1995. Trading hours, information flow, and international cross-listing, *International Review of Financial Analysis* 4:1, 19-34.

Foster F.D. and S. Viswanathan, 1990. A theory of intraday variations in volumes, variances, and trading costs in the securities market, *The Review of Financial Studies* 3:4, 593-624.

Foucault, T., 1999. Order flow composition and trading costs in a dynamic limit order market, *The Journal of Financial Markets* 2:2, 99-134.

Franks, J., R. Harris, and S. Titman, 1991. The post-merger share-price performance of acquiring firms, *The Journal of Financial Economics* 29:1, 81-96.

French, D.W. and T. W. Foster, 2002. Does price discreteness affect the increase in return volatility following stock splits?, *The Financial Review* 37:2, 281-294.

Froot, K.A. and E.M. Dabora, 1999. How are stock prices affected by the location of trade? *The Journal of Financial Economics* 53:2, 189-216.

Gallant, A.R., P.E. Rossi, and G. Tauchen, 1992. Stock prices and volume, *The Review of Financial Studies* 5:2, 199-242.

Garman, M., 1976. Market microstructure, *The Journal of Financial Economics* 3, 257-275.

George, T.J., G. Kaul, and M. Nimalendran, 1991. Estimation of the bid-ask spread and its components: A new approach, *The Review of Financial Studies* 4:4, 623-656.

Glosten, L.R. and L.E. Harris, 1988. Estimating the components of the bid-ask spread, *The Journal of Financial Economics* 21:1, 123-142.

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

Glosten, L.R., 1994. Is the electronic open limit order book inevitable? *The Journal of Finance* 49:4, 1127-61.

Glosten, L.R., R. Jagannathan, and D.E. Runkle, 1993. On the relation between the expected value and the volatility of the nominal excess return on stocks, *The Journal of Finance* 48:5, 1779-1801.

Goldfarb, D., 1970. A family of variable metric updates derived by variational means, *Mathematics of Computing* 24.

Goldfeld, S., R. Quandt, and H. Trotter, 1966. Maximization by quadratic hill climbing, *Econometrica* 34:3, 541-551.

Gosh, A. and W. Ruland, 1998. Managerial ownership, the method of payment for acquisition, and executive job retention, *The Journal of Finance* 53:2, 785-798.

Greene, J., 1997. The impact of limit order executions on trading costs in NYSE stocks, Working Paper. Georgia State University, Atlanta.

Greene, W.H., 2003. Econometric Analysis. 5th Edition. Prentice Hall.

Grinblatt, M, and B.K. Donald, 2000. Stock splits and ex-date returns for Nasdaq stocks: The effects of investor trading and bid-ask spreads, In Security market imperfections in world wide equity markets Cambridge University Press.

Grinblatt, M., R. Masulis, and S. Titman, 1984. The valuation effects of stock splits and stock dividends, *The Journal of Financial Economics* 13:4, 461-490.

Grossman, S. and J. Stiglitz, 1980. On the Impossibility of informationally efficient Markets, *The American Economic Review* 70, 393-408.

Hamilton, J.D., 1994. Time Series Analysis. Princeton University Press.

Handa, P., and R.A. Schwartz, 1996. Limit order trading, *The Journal of Finance* 51:5, 1835-1861.

Harford, J., 1999. Corporate cash reserves and acquisitions, *The Journal of Finance* 54:6, 1969-1997.

Hietala, P., 1989. Asset pricing in partially segmented markets: Evidence from the Finnish market, *The Journal of Finance* 44:3, 697-718.

Ho, T. and H. R. Stoll, 1981. Optimal dealer pricing under transactions and return uncertainty, *The Journal of Financial Economics* 9:1, 47-73.

Howton, S.W. and D.R. Peterson, 1998. An examination of cross-sectional realized stock returns using a varying-risk beta model, *The Financial Review* 33:3, 199-212.

Huang, R. and H. Stoll, 1997. The components of the bid-ask spread: A general approach, *The Review of Financial Studies* 10:4, 995-1034.

Huang, R. and H. Stoll, 1996. Dealer versus auction markets: A paired comparison of execution costs on Nasdaq and the NYSE, *The Journal of Financial Economics* 41:3, 313–357.

Jensen, M.C. and R.S. Ruback, 1983. The market for corporate control: The scientific evidence, *The Journal of Financial Economics* 11:1, 15-50.

Jiang, L. and L. Kryzanowski, 1997. Trading activity, quoted liquidity, and stock volatility, *Multinational Finance Journal* 1:3, 199-227.

Jones, C.M., G. Kaul, and M.L., Lipson, 1994. Transactions, volume, and volatility, *The Review of Financial Studies* 7:4, 631-651.

Jones, C.M., G., Kaul and M.L., Lipson, 1994. Information, trading, and volatility, *The Journal of Financial Economics* 36:1, 127-154.

Karolyi, G. A., 1998. Why do Companies List Shares Abroad? A Survey of the Evidence and its Managerial Implications. New York, NY: Univ. Salomon Bros. Center Monograph, 7.

Karpoff, J., 1987. The relation between prices changes and trading volume: A survey, *The Journal of Financial and Quantitative Analysis* 22:1, 109-126.

Kavajecz, K.A., 1999. A specialist's quoted depth and the limit order book, *The Journal of Finance* 54:2, 747–771.

Kavajecz, K.A., and E.R. Odders-White, 2001. An examination of changes in specialists' posted price schedules, *The Review of Financial Studies* 14:3, 681-704.

Kim, C.J., 1993. Dynamic linear models with Markov-switching, *The Journal of Econometrics* 60:1, 1-22.

Koski, J.L. and R. Michaely, 2000. Prices, liquidity, and the information content of trades, *The Review of Financial Studies* 13:3, 659-696.

Krinsky, I. and J. Lee, 1996. Earning announcements and the components of the bid-ask spread, *The Journal of Finance* 51:4 1523-1535.

Kryzanowski, L. and A., Rubalcava, 2004. International trade-venue clienteles and order-flow competitiveness, Forthcoming in *The Journal of Financial Intermediation.*

Kryzanowski, L. and H. Zhang, 1993. Market behaviour around Canadian stock-split ex-dates, *Journal Of Empirical Finance* 1:1, 57-81.

Kryzanowski, L. and H. Zhang, 1996. Trading patterns of small and large traders around stock split ex-dates, *Journal of Financial Research* 19:1, 75-90.

Kryzanowski, L. and H. Zhang, 2002. Intraday market price integration for shares cross-listed internationally, *Journal of Financial and Quantitative Analysis* 37:2, 243-269.

Kyle, A., 1985. Continuous auctions and insider trading, *Econometrica* 53:6, 1315-1336.

Lakonishok, J. and B. Lev, 1987. Stock splits and stock dividends: why, who, and when, *The Journal of Finance* 42:4, 913-932.

Lamoureux, C.G. and P. Poon, 1987. The market reaction to stock splits, *The Journal of Finance* 42:5, 1347-1370.

Lamoureux, C.G. and W. Lastrapes, 1991. Heteroskedasticity in stock return data: Volume versus GARCH effects, *The Journal of Finance* 45:1, 221-229.

Lee, M.C. and M. Ready, 1991. Inferring trade direction from intraday data, *The Journal of Finance* 46:2, 733-746.

Lee, M.C., B. Mucklow, and M Ready, 1993. Spreads, depths, and the impact of earnings information: An intraday analysis, *The Review of Financial Studies* 6:2, 345-374.

Lin, J., G. Sanger, and G.G. Booth, 1995. Trade size and components of the bid-ask spread, *The Review of Financial Studies* 8:4, 1153-1183.

Lo, A.W., A.C. MacKinlay, and J. Zhang, 2002. Econometric models of limit order execution, *The Journal of Financial Economics* 65:1, 31-71.

Lo, A.W. and C. MacKinlay, 1988. Stock market prices do not follow random walks: Evidence from a simple specification test, *The Review of Financial Studies* 1:1, 41-66.

Loughran, T. and A.M. Vijh, 1997. Do long-term shareholders benefit from corporate acquisitions? *The Journal of Finance* 52:5, 1765-1790.

Madhavan, A., 2000. Market microstructure: A survey, *The Journal of Financial Markets* 3:3, 205-258.

Madhavan, A., M. Richardson, and M. Roomans, 1997. Why do security prices change? A transaction-level analysis of NYSE stocks, *The Review of Financial Studies* 10:4, 1035-1064.

Malatesta, P.H., 1983. The wealth effect of merger activity and the objective functions of merging firms, *The Journal of Financial Economics* 11:1, 155-182

Martin, K.J., 1996. The method of payment in corporate acquisitions, investment opportunities, and management ownership, *The Journal of Finance* 51:4, 1227-1249.

Masson J., 1994. Estimating the realized bid-ask spread using quote revisions, Working Paper, University of Ottawa.

McInish, T. and R. Wood, 1992. An analysis of intraday patterns in bid/ask spreads for NYSE stocks, *The Journal of Finance* 47:2, 753-764.

McNichols, M. and A. Dravid., 1990. Stock dividends, stock splits, and signaling, *The Journal of Finance* 45:3, 857-879.

Merton, R.C., 1987. A simple model of capital market equilibrium with incomplete information, *The Journal of Finance* 42:3, 483-510.

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

Nayar, N, and M.S. Rozeff, 2001. Record date, when-issued, and ex-date effects in stock splits, *The Journal of Financial and Quantitative Analysis* 36:1, 119-139.

Neal, R., and S.M. Wheatley, 1998. Adverse selection and bid-ask spreads: Evidence from closed-end funds, *The Journal of Financial Markets* 1:1, 121-149.

Noronha, G.M., A., Sarin, and S.M., Saudagaran, 1996. Testing for micro-structure effects of international dual listings using intraday data, *The Journal of Banking and Finance* 20:6, 965-983.

Nyholm, K., 2002. Estimating the probability of informed trading, *The Journal of Financial Research* 25:4, 485-505.

O'Hara, M., 1995. Market microstructure theory. Basil Blackwell, Cambridge, MA.

O'Hara, M., 2003. Presidential address: Liquidity and price discovery, *The Journal of Finance* 58:4, 1335-1354.

Odders-White, E.R., 2000. On the occurrence and consequences of inaccurate trade classification, *The Journal of Financial Markets*, 3:3, 259-286.

Ohlson, J.A. and S.H. Penman, 1985. Volatility increases subsequent to stock splits: An empirical aberration, *The Journal of Financial Economics* 14:2, 251-266.

Pagano, M., 1989. Trading volume and asset liquidity, *The Quarterly Journal of Economics* 104:2, 255-274.

Pettengill, G.N., S. Sundaram, and I. Mathur, 1995. The conditional relation between beta and returns, *The Journal of Financial and Quantitative Analysis* 30:1, 101-116.

Pettengill, G.N., S. Sundaram, and I. Mathur, 2002. Payment for risk: Constant beta vs. dual-beta models, *The Financial Review* 37:2, 123-136.

Rosenthal, L. and C., Young, 1990. The seemingly anomalous price behavior of Royal Dutch/Shell and Unilever N.V./PLC, *The Journal of Financial Economics* 26:1, 123-141.

Sandas, P., 2001. Adverse selection and competitive market making: Evidence from a pure limit order book, *The Review of Financial Studies* 14:3, 705-734.

Sarkissian, S. and M.J., Schill, 2004. The overseas listing decision: New evidence of proximity preference, Forthcoming in *The Review of Financial Studies*.

Scholes, M. and J. Williams, 1977. Estimating betas from nonsynchronous data, *The Journal of Financial Economics* 5:3, 309-328.

Schultz, P., 2000. Stock splits, tick size, and sponsorship, *The Journal of Finance* 55:1, 429-450.

Shanno, D.F., 1970. Conditioning of quasi-newton methods for function minimization, *Mathematics of Computing* 24, 647-656.

Shleifer, A. and R. Vishny, 1997. The limits to arbitrage, *The Journal of Finance* 52:1, 35-55.

Shleifer, A. and R. Vishny, 2003. Stock market driven acquisitions, *The Journal of Financial Economics* 70:3, 295-311.

Sofianos, G. and I.M., Werner, 2000. The trades of NYSE floor brokers, *The Journal of Financial Markets* 3:2, 139-176.

Song, M.H. and R.L. Walking, 2000. Abnormal returns to rivals of acquisition targets: A test of the 'acquisition probability hypothesis', *The Journal of Financial Economics* 55:2, 143-171.

Stoll, H., 1978. The Supply of Dealer Services in Securities Markets, *The Journal of Finance* 33:4, 1133-1151.

Stoll, H., 1989. Inferring the components of the bid-ask spread: Theory and empirical tests, *The Journal of Finance* 44:1, 115-134.

Stoll, H., 2001. Market fragmentation, *The Financial Analyst Journal* 57:4, 16-20.

Stulz, R. M. and W. Wasserfallen., 1995. Foreign equity investment restrictions and shareholder wealth maximization: Theory and evidence, *The Review of Financial Studies* 8:4, 1019-1058.

Switzer, L., 1986. The benefits and costs of listing Canadian stocks in U.S. markets, pp 241-254, in L. Sarna (ed.), Corporate structure, finance, and operations, Carswell Co., Toronto.

Tinic, S., 1972. The economics of liquidity services, *The Quarterly Journal of Economics* 86:1, 79-93.

Travlos, N.G., 1987. Corporate takeover bids, method of payment, and bidding firms' stock returns, *The Journal of Finance* 42:4, 943-963.

Van Ness, B., R. Van Ness, and R. Warr, 2001. How well do adverse selection components measure adverse selection? *Financial Management* 30:3, 77-98.

Werner, I.M. and A. W. Kleidon., 1996. U.K. and U.S. trading of British cross-listed shares: An intraday analysis of market integration, *The Review of Financial Studies* 9:2, 619-664.

Weston, J.P., 2000. Competition on the Nasdaq and the impact of recent market reform, *The Journal of Finance* 55:6, 2565-2598.

Wiggins, J.B., 1992. Betas in up and down markets, *The Financial Review* 27:1, 107-123.

Xu, X.E. and H.G., Fung, 2002. Information flows across markets: Evidence from China-backed stocks dual listed in Hong Kong and New York, *The Financial Review* 37:4, 563-588.

Zhang, L., P.A. Mykland and Y. Aït-Sahalia, 2003. A tale of two time scales: Determining integrated volatility with noisy high-frequency data, Working Paper.

APPENDIX: Spread Decomposition and Trading Intensity Models

A. Spread Decomposition Models

A.1 Spread Decomposition Models of George, Kaul and Nimalendran (1991), and of Neal and Wheatley (1998)

George et al (1991) estimate the implied bid-ask spread using a covariance-based model that allows for the possibility of serially correlated returns. Their model is as follows:

$$P_t = M_t + \pi \frac{S}{2} I_t \tag{A1}$$

$$M_t = E_t + M_{t-1} + (1-\pi)\frac{S}{2} I_t + U_t \tag{A2}$$

In (A1) and (A2), P_t is the trade price at time t, M_t is the true value of the security, and I_t is the trade indicator that is equal to 1 for a seller-initiated trade and –1 for a buyer-initiated trade. S is the quoted bid-ask spread, π is the order processing component of the quoted spread, E_t is the expected return, and U_t is the new public information. The return from transaction prices then is given by:

$$\Delta P_t \equiv R_t = E_t + \frac{S}{2} I_t - \pi \frac{S}{2} I_{t-1} + U_t \tag{A3}$$

The bid-based return is equal to:

$$\Delta B_t \equiv R_{B,t} = E_t + (1-\pi)\frac{S}{2} I_t + U_t \tag{A4}$$

George et al eliminate the (time varying) expected return by subtracting the bid-based return from the trade price-based return. This yields:

$$RD_{B,t} \equiv R_t - R_{B,t} = \pi \frac{S}{2}(I_t - I_{t-1}) \tag{A5}$$

Assuming that the trade indicators are not correlated unconditionally, George et al derive the following equation:

$$2 \times \sqrt{-COV\left(RD_{B,t}, RD_{B,t-1}\right)_i} = \pi S_i \tag{A6}$$

In (A6), COV refers to covariance, and the subscript refers to firm i.

Letting $Y_i = 2 \times \sqrt{-COV\left(RD_{B,t}, RD_{B,t-1}\right)_i}$, the George et al model can be implemented by running the following cross-section regression:

$$Y_i = \pi_0 + \pi \times S_i + \varepsilon_i \tag{A7}$$

where S_i is the average posted bid-ask spread.

One of the shortcomings of this covariance model is the assumption that the bid-ask spread is constant. Neal and Wheatley (1998) use a regression approach, as opposed to the covariance approach, and allow for time variability in the posted bid-ask spreads. Their testable relationship using mid-quote-based returns instead of bid-based returns is then:

$$2RD_{M,t} = \pi_0{}' + \pi'\left(S_t I_t - S_{t-1} I_{t-1}\right) + v_t \tag{A8}$$

where $RD_{M,t} = R_t - R_{M,t}$; $R_{M,t} = M_t - M_{t-1}$; and M_t or the true price is equal to the mid-quote.

A.2 Spread Decomposition Model of Masson (1994)

The advantage of the Masson model is that it allows the spread and its components to be time variant. However, their unconditional means need to be finite constants. Masson assumes that the transaction price at time t is given by $p_t = m_t + \frac{1}{2} I_t S_t$, where m_t is the prevailing mid-quote, I_t is the actual trade sign, and S_t is the total bid-ask spread. The quote mid-point is equivalent to the true value of the traded asset. Since only the informational part of the spread has a permanent impact on the true value, the new quote mid-point right after time t trade moves to $m_t^r = p_t + \frac{1}{2} I_t A_t$. This change reflects the market maker's revised valuation of the traded asset. m_t^r is the quote mid-point just after the trade, and A_t is the adverse selection component of the bid-ask spread. The true value still coincides with the quote mid-point because there is no inventory effect. Masson shows that $m_t^r = p_t - \frac{1}{2} I_t C_t$, where $C_t = S_t - A_t$ is the temporary component of the bid-ask spread.

Both spread components are assumed to follow independent Poisson processes with intensity parameters of λ_A and λ_C, respectively. The quoted spread then follows a Poisson process with intensity

$\lambda_A + \lambda_C$. The realized spread can be computed as: $C_t = 2 \times |m_t^r - p_t|$, and the intensity parameter λ_C can be estimated using:

$$\hat{\lambda}_C = \frac{2}{T} \times \sum_{t=1}^{T} |m_t^r - p_t| \qquad \text{(A9)}$$

where T denotes the number of trades, and its variance is given by $\hat{\lambda}_C / T$. $\hat{\lambda}_A$ is estimated as the difference $\overline{S} - \hat{\lambda}_C$, where $\overline{S}$ is the average quoted spread. The variance of $\hat{\lambda}_A$ is equal to $\hat{\lambda}_A / T$.

A.3 <u>Decomposition Model of Glosten and Harris (1988)</u>

In their model, Glosten and Harris (1988) consider two components of the bid-ask spread; namely, the permanent (information driven) and the temporary (mainly due to order processing cost) components. The permanent component of the spread should be positively related to trade size so that informed traders are willing to trade more with more pronounced information asymmetry.

Glosten and Harris model the security price process as follows:

$$p_t = m_t + I_t C_t \qquad \text{(A10)}$$

$$m_t = m_{t-1} + I_t Z_t + e_t \qquad \text{(A11)}$$

In these equations, p_t is the observed trade price at time t, m_t is the true unobserved price, I_t is a trade indicator variable, and e_t is the new public information revealed at time t. C_t and Z_t are the temporary and permanent components of the bid-ask spread, which are related to trade size through:

$$C_t = c_0 + c_1 V_t \qquad \text{(A12)}$$

$$Z_t = z_0 + z_1 V_t \qquad \text{(A13)}$$

where V_t is the trade volume in number of shares.

Since returns can be computed as the change in the (log) transaction prices, we can write:

$$r_t = p_t - p_{t-1} = c_0(I_t - I_{t-1}) + c_1 V_t (I_t - I_{t-1}) + z_0 I_t + z_1 V_t I_t + e_t \qquad \text{(A14)}$$

This model is estimated by regressing the returns on $(I_t - I_{t-1})$, $V_t(I_t - I_{t-1})$, I_t and $V_t I_t$, and the implied spread by $S_t = 2[c_0 + z_0 + (c_1 + z_1)\overline{V}]$, where $\overline{V}$ is the average number of shares per trade.

The temporary component of the spread is given by $2\left(c_0 + c_1\bar{V}\right)$, and the permanent component is equal to $2\left(z_0 + z_1\bar{V}\right)$. The adverse selection component as a percentage of the effective spread can be computed as:

$$\pi_{GH} = \frac{1}{1 + \dfrac{c_0 + c_1\bar{V}}{z_0 + z_1\bar{V}}} \tag{A15}$$

Its variance is computed using the delta method.

As discussed by GH, the parameters c_1 and z_0 should not be significantly different from zero. In this case, the adverse selection component as a percentage of the effective spread can be computed as:

$$\pi'_{GH} = \frac{1}{\dfrac{c_0}{z_1\bar{V}} + 1}, \tag{A16}$$

with a variance given by:

$$\begin{bmatrix} -\dfrac{1}{z_1\bar{V}\left(\dfrac{c_0}{z_1\bar{V}}+1\right)^2} & \dfrac{c_0}{z_1^2\bar{V}\left(\dfrac{c_0}{z_1\bar{V}}+1\right)^2} \end{bmatrix} COV\left(\hat{c}_0, \hat{z}_1\right) \begin{bmatrix} -\dfrac{1}{z_1\bar{V}\left(\dfrac{c_0}{z_1\bar{V}}+1\right)^2} \\ \dfrac{c_0}{z_1^2\bar{V}\left(\dfrac{c_0}{z_1\bar{V}}+1\right)^2} \end{bmatrix} \tag{A17}$$

A.4 <u>Spread Decomposition Model of Lin, Sangher and Booth (1995)</u>

The main feature of the Lin, Sangher and Booth (LSB) model is its ability to deal with trades that occur inside the bid-ask spread through the effective spread. It can be developed as follows. Let $M_t = \left(A_t + B_t\right)/2$ be the quote mid-point, and $Z_t = P_t - M_t$ be the difference between the trade price and the prevailing quote mid-point at the time of the trade. Hence, $2 \times \left|Z_t\right|$ is the effective spread, given that trades may occur inside the quoted bid-ask spread. Denoting λ as the proportion of the effective spread due to adverse selection, LSB estimate this parameter using the following regression:

$$\Delta M_t = M_t - M_{t-1} = \lambda Z_{t-1} + e_t \tag{A18}$$

Logarithmic transformations of the mid-quotes and prices are used to estimate the adverse information parameter λ. In this thesis and to be consistent with the other spread decomposition models estimated herein, we report the temporary cost component as a proportion of the total quoted spread $\pi = (1-\lambda)$.

A.5 Decomposition Model of Madhavan, Richardson and Roomans (MRR)

Madhavan et al use an approach similar to Huang and Stoll (1997) that is based on the trade indicator variable I_t. Trades can take place either at the bid ($I_t = -1$), at the ask ($I_t = +1$) or in between ($I_t = 0$). The latter case has an unconditional probability denoted by λ. Changes in prices can be caused either by the arrival of new public information (ε_t with variance given by σ_ε^2) or by the surprise in the order flow. In the latter case, the return price is equal to $\theta\left(I_t - E\langle I_t | I_{t-1}\rangle\right)$, where θ is linked to the private information revealed through the order flow. It is the part of the half posted spread due to adverse selection.

The expected final value u_t of the security given the information set $\{\varepsilon_t, I_t\}$ is equal to:

$$u_t = E\langle V_t | \varepsilon_t, I_t\rangle = u_{t-1} + \theta\left(I_t - E\langle I_t | I_{t-1}\rangle\right) + \varepsilon_t \tag{A19}$$

Assuming that the fixed cost per share for supplying liquidity is ϕ, then the outstanding posted quotes and the trade price at time t are given by:

$$\text{Ask: } A_t = u_{t-1} + \theta\left(1 - E\langle I_t | I_{t-1}\rangle\right) + \phi + \varepsilon_t \tag{A20}$$

$$\text{Bid: } B_t = u_{t-1} + \theta\left(-1 - E\langle I_t | I_{t-1}\rangle\right) - \phi + \varepsilon_t \tag{A21}$$

$$\text{Price: } p_t = u_t + \phi I_t + \xi_t = u_{t-1} + \theta\left(I_t - E\langle I_t | I_{t-1}\rangle\right) + \varepsilon_t + \phi I_t + \xi_t \tag{A22}$$

where ξ_t is a price rounding error, whose variance is σ_ξ^2.

Letting $\gamma = \Pr\langle I_t = I_{t-1} | I_t \neq 0\rangle$ be the probability of trade continuation and $\rho = E\left(I_t I_{t-1}\right)/V\left(I_t\right) = 2\gamma - (1-\lambda)$ be the first-order autocorrelation of the trade indicator, MRR compute the change in transaction prices as: $p_t - p_{t-1} = \alpha + (\phi + \theta)I_t - (\phi + \rho\theta)I_{t-1} + \eta_t$ where $\eta_t = \varepsilon_t + \xi_t - \xi_{t-1}$. Letting $\mu_t = p_t - p_{t-1} - (\phi + \theta)I_t + (\phi + \rho\theta)I_{t-1}$, then $\eta_t = \mu_t - \alpha$.

The seven parameters $\left(\theta, \phi, \lambda, \rho, \alpha, \sigma_\varepsilon^2, \sigma_\xi^2\right)$ can be estimated using the generalized method of moments or GMM. The moment conditions are:

$$E\begin{pmatrix} I_t I_{t-1} - I_{t-1}^2 \rho \\ |I_t| - (1-\lambda) \\ \mu_t - \alpha \\ (\mu_t - \alpha) I_t \\ (\mu_t - \alpha) I_{t-1} \\ (\mu_t - \alpha)^2 - (\sigma_\varepsilon^2 + 2\sigma_\xi^2) \\ (\mu_t - \alpha)(\mu_{t-1} - \alpha) + \sigma_\xi^2 \end{pmatrix} = 0, \tag{A23}$$

where the input data consist of transaction prices and trade signs p_t and I_t. The system is just identified, and the parameters of interest are θ and ϕ, respectively, or the permanent and the transitory components of the half-implied spread. The total implied posted spread is $2(\theta + \phi)$. The adverse selection component contribution to the total spread is $\theta/(\theta + \phi)$.

In MRR, the Newey-West procedure is used to estimate a heteroskedastic consistent covariance matrix for the parameters. The delta method is used to compute the standard errors of the spread decomposition in percentage. The variance of price changes is equal to:

$$\operatorname{var}(\Delta p_t) = \sigma_\varepsilon^2 + 2\sigma_\xi^2 + (1-\lambda)\left[(\theta+\phi)^2 + (\theta\rho+\phi)^2 - 2(\theta+\phi)(\theta\rho+\phi)\rho\right] \tag{A24}$$

(A24) can be decomposed into five components. The first component, σ_ε^2, is due to the release of new public information. The second component is caused by adverse information and regroups all terms involving the parameter θ. The third component is related to the temporary component of the bid-ask spread ϕ, and is related to noise trading and is equal to $2(1-\lambda)(1-\rho)\phi^2$. MRR call the third component the volatility arising from transaction costs alone. The fourth component is an interaction term between asymmetric information caused volatility and transaction cost caused volatility. The fifth and last component is $2\sigma_\xi^2$ or price discreteness induced volatility. The sum of the last four volatility components represents the trading frictions volatility.

B. The Trading Intensity Model of Easley, Kiefer, O'Hara and Paperman or EKOP (1996)

The trading intensity model of Easley et al (EKOP) is based on a sequential repeated game between the market maker and informed and uninformed traders as in Glosten and Milgrom (1985), and Easley and O'Hara (1987). At the beginning of every trading day, a material event may take place with a probability equal to α. Conditional on its occurrence, the event has a probability of δ to have a negative impact on the stock value. On information days, informed and uninformed traders trade. Informed traders arrive to the marketplace with an intensity of μ, and uninformed traders arrive with an intensity of ε per day. The arrivals of both types of traders are assumed to follow Poisson processes. B_i and S_i are used to denote the number of buyer and seller initiated trades on day i by all traders, respectively.

The likelihood of observing B_i and S_i on day i is the sum of three terms:

$$\begin{aligned} L\langle (B_i,S_i)|\Theta\rangle &= (1-\alpha)e^{-\varepsilon}\frac{\varepsilon^{B_i}}{B_i!}e^{-\varepsilon}\frac{\varepsilon^{S_i}}{S_i!}+\alpha\delta e^{-\varepsilon}\frac{\varepsilon^{B_i}}{B_i!}e^{-(\mu+\varepsilon)}\frac{(\mu+\varepsilon)^{S_i}}{S_i!} \\ &+\alpha(1-\delta)e^{-(\mu+\varepsilon)}\frac{(\mu+\varepsilon)^{B_i}}{B_i!}e^{-\varepsilon}\frac{\varepsilon^{S_i}}{S_i!} \end{aligned} \tag{A25}$$

The first term in (A25) corresponds to the case of a day with no news events. In this case, all traders are uninformed. The second term is linked to a bad event day, and the third to a good event day. The parameter vector to be estimated is $\Theta = (\alpha, \delta, \varepsilon, \mu)$ using a data set consisting of number of buys and sells. In EKOP, α and δ are constrained to be inside the interval $[0,1]$ through a logit transformation. In addition, ε and μ are restricted to be positive by a logarithmic transformation.

Over i independent days, the likelihood function is:

$$L\langle (B,S)|\Theta\rangle = \prod_{i}^{I}\left[L\langle (B_i,S_i)|\Theta\rangle\right] \tag{A26}$$

Herein, we maximize this function using several numerical methods; namely, the Newton and Quasi-Newton algorithms (as developed by Broyden, 1970; Fletcher, 1970; Goldfarb, 1970; and Shanno, 1970; and by Davidon, 1959; Fletcher and Powell, 1963, respectively), a combined Quasi-Newton with a Line search with analytic derivation of the gradient and the Hessian, and the quadratic hill-climbing algorithm of Goldfeld, Quandt and Trotter (1966) as used by EKOP. To reduce the probability of being trapped in a local maximum, we use several starting points for the various algorithms.

The parameter of interest is the probability of informed trade, which is given by:

$$\mathrm{PI} = \alpha\mu/(\alpha\mu + 2\varepsilon) \tag{A27}$$

Its standard error is equal to:

$$VAR(PI)=\begin{bmatrix}\frac{2\mu\varepsilon}{(\alpha\mu+2\varepsilon)^2} & 0 & \frac{2\alpha\varepsilon}{(\alpha\mu+2\varepsilon)^2} & -\frac{2\alpha\mu}{(\alpha\mu+2\varepsilon)^2}\end{bmatrix} COV(\alpha,\delta,\mu,\varepsilon)\begin{bmatrix}\frac{2\mu\varepsilon}{(\alpha\mu+2\varepsilon)^2}\\ 0\\ \frac{2\alpha\varepsilon}{(\alpha\mu+2\varepsilon)^2}\\ -\frac{2\alpha\mu}{(\alpha\mu+2\varepsilon)^2}\end{bmatrix} \quad \text{(A28)}$$

An examination of the behavior of the trading intensity parameters μ and ε around the announcement and effective dates is important in understanding the impact of such events for acquisition targets and acquirers.

Table 1. Descriptive statistics

Statistic	Price	Size	Transactions	Volume
Mean	38.29	1,601,161,118.48	687.40	800,031.09
Median	32.39	336,786,599.48	181.17	200,029.17
Maximum	157.00	84,613,124,966.70	28,556.08	29,775,183.33
Minimum	1.08	1,439,762.07	6.08	975.00
Std. Dev.	23.92	5,860,823,426.98	2,152.79	2,311,106.66
Skewness	2.16	10.48	9.16	8.62
Kurtosis	9.58	138.45	105.22	94.86

Price and size are measured in dollars. For every firm, the average per-share price is computed for the five trading days preceding the effective split date. Size is measured as the market value of equity, which is obtained by multiplying the number of outstanding shares by the closing share price at the end of each month. If a company has more than one class of shares, the combined market values of all share classes are used. The average equity value for the 12 trailing months preceding the effective split date is used. Transactions and volume are the average monthly number of trades and the traded volume in number of shares over the 12 months before the stock split effective date, respectively.

Table 2. Liquidity and trading activity changes around splits

Panel A. Quoted spread in dollars and as a proportion (percent of the share price)						
	Pre-split		**Post-split**		**Difference**	
Statistic	**Dollar Spread**	**% Spread**	**Dollar Spread**	**% Spread**	**Dollar Spread**	**% Spread**
Mean	0.571	1.961	0.362	2.346	-0.210	0.386
Standard deviation	0.616	1.473	0.372	1.777	0.487	1.229
Median	0.419	1.586	0.285	1.970	-0.098	0.233
t-stat	16.211***	23.290***	17.023***	23.097***	-7.539***	5.489***
Wilcoxon					12.482***	6.695***
Panel B. Effective spread in dollars and as a proportion (percent of the share price)						
	Pre-split		**Post-split**		**Difference**	
Statistic	**Dollar Spread**	**% Spread**	**Dollar Spread**	**% Spread**	**Dollar Spread**	**% Spread**
Mean	0.379	1.346	0.240	1.647	-0.139	0.301
Standard deviation	0.356	1.082	0.156	1.265	0.271	0.794
Median	0.292	1.106	0.202	1.377	-0.075	0.198
t-stat	18.639***	21.748***	27.028***	22.763***	-8.957***	6.635***
Wilcoxon					12.945***	8.0016***
Panel C. Dollar volume and dollar depth around stock splits (thousand dollars)						
	Pre-split		**Post-split**		**% Change**	
Statistic	**Depth**	**$ Volume**	**Depth**	**$ Volume**	**Depth**	**$ Volume**
Mean	54.965	1,631.672	47.558	1,729.065	-4.326	74.058
Standard deviation	54.578	5,621.230	51.509	6,002.203	64.461	291.153
Median	38.604	228.036	32.134	258.625	-16.946	12.172
t-stat	17.617***	5.078***	16.151***	5.039***	-1.1739***	4.449***
Wilcoxon					5.095***	4.182***
Panel D. Daily number of trades and volume (number of shares in thousand)						
	Pre-split		**Post-split**		**% Change**	
Statistic	**# Trades**	**Volume**	**# Trades**	**Volume**	**# Trades**	**Volume**
Mean	29.779	40.094	50.277	75.791	91.022	206.882
Standard deviation	71.683	101.063	147.939	185.901	169.956	428.257
Median	8.410	9.528	12.156	19.198	46.841	97.872
t-stat	7.267***	6.470***	5.945***	6.649***	9.369***	7.879***
Wilcoxon					10.689***	12.443***

The sample contains all of the 306 split stocks from the period 1985-1999. The pre-split period covers 60 trading days, and ends 20 days before the split announcement date. The post-split period also covers 60 trading days and starts 20 days after the split becomes effective. The means are cross-section averages. % spread is the proportional (per-dollar) quoted spread. Difference corresponds to the difference of the post-split values for the measure less its pre-split value. % change is the percentage change on a post-split basis. Depth is the average posted depth at the bid and the ask quotes. Spreads and depth are averaged for each stock intra-day, then over the corresponding event window, then for the cross-section. Volume and number of trades are measured on a daily basis. Dollar volume is the sum over a given day of the number of shares times the trading price of each trade. *, ** and *** correspond to significance levels of 10, 5 and 1 percent levels, respectively.

Table 3. Spread decomposition results

Model	Statistic	π	Temporary[†]	Permanent[†]	Temporary % [‡]	Permanent %[‡]
Panel A. Pre-split						
GKN	Mean	0.7740	0.4421	0.1291	1.34	0.39
	Median	-	0.3245	0.0947	1.23	0.36
NW	Mean	0.4350	0.2311	0.3402	0.78	1.18
	Median	0.4740	0.1613	0.2078	0.6384	0.8350
Masson	Mean	0.7398	0.4063	0.1649	1.43	0.54
	Median	0.7328	0.3069	0.0980	1.17	0.39
GH	Mean	0.8345	0.1963	0.0656	0.69	0.22
	Median	0.8403	0.1528	0.0279	0.58	0.10
LSB	Mean	0.7906	0.4344	0.1369	1.51	0.45
	Median	0.8456	0.3071	0.0577	1.18	0.22
MRR	Mean	0.2846	0.0659	0.1461	0.27	0.43
	Median	0.1106	0.0169	0.1115	0.06	0.41
Panel B. Post-split						
GKN	Mean	0.8361	0.3023	0.0592	1.68	0.33
	Median	-	0.2383	0.0467	1.65	0.32
NW	Mean	0.4680	0.1445	0.2170	1.01	1.34
	Median	0.4998	0.1221	0.1422	0.83	1.01
Masson	Mean	0.7446	0.2550	0.1065	1.71	0.64
	Median	0.7448	0.2126	0.0714	1.42	0.49
GH	Mean	0.8718	0.1331	0.0346	0.92	0.22
	Median	0.8649	0.1163	0.0197	0.80	0.12
LSB	Mean	0.8347	0.291	0.0705	1.91	0.44
	Median	0.8673	0.2307	0.0354	1.63	0.24
MRR	Mean	0.5349	0.0619	0.0549	0.63	0.20
	Median	0.2478	0.0157	0.0640	0.17	0.36
Panel C. Change						
GKN	Mean	0.0622	$0.7902^{\lozenge\lozenge\lozenge}$	$0.5305^{\lozenge\lozenge\lozenge}$	$0.44^{\lozenge\lozenge\lozenge}$	$-0.06^{\lozenge\lozenge}$
	Median	-	0.7877^{***}	0.5289^{***}	0.27^{***}	-0.03^{***}
NW	Mean	$0.0325^{\lozenge}$	$0.6715^{\lozenge\lozenge\lozenge}$	$0.8824^{\lozenge\lozenge\lozenge}$	$0.23^{\lozenge\lozenge\lozenge}$	$0.16^{\lozenge}$
	Median	0.0105^{*}	0.7072^{*}	0.6429^{***}	0.15^{***}	0.08^{*}
Masson	Mean	0.0049	$0.7334^{\lozenge\lozenge\lozenge}$	$0.8930^{\lozenge\lozenge\lozenge}$	$0.28^{\lozenge\lozenge\lozenge}$	$0.11^{\lozenge\lozenge\lozenge}$
	Median	0.0059	0.7188^{***}	0.6926^{***}	0.18^{***}	0.05^{***}
GH	Mean	$0.0374^{\lozenge\lozenge}$	$0.7003^{\lozenge\lozenge\lozenge}$	$0.6382^{\lozenge\lozenge\lozenge}$	$0.23^{\lozenge\lozenge\lozenge}$	0.00
	Median	0.0199^{***}	0.7531^{***}	0.4914^{**}	0.18^{***}	0.00
LSB	Mean	$0.0440^{\lozenge\lozenge\lozenge}$	$0.7453^{\lozenge\lozenge\lozenge}$	$0.7640^{\lozenge\lozenge\lozenge}$	$0.40^{\lozenge\lozenge\lozenge}$	-0.02
	Median	0.0279^{***}	0.7589^{***}	0.5168^{**}	0.28^{***}	0.00
MRR	Mean	$0.2375^{\lozenge\lozenge\lozenge}$	$0.6611^{\lozenge\lozenge}$	$0.2987^{\lozenge\lozenge\lozenge}$	$0.36^{\lozenge\lozenge\lozenge}$	$-0.21^{\lozenge\lozenge\lozenge}$
	Median	0.1041^{***}	0.6351	0.5204^{***}	0.05^{***}	-0.02^{**}

The sample contains all of the 306 split stocks for the period 1985-1999. The pre-split period covers 60 trading days, and ends 20 days before the split announcement date. The post-split period also covers 60 trading days and starts 20 days after the split becomes effective. † in panel C corresponds to the ratio of the cost in cents after to the cost before the split. ‡ in panel C corresponds to the difference between the percentage cost after split less the cost before the split. π is the temporary contribution to the total spread. For the GKN model, the reported change in π in panel C is the difference between the reported π estimates in panels B and C. $^{\lozenge}$, $^{\lozenge\lozenge}$ and $^{\lozenge\lozenge\lozenge}$ indicate that the t-stat is significant at the 10, 5 and 1 percent levels, respectively. *, ** and *** indicate that the (unreported) Wilcoxon rank signed test that the ratio for dollar costs is equal to 1 or the difference for π and proportional costs is equal to zero is significant at the 10, 5 and 1 percent levels, respectively.

Table 4. Changes post-split in the spread decomposition results for the per-share price-sorted sub-samples

Model	Statistic	π	Temporary†	Permanent†	Temporary % ‡	Permanent %‡
Panel A. Low price per share						
GKN	Mean	0.2275	1.0479$^{\Diamond\Diamond\Diamond}$	0.2459$^{\Diamond\Diamond\Diamond}$	1.13$^{\Diamond\Diamond\Diamond}$	-0.51$^{\Diamond\Diamond\Diamond}$
	Median	-	0.9997***	0.2346***	0.73***	-0.36***
NW	Mean	0.0353	0.7375$^{\Diamond\Diamond\Diamond}$	1.0361	0.27$^{\Diamond\Diamond}$	0.35$^{\Diamond}$
	Median	-0.0012	0.6989***	0.7309***	0.21***	0.19**
Masson	Mean	0.0061	0.7787$^{\Diamond\Diamond\Diamond}$	0.8270$^{\Diamond\Diamond\Diamond}$	0.42$^{\Diamond\Diamond\Diamond}$	0.20$^{\Diamond\Diamond}$
	Median	0.0084	0.7349***	0.7267***	0.25***	0.07**
GH	Mean	-0.0064	0.7623$^{\Diamond\Diamond\Diamond}$	0.7286$^{\Diamond\Diamond}$	0.31$^{\Diamond\Diamond\Diamond}$	0.02
	Median	0.0090	0.7725***	0.5480***	0.24***	0.02
LSB	Mean	0.0414$^{\Diamond\Diamond}$	0.8679$^{\Diamond\Diamond\Diamond}$	0.7728$^{\Diamond\Diamond}$	0.59$^{\Diamond\Diamond\Diamond}$	0.03
	Median	0.0264*	0.7882***	0.5884**	0.40***	0.02
MRR	Mean	0.4371$^{\Diamond\Diamond\Diamond}$	1.1180	0.0969$^{\Diamond\Diamond\Diamond}$	0.54$^{\Diamond\Diamond\Diamond}$	-0.09$^{\Diamond}$
	Median	0.1476***	1.0994	0.4744***	0.14***	-0.08
Panel B. Medium price per share						
GKN	Mean	-0.1394	0.6543$^{\Diamond\Diamond\Diamond}$	-0.7050$^{\Diamond\Diamond\Diamond}$	0.06$^{\Diamond}$	0.28$^{\Diamond\Diamond\Diamond}$
	Median	-	0.6759***	-0.7282***	0.03***	0.26***
NW	Mean	0.0547$^{\Diamond}$	0.4549$^{\Diamond\Diamond\Diamond}$	0.8185$^{\Diamond\Diamond\Diamond}$	0.23$^{\Diamond\Diamond}$	0.12
	Median	0.0183**	0.7853***	0.6709***	0.17***	0.03
Masson	Mean	0.0022	0.7554$^{\Diamond\Diamond\Diamond}$	0.7296$^{\Diamond\Diamond\Diamond}$	0.26$^{\Diamond\Diamond\Diamond}$	0.08$^{\Diamond\Diamond}$
	Median	0.0043	0.7594***	0.6978***	0.19***	0.05*
GH	Mean	0.0396$^{\Diamond\Diamond}$	0.7254$^{\Diamond\Diamond\Diamond}$	-1.1652$^{\Diamond\Diamond}$	0.22$^{\Diamond\Diamond\Diamond}$	-0.01
	Median	0.0209**	0.8106***	0.5683***	0.19***	0.01
LSB	Mean	0.0524$^{\Diamond\Diamond\Diamond}$	0.8390$^{\Diamond\Diamond\Diamond}$	0.7064$^{\Diamond\Diamond\Diamond}$	0.40$^{\Diamond\Diamond\Diamond}$	-0.05
	Median	0.0266**	0.7712***	0.5471***	0.29***	-0.01
MRR	Mean	0.1159$^{\Diamond}$	0.0291$^{\Diamond\Diamond\Diamond}$	0.3863$^{\Diamond\Diamond\Diamond}$	0.22$^{\Diamond\Diamond}$	-0.06
	Median	0.1049**	0.3868***	0.5214***	0.05***	-0.01
Panel C. High price per share						
GKN	Mean	-0.0586	0.6190$^{\Diamond\Diamond\Diamond}$	1.1138$^{\Diamond\Diamond\Diamond}$	0.07$^{\Diamond}$	0.12$^{\Diamond\Diamond\Diamond}$
	Median	-	0.6174***	1.1109**	0.11***	0.08***
NW	Mean	0.0083	0.7308$^{\Diamond\Diamond\Diamond}$	0.7936$^{\Diamond\Diamond}$	0.19$^{\Diamond\Diamond\Diamond}$	0.00
	Median	0.0115	0.6945***	0.5656***	0.12***	0.04
Masson	Mean	0.0133	0.6669$^{\Diamond\Diamond\Diamond}$	0.6829$^{\Diamond\Diamond\Diamond}$	0.16$^{\Diamond\Diamond\Diamond}$	0.03
	Median	0.0063	0.6535***	0.6356***	0.12***	0.03*
GH	Mean	0.0790	0.6139$^{\Diamond\Diamond\Diamond}$	0.6418$^{\Diamond}$	0.16$^{\Diamond\Diamond\Diamond}$	0.00
	Median	0.0242**	0.6969***	0.4490***	0.10***	0.00
LSB	Mean	0.0384$^{\Diamond\Diamond\Diamond}$	0.7229$^{\Diamond\Diamond\Diamond}$	0.5992$^{\Diamond\Diamond\Diamond}$	0.23$^{\Diamond\Diamond\Diamond}$	-0.04
	Median	0.0334***	0.6954***	0.4255***	0.18***	0.00
MRR	Mean	0.1642$^{\Diamond\Diamond\Diamond}$	0.8504	0.4012$^{\Diamond\Diamond\Diamond}$	0.31$^{\Diamond\Diamond\Diamond}$	-0.19$^{\Diamond\Diamond}$
	Median	0.0734***	0.5966**	0.5475***	0.03***	0.01

The sample contains all of the 306 split stocks for the period 1985-1999. The pre-split period covers 60 trading days, and ends 20 days before the split announcement date. The post-split period also covers 60 trading days and starts 20 days after the split becomes effective. The stocks are sorted based on their price per share on an annual basis to form three equal terciles. The low and high price samples each contain the 102 split stocks falling in the first and third terciles. † indicates that the ratio of the cost in cents after to the cost before the split is reported in the respective columns. ‡ indicates that the difference between the percentage cost after split less the cost before the split is reported in the respective columns. π is the temporary contribution to the total spread. $^{\Diamond}$, $^{\Diamond\Diamond}$ and $^{\Diamond\Diamond\Diamond}$ indicate that the t-stat is significant at the 10, 5 and 1 percent levels, respectively. *, ** and *** indicate that the (unreported) Wilcoxon rank signed test that the ratio for dollar costs is equal to 1 or the difference for π and proportional costs is equal to zero is significant at the 10, 5 and 1 percent levels, respectively.

Table 5. The results for the estimation of the Kiefer, Easley, O'Hara and Paperman (1996) model

Sample	Statistic	α	δ	μ	ε	PIN
Panel A. Pre-split						
All splits	Mean	0.3695	0.5010	18.3814	11.7806	0.3241
	Sigma	0.1747	0.2669	31.4385	30.8273	0.1411
	Median	0.3623	0.5019	7.5966	2.9621	0.3006
	Average s.e. †	0.0902	0.1139	1.3445	0.2915	0.1010
	t-stat	37.0057***	32.8373***	10.2277***	6.6849***	40.1918***
5 day rule	Mean	0.3787	0.4977	20.6429	13.4521	0.3000
	Sigma	0.1719	0.2672	33.1281	32.7436	0.1136
	Median	0.3716	0.4895	8.6617	3.6010	0.2882
	Average s.e.	0.0861	0.1085	1.4246	0.3213	0.0899
	t-stat	35.9251***	30.3804***	10.1629***	6.7005***	43.0746***
Panel B. Post-split						
All splits	Mean	0.3996	0.3937	22.0248	20.7999	0.3041
	Sigma	0.1702	0.2534	36.0528	67.7977	0.1264
	Median	0.3803	0.3683	8.6523	4.0840	0.2893
	Average s.e. †	0.0889	0.1085	1.4466	0.3777	0.0901
	t-stat	41.0603***	27.1852***	10.6865***	5.3667***	42.0820***
5 day rule	Mean	0.4111	0.3869	24.6410	23.8000	0.2828
	Sigma	0.1720	0.2503	37.9113	72.3211	0.1040
	Median	0.3936	0.3630	10.7781	5.7399	0.2781
	Average s.e.	0.0855	0.1065	1.5456	0.4169	0.0811
	t-stat	38.9748***	25.2120***	10.6006***	5.3673***	44.3583***
Panel C. Change trading						
All splits	Mean	0.0301	-0.1072	0.6752	1.1647	-0.0199
	Sigma	0.2261	0.3064	1.5471	2.8654	0.1316
	Median	0.0157**	-0.0891***	0.2380***	0.5025***	-0.0176***
	t-stat	2.3283**	-6.1215***	7.6345***	7.1101***	-2.6501***
5 day rule	Mean	0.0325	-0.1109	0.6573	0.9775	-0.0172
	Sigma	0.2285	0.3068	1.5673	1.9025	0.1127
	Median	0.0184**	-0.0873***	0.2350***	0.5179***	-0.0176***
	t-stat	2.3179**	-5.8944***	6.8398***	8.3796***	-2.4908**

The sample of all splits contains all of the 306 split stocks for the period 1985-1999. The 5-day sub-sample contains only the split stocks that did trade on more than 5 days. The pre-split period covers 60 trading days, and ends 20 days before the split announcement date. The post-split period also covers 60 trading days and starts 20 days after the split becomes effective. α, δ, μ and ε are: the probability of daily event occurrence; the probability that the event, conditional on its occurrence, has a negative impact on the stock; the trading intensity of the informed traders as measured by the number of trades conditional on the occurrence of an event; and the trading intensity of the uninformed traders. PIN is the probability of informed trading. Changes in the five estimated parameters are reported in panel C. For the α, δ and PIN estimates, the average and median differences are reported. For the μ and ε parameters, the average ratios (post-split over pre-split) less one are reported as the measures of change. *, ** and *** indicate that the mean (median) is significantly different from zero based on the t-test (unreported Wilcoxon rank test) values at the 10, 5 and 1 percent levels, respectively.

Table 6. The results for the estimation of the Kiefer, Easley, O'Hara and Paperman (1996) model for the low and high per-share price sub-samples

Sample	Statistic	α	δ	μ	ε	PIN
Panel A. Pre-split						
Low price	Mean	0.3645	0.4743	13.4924	6.9000	0.3643
	Sigma	0.1533	0.2443	25.0021	19.6368	0.1350
	Median	0.3542	0.4434	7.0137	2.1972	0.3443
	t-stat	24.1352***	19.7009***	5.4769***	3.5661***	27.3932***
High price	Mean	0.3791	0.5442	28.9203	20.9434	0.2862
	Sigma	0.1995	0.2840	43.7847	46.5524	0.1356
	Median	0.3673	0.5492	10.0517	4.6467	0.2676
	t-stat	0.0878	0.1048	1.6740	0.3822	0.0925
Panel B. Post-split						
Low price	Mean	0.4072	0.4098	15.9772	11.4361	0.3556
	Sigma	0.1782	0.2490	27.7680	49.3589	0.1325
	Median	0.3988	0.4041	6.6532	3.0642	0.3224
	t-stat	23.1896***	16.7060***	5.8395***	2.3514**	27.2426***
High price	Mean	0.4076	0.3932	33.0807	39.5418	0.2547
	Sigma	0.1844	0.2515	50.7873	102.1552	0.1167
	Median	0.3824	0.3579	10.9200	7.8641	0.2277
	t-stat	22.4331***	15.8667***	6.6106***	3.9284***	22.1506***
Panel C. Change trading						
Low price	Mean	0.0427	-0.0645	0.5267	1.1270	-0.0087
	Sigma	0.2194	0.2771	1.3071	3.8294	0.1287
	Median	0.0265**	-0.0448**	0.1243	0.3381*	-0.0036
	t-stat	1.9747*	-2.3623**	4.0897***	2.9868***	-0.6840
High price	Mean	0.0285	-0.1511	0.7585	1.0140	-0.0315
	Sigma	0.2606	0.3382	1.8307	1.3290	0.1382
	Median	0.0113	-0.1368*	0.2537*	0.7251*	-0.0239*
	t-stat	1.1103	-4.5339***	4.2048***	7.7432***	-2.3115**

The sample of all splits contains all of the 306 split stocks for the period 1985-1999. The stocks are sorted based on their price per share on an annual basis to form three equal terciles. The low and high price sub-samples each contain the 102 split stocks falling in the first and third terciles. The pre-split period covers 60 trading days, and ends 20 days before the split announcement date. The post-split period also covers 60 trading days and starts 20 days after the split becomes effective. α, δ, μ and ε are: the probability of daily event occurrence; the probability that the event, conditional on its occurrence, has a negative impact on the stock; the trading intensity of the informed traders as measured by the number of trades conditional on the occurrence of an event; and the trading intensity of the uninformed traders. PIN is the probability of informed trading. Changes in the five estimated parameters are reported in panel C. For the α, δ and PIN estimates, the average and median differences are reported. For the μ and ε parameters, the average ratios (post-split over pre-split) less one are reported as the measures of change. *, ** and *** indicate that the mean (median) is significantly different from zero based on the t-test (unreported Wilcoxon rank test) values at the 10, 5 and 1 percent levels, respectively.

Table 7. Component Garch results

Components		No	No	Yes	Yes		No	No	Yes	Yes
Asymmetry		No	Yes	No	Yes		No	Yes	No	Yes
Statistics	**Parameter**					**Parameter**				
Mean	$1000\times\alpha$	0.737	0.588	0.671	0.864	ρ	0.444	0.445	0.745	0.347
Sigma		0.628	0.418	0.382	0.606		0.467	0.48	0.812	0.334
Median		1.753	1.891	1.711	1.851		0.345	0.351	0.224	0.08
t-stat		4.309***	3.184***	4.019***	4.782***		13.204***	12.991***	34.172***	44.533***
Mean	β^{up}	0.921	0.983	0.91	0.881	ϕ	0.211	0.185	0.148	0.121
Sigma		0.876	0.905	0.81	0.798		0.161	0.144	0.075	0.124
Median		0.901	1.154	0.777	0.638		0.175	0.183	0.315	0.056
t-stat		10.475***	8.729***	12.006***	14.146***		12.316***	10.37***	4.827***	22.323***
Mean	β^{down}	0.808	0.843	0.826	0.822	$1000\times\theta_1$	0.048	0.067	-0.129	-0.0245
Sigma		0.77	0.828	0.779	0.788		0.023	0.025	0.005	-0.024
Median		0.569	0.694	0.541	0.56		0.158	0.118	1.035	0.0423
t-stat		14.546***	12.459***	15.658***	15.026***		3.102***	5.812***	-1.275	-5.630***
Mean	β^{*up}	-0.046	-0.111	-0.024	0.081	μ			0.048	0.085
Sigma		0.005	-0.02	0.007	0.058				0.088	0.077
Median		0.709	0.984	0.674	0.597				0.353	0.053
t-stat		-0.659	-1.152	-0.367	1.382				1.383	16.658***
Mean	β^{*down}	0.302	0.258	0.301	0.218	γ		0.068		0.083
Sigma		0.204	0.217	0.212	0.146			0.034		0.089
Median		0.607	0.68	0.598	0.691			0.316		0.047
t-stat		5.102***	3.896***	5.147***	3.231***			2.194**		17.89***
Mean	$1000\times\kappa_1$	6.014	3.526	3.81	1.381	ψ			0.046	0.147
Sigma		3.493	3.084	3.515	2.073				-0.004	0.134
Median		28.42	25.505	20.668	25.285				0.528	0.07
t-stat		2.168**	1.416	1.889*	0.56				0.886	21.579***
Mean	$1000\times\kappa_2$	8.583	14.317	25.945	5.723	$1000\times\theta_2$			0.318	1.182
Sigma		5.138	5.72	5.661	5.112				-0.005	0.724
Median		30.997	69.698	147.109	30.763				2.111	1.124
t-stat		2.837***	2.105**	1.807*	1.906*				2.543**	16.729***
Mean	$1000\times\omega$	0.143	0.205	0.529	0.399	$1000(\theta_1+\theta_2)$			0.266	1.174
Sigma		0.08	0.078	0.316	0.34				0.017	0.507
Median		0.193	0.485	0.759	0.319				1.3	1.722
t-stat		7.586***	4.323***	7.146***	12.838***				2.099**	6.989***

The sample consists of 105 split stocks from the period 1985-1999. To be included in this sample, a stock split needs at least 500 data points and it needs to avoid a split during the 800 calendar days before the announcement and after the effective stock split date. For each stock, the estimation window corresponds to the period starting one calendar year before the announcement day and ends one calendar year after the split becomes effective. Standard errors are computed as in Bollerslev and Wooldridge (1992). For each split stock, the following mean equation for daily returns is estimated:

$$R_{i,t} = \alpha_i + \beta_i^{up} \times R_{m,t}^{up} + \beta_i^{down} \times R_{m,t}^{down} + \beta_i^{*up} \times R_{m,t}^{up} \times I_{a,t} + \beta_i^{*down} \times R_{m,t}^{down} \times I_{a,t} + \kappa_1 \times I_{announc,t} + \kappa_2 \times I_{effect,t} + \varepsilon_{i,t} .$$

Table 7. Continued.

Cross-sectional averages are reported in the table, and each column in the table corresponds to one of the following GARCH specifications:

No component without asymmetry:

$$h_{i,t} = \omega + \phi \times \varepsilon_{i,t-1}^2 + \rho \times h_{i,t-1} + \theta \times I_{a,t}$$

No component with asymmetry:

$$h_{i,t} = \omega + \phi \times \varepsilon_{i,t-1}^2 + \gamma \times \varepsilon_{i,t-1}^2 \times I_{\varepsilon_{i,t-1}} + \rho \times h_{i,t-1} + \theta \times I_{a,t}$$

Component without asymmetry:

$$h_{i,t} - q_{i,t} = \mu \times \left(\varepsilon_{i,t-1}^2 - q_{i,t-1}\right) + \psi \times \left(h_{i,t-1} - q_{i,t-1}\right) + \theta_2 \times I_{a,t}$$

$$q_{i,t} = \omega + \rho \times \left(q_{i,t-1} - \omega\right) + \phi \times \left(\varepsilon_{i,t-1}^2 - h_{i,t-1}\right) + \theta_1 \times I_{a,t}$$

Component with asymmetry:

$$h_{i,t} - q_{i,t} = \mu \times \left(\varepsilon_{i,t-1}^2 - q_{i,t-1}\right) + \gamma \times \left(\varepsilon_{i,t-1}^2 - q_{i,t-1}\right) \times I_{\varepsilon_{i,t-1}} + \psi \times \left(h_{i,t-1} - q_{i,t-1}\right) + \theta_2 \times I_{a,t}$$

$$q_{i,t} = \omega + \rho \times \left(q_{i,t-1} - \omega\right) + \phi \times \left(\varepsilon_{i,t-1}^2 - h_{i,t-1}\right) + \theta_1 \times I_{a,t}$$

Table 8. Volatility decomposition results

Sample	Statistic	Public		Noise		Asymmetric		Discrete	
		Pre-split	Post-split	Pre-split	Post-split	Pre-split	Post-split	Pre-split	Post-split
Panel A. Volatility components									
All	Mean	0.04464	0.06229	0.01753	0.03230	0.01398	0.01663	0.02581	0.05856
	Median	0.01562	0.02356	0.00416	0.01231	0.00928	0.01011	0.00791	0.01770
	Ratio†		1.42744$^{\Diamond,*}$		1.97083$^{\Diamond,*}$		1.16037$^{\Diamond,*}$		2.20682$^{\Diamond,*}$
Low price	Mean	0.02642	0.04400	0.00555	0.01462	0.00200	0.00270	0.01889	0.03851
	Median	0.01562	0.02384	0.00397	0.01130	0.00174	0.00239	0.00794	0.01838
	Ratio		1.58507$^{\Diamond,*}$		2.75547$^{\Diamond,*}$		1.35727$^{\Diamond,*}$		2.16190$^{\Diamond,*}$
High price	Mean	0.09307	0.13071	0.03556	0.06274	0.03273	0.04161	0.03668	0.06269
	Median	0.04159	0.05323	0.01941	0.03665	0.01095	0.01480	0.01201	0.01793
	Ratio		1.35280$^{\Diamond,*}$		1.77057$^{\Diamond,*}$		1.25357$^{\Diamond,*}$		1.79213$^{\Diamond,*}$
Panel B. Volatility components as proportion of total volatility									
All	Mean	0.38975	0.38862	0.16830	0.18939	0.04633	0.03999	0.22478	0.22154
	Median	0.41260	0.42553	0.11677	0.14788	0.02165	0.02222	0.21295	0.20450
	Difference‡		-0.00200		0.01959$^{\Diamond,*}$		0.00016		-0.00280
Low price	Mean	0.34549	0.31751	0.14281	0.17004	0.03801	0.04009	0.20899	0.22339
	Median	0.36266	0.34026	0.09931	0.14465	0.02002	0.02577	0.19279	0.21821
	Difference		-0.01265$^{\Diamond,*}$		0.01959$^{\Diamond,**}$		0.0046$^{\Diamond,**}$		0.00827
High price	Mean	0.41906	0.46877	0.19477	0.20088	0.03365	0.03178	0.25132	0.21773
	Median	0.44513	0.48081	0.13833	0.14881	0.02089	0.02222	0.23563	0.20222
	Difference		0.00548$^{\Diamond\Diamond\Diamond,**}$		0.01033$^{\Diamond\Diamond,***}$		-0.00218		-0.02570

The sample of all splits contains all of the 306 split stocks for the period 1985-1999. The stocks are sorted based on their price per share on an annual basis to form three equal terciles. The low and high price sub-samples each contain the 102 split stocks falling in the first and third terciles. The pre-split period covers 60 trading days, and ends 20 days before the split announcement date. The post-split period also covers 60 trading days and starts 20 days after the split becomes effective. Public correspond to the volatility induced by the arrival of new public information. Noise volatility is caused by the bouncing of prices between the bid and ask due to the temporary component of the spread. Asymmetric is the volatility due to the private information revealed through trading. Discrete is the volatility caused by price discreetness† Ratio is the mean ratio of the values of the corresponding volatility component for the post- to the pre-split period. The null hypothesis is that this ratio is equal to one. ‡ Difference is the mean change in the volatility proportions from the pre- to post-split periods. The null hypothesis is that the difference is zero. $^{\Diamond}$, $^{\Diamond\Diamond}$ and $^{\Diamond\Diamond\Diamond}$ indicates that the t-stat is significant at the 10, 5 and 1 percent levels, respectively. *, ** and *** indicates that the median is significantly different from the stated value at the 10, 5 and 1 percent levels, respectively.

Table 9. Realized volatility decomposition

Statistic	ω	α	β	θ1	θ2
Min	-3.16757	-0.50457	-1.03022	-17.93988	-15.95696
First quartile	0.47213	0.66176	-0.84011	-0.58086	-0.19856
Median	0.69638	0.85406	-0.68745	-0.10937	0.08284
Mean	45.97805	0.68225	-0.60109	-0.16647	11.60146
Third quarter	1.21437	0.94576	-0.46404	0.23843	0.78954
Max	5618.74969	1.00000	0.55857	24.19259	944.15724
SD	474.63387	0.41289	0.33111	3.22170	69.87484
t-stat	1.44334	24.61980	-27.04866	-0.76990	2.47382
p-value	0.15033	0.00000	0.00000	0.44218	0.01412

The following ARMAX model is fitted:

$$Log(1 + RV_t) = \varpi + \alpha Log(1 + RV_{t-1}) + \varepsilon_t + \beta\varepsilon_{t-1} + \theta_1.I_{a,t} + \theta_2.I_{e,t} \quad (6)$$

where $Log(1 + RV_t)$ is the natural logarithm of one plus the realized volatility during day t,

RV_t is the realized volatility measured as the sum of quadratic variations within a single trading day, $RV_t = \sum_{i=2}^{n_t}(p_{ti} - p_{t,i-1})^2$,

n_t is the number of trades during date t,
$p_{t,i}$ is the logarithm of the i^{th} trade during day t,
$I_{a,t}$ is a dummy variable equal to 1 if after the announcement date, and is zero otherwise,

$I_{e,t}$ is a dummy variable equal to 1 for the day preceding, the day of and the day after the split becomes effective, and is zero otherwise, and

θ_1 and θ_2 correspond to the impact of the stock split on respectively the true and the temporary volatility.

Table 10. Descriptive statistics

	Per share price				Total assets (millions $)			
	NASDAQ-listed		NYSE-listed		NASDAQ-listed		NYSE-listed	
Statistic	Acquirers	Targets	Acquirers	Targets	Acquirers	Targets	Acquirers	Targets
Min	1.0967	1.0255	3.5901	1.2887	6.8170	8.6360	107.8760	22.5240
Median	16.4249	8.5380	27.6537	20.5218	240.2400	120.1230	1,880.2650	1,547.0910
Mean	22.5554	12.8416	33.2025	24.5332	792.7863	578.1291	13,036.4100	12,209.7500
Max	145.9328	218.2576	141.3174	80.6494	18,150.7500	18,457.0700	276,229.0000	254,170.0000
SD	21.6261	19.9910	21.0465	17.7117	1,875.5190	1,893.0190	39,655.1800	37,858.2700
Skewness	2.3818	6.4686	1.7826	0.9998	5.9379	7.8054	5.0931	4.9342
Kurtosis	10.8913	57.5881	7.8816	3.4754	46.5596	69.3556	30.1991	28.5198
	Total Capitalization (millions $)				**Trading Volume (millions of shares)**			
	NASDAQ-listed		NYSE-listed		NASDAQ-listed		NYSE-listed	
Statistic	Acquirers	Targets	Acquirers	Targets	Acquirers	Targets	Acquirers	Targets
Min	9.8816	4.4764	74.0939	8.6027	0.6838	1.0941	0.7947	0.6023
Median	458.2766	105.3195	1,765.4882	1,030.0990	54.5353	23.4423	69.6403	40.0615
Mean	1,547.3526	451.0163	11,080.2983	4,523.4038	190.9704	58.0092	211.7452	109.2148
Max	18,955.5300	13,705.4053	216,048.9564	72,929.6438	1421.0050	659.8610	2766.5080	1471.0960
SD	2,932.9111	1,283.6004	30,039.9201	10,690.5807	321.6980	96.2038	388.1877	217.2898
Skewness	3.2190	7.4910	4.4436	4.1381	2.3485	3.5501	3.3623	3.9429
Kurtosis	14.3372	70.7270	24.4800	23.0031	7.8324	18.7507	16.8142	21.3101

The per-share price is the average price during the pre-announcement window. The pre-announcement window covers 45 trading days and ends 20 days before the announcement date of the tender offer. Total assets, total capitalization and trading volume are from the Compustat database. Total assets (data item 6 in Compustat) and total capitalization (data item 24 times data item 25 in Compustat) are as the end of the calendar year preceding the announcement of the tender offer. In case of a new company, the most recent quarterly figure preceding the announcement is used. Trading volume is the total number of shares traded during the calendar year preceding the announcement as reported on data item 28 in the Compustat database.

Table 11. Liquidity and trading activity for targets

Panel A. NASDAQ-listed targets

Payment Method	$ quoted spread[1]			% quoted spread[2]			$ effective spread[3]		
	Pre-†	Ann.‡	Ratio§	Pre-	Ann.	Difference	Pre-	Ann.	Ratio
All	0.170	0.110	0.678[a]	0.030	0.018	-0.012[a]	0.146	0.096	0.681[a]
	(0.130)	(0.087)	(0.646[a])	(0.023)	(0.011)	(-0.009[a])	(0.117)	(0.071)	(0.645[a])
Cash	0.161	0.085	0.589[a]	0.032	0.015	-0.016[a]	0.138	0.072	0.580[a]
	(0.130)	(0.068)	(0.526[a])	(0.026)	(0.010)	(-0.015[a])	(0.121)	(0.060)	(0.525[a])
Shares	0.169	0.123	0.764[a]	0.029	0.021	-0.008[a]	0.148	0.106	0.773[a]
	(0.142)	(0.105)	(0.737[a])	(0.020)	(0.014)	(-0.004[a])	(0.121)	(0.088)	(0.740[a])
	$ effective weighted spread[4]			% effective spread[5]			% effective weighted spread[6]		
	Pre-	Ann.	Ratio	Pre-	Ann.	Difference	Pre-	Ann.	Difference
All	0.148	0.097	0.702[a]	0.026	0.016	-0.010[a]	0.026	0.016	-0.010[a]
	(0.117)	(0.075)	(0.669[a])	(0.021)	(0.010)	(-0.008[a])	(0.020)	(0.010)	(-0.008[a])
Cash	0.138	0.072	0.589[a]	0.027	0.013	-0.015[a]	0.027	0.013	-0.014[a]
	(0.117)	(0.06)	(0.521[a])	(0.023)	(0.008)	(-0.013[a])	(0.023)	(0.008)	(-0.013[a])
Shares	0.149	0.112	0.803[a]	0.025	0.018	-0.007[a]	0.024	0.018	-0.006[a]
	(0.126)	(0.092)	(0.789[a])	(0.018)	(0.011)	(-0.005[a])	(0.018)	(0.012)	(-0.004[a])
	nb trades[7]			nb buy[8]			nb sell[9]		
	Pre-	Ann.	Ratio	Pre-	Ann.	Ratio	Pre-	Ann.	Ratio
All	319.106	989.773	6.820[a]	162.768	463.622	6.522[a]	156.338	526.151	7.438[a]
	(65.889)	(337.000)	(4.130[a])	(29.489)	(141.667)	(3.735[a])	(36.356)	(194.667)	(4.710[a])
Cash	165.156	538.380	7.001[a]	81.471	183.859	5.439[a]	83.684	354.522	8.572[a]
	(45.244)	(260.333)	(4.430[a])	(23.933)	(84.333)	(3.496[a])	(21.622)	(167.667)	(5.862[a])
Shares	452.260	1166.167	6.143[a]	232.002	585.889	6.859[a]	220.257	580.278	6.026[a]
	(130.011)	(397.833)	(4.006[a])	(54.556)	(196.667)	(4.023[a])	(64.244)	(221.167)	(4.070[a])
	volume shares (thousands)[10]			$ volume (millions)[11]			$ volume buy (millions)[12]		
	Pre-	Ann.	Ratio	Pre-	Ann.	Ratio	Pre-	Ann.	Ratio
All	241.841	1500.494	14.930[a]	8.373	45.056	23.825[a]	4.371	21.306	17.558[a]
	(77.173)	(622.033)	(8.773[a])	(0.261)	(5.177)	(11.596[a])	(0.126)	(1.566)	(8.846[a])
Cash	155.485	1558.831	20.976[a]	1.638	21.120	35.451[a]	0.829	6.871	21.731[a]
	(41.32)	(725.133)	(14.239[a])	(0.216)	(5.451)	(22.037[a])	(0.082)	(1.365)	(11.902[a])
Shares	261.541	1228.764	9.960[a]	14.663	58.967	14.045[a]	7.691	29.626	13.688[a]
	(115.549)	(514.083)	(6.431[a])	(0.373)	(4.076)	(8.420[a])	(0.177)	(1.718)	(8.270[a])
	$ volume sell (millions)[13]			$ depth (thousands)[14]			average $ vol. per trade (thousands)[15]		
	Pre-	Ann.	Ratio	Pre-	Ann.	Ratio	Pre-	Ann.	Ratio
All	4.003	23.750	30.415[a]	7.608	65.997	10.915[a]	8.069	18.640	2.565[a]
	(0.143)	(3.339)	(13.374[a])	(5.041)	(22.685)	(3.373[a])	(5.194)	(10.859)	(1.904[a])
Cash	0.809	14.249	48.558[a]	5.786	118.484	21.596[a]	6.060	22.690	3.734[a]
	(0.119)	(4.066)	(29.006[a])	(4.384)	(60.095)	(12.421[a])	(4.44)	(13.723)	(3.239[a])
Shares	6.972	29.341	15.223[a]	8.473	22.037	2.710[a]	8.716	14.553	1.720[a]
	(0.190)	(2.558)	(8.051[a])	(5.327)	(11.336)	(1.956[a])	(5.572)	(9.411)	(1.596[a])

Panel B. NYSE-listed targets

Sample	$ quoted spread[1]			% quoted spread[2]			$ effective spread[3]		
	Pre-†	Ann.‡	Ratio§	Pre-	Ann.	Difference§§	Pre-	Ann.	Ratio
All	0.133	0.099	0.748[a]	0.012	0.008	-0.004[a]	0.090	0.109	1.218[a]
	(0.118)	(0.092)	(0.759[a])	(0.006)	(0.004)	(-0.002[a])	(0.081)	(0.078)	(0.919[a])
Cash	0.150	0.101	0.673[a]	0.015	0.010	-0.005[a]	0.100	0.081	0.839[a]
	(0.132)	(0.095)	(0.683[a])	(0.011)	(0.007)	(-0.003[a])	(0.087)	(0.079)	(0.767[a])
Shares	0.125	0.102	0.815[a]	0.007	0.006	-0.002[a]	0.087	0.192	2.059[c]
	(0.119)	(0.105)	(0.823[a])	(0.005)	(0.004)	(-0.001[a])	(0.082)	(0.082)	(0.943)
	$ effective weighted spread[4]			% effective spread[5]			% effective weighted spread[6]		
	Pre-	Ann.	Ratio	Pre-	Ann.	Difference	Pre-	Ann.	Difference
All	0.110	0.124	1.085[a]	0.008	0.007	-0.002[a]	0.009	0.007	-0.002[a]
	(0.104)	(0.091)	(0.847[a])	(0.004)	(0.004)	(-0.001[a])	(0.005)	(0.004)	(-0.001[a])
Cash	0.119	0.096	0.832[a]	0.010	0.008	-0.002[a]	0.012	0.009	-0.002[a]
	(0.108)	(0.091)	(0.765[a])	(0.007)	(0.005)	(-0.002[a])	(0.009)	(0.007)	(-0.002[a])
Shares	0.111	0.220	1.768[b]	0.005	0.005	0.000	0.006	0.006	0.000
	(0.108)	(0.098)	(0.885)	(0.003)	(0.003)	(0.000)	(0.004)	(0.004)	(0.000)

Table 11. Continued.

	nb trades[7]			nb buy[8]			nb sell[9]		
	Pre-	Ann.	Ratio	Pre-	Ann.	Ratio	Pre-	Ann.	Ratio
All	240.800	666.083	3.772^a	128.911	286.650	3.044^a	111.889	379.432	4.593^a
	(126.089)	(411)	(2.926^a)	(68.978)	(171.667)	(2.413^a)	(58.422)	(241.667)	(3.675^a)
Cash	97.356	314.279	4.063^a	51.228	108.238	3.086^a	46.128	206.041	5.171^a
	(74.667)	(205)	(3.291^a)	(39.778)	(68.667)	(2.329^a)	(37.978)	(138)	(3.958^a)
Shares	450.794	1252.897	3.929^a	240.950	535.256	3.115^a	209.844	717.641	4.781^a
	(269.567)	(817.5)	(2.724^a)	(141.489)	(376.167)	(2.639^a)	(132.778)	(431.167)	(3.062^a)
	volume shares (thousands)[10]			**\$ volume (millions)[11]**			**\$ volume buy (millions)[12]**		
	Pre-	Ann.	Ratio	Pre-	Ann.	Ratio	Pre-	Ann.	Ratio
All	375.857	2698.481	11.479^a	11.810	97.958	15.286^a	6.356	42.724	11.897^a
	(161.296)	(1551.8)	(7.898^a)	(2.892)	(29.459)	(9.050^a)	(1.455)	(14.316)	(7.358^a)
Cash	138.267	1480.733	12.631^a	3.113	41.653	17.676^a	1.628	14.346	12.319^a
	(82.073)	(791.467)	(9.728^a)	(0.781)	(13.508)	(11.931^a)	(0.43)	(4.829)	(7.294^a)
Shares	722.754	4735.736	10.669^a	28.850	205.456	13.006^a	15.634	88.439	11.132^a
	(409.788)	(2128.083)	(6.618^a)	(9.649)	(68.969)	(7.850^a)	(5.357)	(37.059)	(7.006^a)
	\$ volume sell (millions)[13]			**\$ depth (thousands)[14]**			**average \$ vol. per trade (thousands)[15]**		
	Pre-	Ann.	Ratio	Pre-	Ann.	Ratio	Pre-	Ann.	Ratio
All	5.454	55.235	19.822^a	82.883	523.185	9.927^a	29.099	85.690	3.072^a
	(1.433)	(16.861)	(11.123^a)	(45.815)	(211.759)	(3.416^a)	(23.981)	(62.591)	(2.444^a)
Cash	1.485	27.307	24.312^a	78.743	832.640	16.685^a	20.290	72.017	3.387^a
	(0.334)	(7.684)	(13.222^a)	(29.883)	(228.466)	(7.352^a)	(13.837)	(41.843)	(2.379^a)
Shares	13.216	117.016	15.630^a	104.311	259.815	3.260^a	41.697	98.919	2.437^a
	(4.293)	(35.244)	(7.870^a)	(80.814)	(203.041)	(2.268^a)	(27.892)	(81.238)	(2.317^a)

This table presents mean and median statistics where the median statistics are in parentheses. [1] Average quoted dollar spread. [2] Average percent (per-dollar) quoted spread. [3] Average dollar effective spread. [4] Average dollar effective spread weighted by transaction value. [5] Average percent (per-dollar) effective spread. [6] Average percent effective spread weighted by transaction value. [7] Average number of transactions per day. [8] Average daily number of buyer-initiated trades. [9] Average daily number of seller-initiated trades. [10] Average daily volume measured by number of shares traded. [11] Average daily dollar volume. [12] Average daily dollar volume of buyer-initiated trades. [13] Average daily dollar volume of seller-initiated trades. [14] Average dollar depth, where depth is measured as the average of the dollar depth at ask and the dollar depth at bid. [15] Average dollar volume per trade. † Corresponds to the pre-announcement window, which covers the 45 trading days that end 20 days before the announcement. ‡ Corresponds to the announcement window (i.e., the announcement day, one day before and the day after). § Ratio of the considered statistic for the announcement window divided by the corresponding value pre-announcement. §§ Value of the statistic for the announcement window less its value during the pre-announcement window. The paired t-test is used to test the mean, and the Wicoxon signed ranks test is used to test the median. The test is if the mean or median difference (ratio) is zero (one). ^{a}, ^{b} and ^{c} correspond to significance levels of 1, 5 and 10%, respectively.

Table 12. Liquidity and trading activity for acquirers

Panel A. NASDAQ-listed acquirers												
	Pre-†	Post-eff.‡	Ann.††	Eff.‡‡	Pre-	Post-eff.	Ann.	Eff.	Pre-	Post-eff.	Ann.	Eff.
	$ quoted spread[1]				% quoted spread[2]				$ effective spread[3]			
All	0.175	0.123	0.154	0.139	0.015	0.013	0.014	0.014	0.118	0.086	0.109	0.098
	(0.132[a])	(0.093[a])	(0.117[b])	(0.104[a])	(0.010)	(0.007[a])	(0.009[a])	(0.008[a])	(0.110[a])	(0.109)	(0.105)	(0.093[b])
Cash	0.199	0.154	0.170	0.179	0.013	0.011	0.012	0.013	0.173	0.132	0.145	0.150
	(0.153)	(0.118[a])	(0.125[b])	(0.131[b])	(0.009)	(0.007[a])	(0.008)	(0.008)	(0.124)	(0.105[a])	(0.110[b])	(0.115)
Shares	0.146	0.091	0.124	0.103	0.014	0.014	0.014	0.014	0.135	0.084	0.118	0.093
	(0.107[a])	(0.079[a])	(0.097[a])	(0.087[a])	(0.009)	(0.008)	(0.008[c])	(0.007[c])	(0.102[a])	(0.074[a])	(0.098[a])	(0.082[a])
	$ effective weighted spread[4]				% effective spread[5]				% effective weighted spread[6]			
All	0.135	0.099	0.119	0.111	0.009	0.007	0.008	0.007	0.009	0.008	0.009	0.009
	(0.105[a])	(0.104)	(0.104)	(0.094[a])	(0.012[a])	(0.012)	(0.015[a])	(0.017[a])	(0.012[a])	(0.012)	(0.015[a])	(0.016[a])
Cash	0.182	0.143	0.154	0.165	0.011	0.009	0.010	0.010	0.012	0.010	0.011	0.011
	(0.143)	(0.119[a])	(0.112[a])	(0.129[b])	(0.008)	(0.006[b])	(0.006)	(0.008)	(0.009)	(0.007[a])	(0.007)	(0.009)
Shares	0.148	0.098	0.135	0.106	0.012	0.013	0.013	0.013	0.013	0.014	0.013	0.014
	(0.121[a])	(0.086[a])	(0.119[b])	(0.095[a])	(0.008)	(0.007)	(0.008[c])	(0.006[b])	(0.009)	(0.008)	(0.009)	(0.007[b])
	$ depth (thousands)[7]				nb trades[8]				nb shares (thousands)[9]			
All	12.867	10.835[a]	12.670	11.686[a]	1500.536	1614.119	1733.042	1877.623	866.658	978.438	1056.054	1084.773
	(9.094)	(8.572[a])	(8.886[a])	(8.833[a])	(253.043)	(314.217[a])	(324.000[a])	(324.000[a])	(197.693)	(230.420[a])	(234.667[a])	(222.200[b])
Cash	12.453[a]	10.982[a]	12.045	11.472	1051.663	992.231	1168.347	1121.255	676.950	618.191	729.091	603.481
	(9.048)	(8.884[a])	(8.643[a])	(8.939)	(162.554)	(197.457[a])	(240.833[b])	(268.667[b])	(119.742)	(152.411)	(134.083)	(120.117)
Shares	14.729[b]	10.980[a]	14.446	12.442[a]	2122.908	2081.683	2287.786	2277.259	1209.587	1419.696	1464.867	1441.844
	(9.909[b])	(9.176[a])	(10.417)	(9.537[b])	(483.435)	(530.696)	(516.333[b])	(462.667)	(361.267)	(408.470[b])	(432.167[b])	(329.967[c])
	dol volume (millions)[10]				nb buy[11]				vol buy (millions)[12]			
All	31.220	26.926	37.494	33.903	779.442	836.184	899.526	994.573	16.210	13.996	19.242	17.888
	(2.803)	(2.864)	(2.939[a])	(2.903)	(124.391)	(163.326[a])	(179.000[a])	(161.667[a])	(1.402)	(1.404)	(1.382)	(1.351)
Cash	19.602	17.823	20.289	19.249	543.759	512.915	610.843	591.843	10.176	9.258	10.719	10.168
	(2.781)	(2.774)	(2.243)	(2.173)	(84.804)	(97.228[a])	(122.333[b])	(135.167[b])	(1.365)	(1.353)	(1.244)	(1.176)
Shares	39.569	28.929	47.685	36.851	1102.222	1070.960	1200.010	1184.915	20.545	14.922	24.879	19.498
	(5.482)	(5.64)	(5.061[c])	(4.104)	(255.565)	(277.283)	(267.333[b])	(242.000)	(2.879)	(2.978)	(2.282[c])	(2.098)
	nb sell[13]				vol sell (millions)[14]				average $ vol. per trade (thousands)[15]			
All	721.094	777.935	833.516	883.050	15.009	12.930	18.251	16.014	13.711	11.066	13.527	11.771
	(130.239)	(148.848[a])	(145.000[a])	(154.333[a])	(1.400)	(1.479)	(1.408[b])	(1.386)	(11.854[a])	(10.028[a])	(10.697[b])	(9.718[a])
Cash	507.905	479.316	557.505	529.412	9.426	8.565	9.569	9.082	15.200	13.203	14.285	11.906
	(79.641)	(99.054[a])	(110.333[c])	(120.167[b])	(1.314)	(1.414)	(1.064)	(1.164)	(12.555)	(12.293[b])	(10.471[b])	(9.668[a])
Shares	1020.686	1010.723	1087.776	1092.343	19.023	14.008	22.806	17.353	12.948	9.648	12.708	11.144
	(241.239)	(253.413)	(276.333[c])	(237.333)	(2.724)	(2.617)	(2.779)	(2.127)	(10.977)	(9.495[a])	(10.832)	(10.064[b])
Panel B. NYSElisted acquirers												
	Pre-†	Post-eff.‡	Ann.††	Eff.‡‡	Pre-	Post-eff.	Ann.	Eff.	Pre-.	Post-eff.	Ann.	Eff.
Sample	$ quoted spread[1]				% quoted spread[2]				$ effective spread[3]			
All	0.112[a]	0.083[a]	0.105[a]	0.090[a]	0.005[a]	0.004	0.005	0.004	0.084[a]	0.067[a]	0.083	0.085
	(0.100)	(0.072[a])	(0.099)	(0.080[b])	(0.004[a])	(0.003[a])	(0.004)	(0.003)	(0.079[a])	(0.059[a])	(0.074)	(0.063[a])
Cash	0.106[a]	0.082[a]	0.100	0.091[a]	0.005[a]	0.003[a]	0.004	0.004[a]	0.082[a]	0.066[a]	0.076[a]	0.084[a]
	(0.096[a])	(0.072[a])	(0.091[a])	(0.081[a])	(0.003)	(0.003)	(0.003)	(0.003)	(0.078[a])	(0.057[a])	(0.071[b])	(0.062[a])
Shares	0.122[a]	0.084[a]	0.103[a]	0.091[a]	0.004[a]	0.003	0.003	0.003	0.091[a]	0.068[a]	0.093	0.073[a]
	(0.121[b])	(0.074[a])	(0.103[a])	(0.081[a])	(0.004)	(0.002[a])	(0.003)	(0.002)	(0.088[b])	(0.066[a])	(0.074)	(0.057[b])
	$ effective weighted spread[4]				% effective spread[5]				% effective weighted spread[6]			
All	0.115[a]	0.094[a]	0.119[b]	0.117	0.004[a]	0.003[a]	0.004	0.003[a]	0.005[a]	0.004[a]	0.005	0.004[a]
	(0.110[a])	(0.086[a])	(0.098)	(0.082[a])	(0.003[a])	(0.002[a])	(0.003)	(0.002[a])	(0.003[a])	(0.003)	(0.004[b])	(0.004[b])
Cash	0.114[a]	0.093[a]	0.106[a]	0.117[a]	0.003	0.003	0.00[a]	0.003	0.005	0.004	0.004	0.004
	(0.109[a])	(0.085[a])	(0.091[a])	(0.080[a])	(0.003)	(0.002)	(0.00[b])	(0.002)	(0.004[b])	(0.003[a])	(0.003[a])	(0.003[a])
Shares	0.123[a]	0.095[a]	0.151[a]	0.098[a]	0.003	0.002	0.002	0.002	0.004[a]	0.003[a]	0.003[a]	0.003[a]
	(0.122[b])	(0.100)	(0.100)	(0.088[b])	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)

Table 12. Continued.

	$ depth (thousands)[7]				nb trades[8]				nb shares (thousands)[9]			
All	76.005[a]	47.328[a]	73.000[a]	55.376[a]	606.408[a]	772.433[a]	750.768[a]	800.856[a]	934.874	1170.514[a]	1303.756[a]	1327.746[a]
	(52.414[a])	(37.888[a])	(47.715[b])	(43.533[a])	(267.804)	(363.130[a])	(317.000[a])	(368.333[a])	(284.743)	(318.091[a])	(335.400[a])	(316.500[a])
Cash	74.268[a]	47.791[a]	65.895[a]	49.723[a]	713.108[a]	839.725[a]	869.948[a]	889.824[a]	1133.428	1326.072[a]	1554.890[a]	1492.816
	(45.086[b])	(37.970[a])	(41.430[a])	(42.371[a])	(295.666)	(374.598[a])	(324.333[a])	(412.000[a])	(298.282)	(295.630[a])	(299.417)	(315.983)
Shares	77.733[a]	49.596[a]	82.946[a]	58.601[a]	640.987[a]	1014.585[a]	754.667[a]	966.767[a]	847.624[a]	1349.740[a]	974.860[a]	1270.358[a]
	(57.550[b])	(42.881[a])	(68.252)	(45.754[a])	(404.707)	(478.852[a])	(546.333[a])	(522.333[a])	(419.747)	(499.672[b])	(536.017[b])	(567.883[a])
	dol volume (millions)[10]				nb buy[11]				vol buy (millions)[12]			
All	32.565[a]	35.769	40.461[a]	40.410[a]	326.289[a]	417.135[a]	400.185[a]	436.499[a]	17.851	19.726[a]	21.696[a]	22.857[a]
	(7.679[a])	(9.554[a])	(8.520[a])	(8.434[a])	(144.022)	(203.152[a])	(166.667[a])	(206.667[a])	(3.94)	(5.503[a])	(4.278[a])	(4.811[a])
Cash	38.046	40.474	45.019[a]	40.752	384.689	450.541[a]	458.136[a]	473.735[a]	20.820	22.260	23.602	22.440
	(8.426)	(9.651[a])	(8.311)	(8.029)	(165.735)	(212.489[a])	(170.000[a])	(210.667[a])	(4.731)	(5.461[b])	(4.362)	(4.482)
Shares	42.024[a]	44.268[a]	44.183[a]	60.081[a]	342.740[a]	550.836[a]	416.983[a]	527.367[a]	22.633	24.324	25.174	33.698
	(15.047)	(13.695[b])	(20.363[a])	(16.227[c])	(224.728)	(270.151[a])	(278.833[a])	(261.833[a])	(8.588)	(7.507[b])	(12.353[a])	(8.723)
	nb sell[13]				vol sell (millions)[14]				average $ vol. p. trade (thousands)[15]			
All	280.119	355.298[a]	350.583	364.357[a]	14.714[a]	16.043[a]	18.765[a]	17.553	36.276[a]	30.862[a]	38.769	34.465
	(123.711)	(150.913[a])	(137.333[a])	(160.667[a])	(3.502)	(4.305[a])	(3.802[a])	(3.812[b])	(28.462)	(24.529[a])	(27.92)	(26.351)
Cash	328.420	389.184[a]	411.812[a]	416.090[a]	17.226	18.214[a]	21.417	18.312	36.431	31.416[a]	36.389	32.285[a]
	(131.393)	(164.761[a])	(142.833[a])	(179.333[a])	(3.670)	(4.357[a])	(3.734)	(3.366)	(26.911)	(24.567[a])	(25.688)	(25.073[a])
Shares	298.248[a]	463.749[a]	337.683[a]	439.400[a]	19.391[a]	19.944[a]	19.009[a]	26.383[a]	42.084[a]	33.342[a]	45.027[a]	40.037
	(178.413)	(205.380[a])	(243.000[a])	(257.167[a])	(6.459)	(6.046[b])	(8.010[b])	(7.504[c])	(35.255)	(26.058[a])	(36.517[c])	(29.309)

This table presents mean statistics and median statistics in the parentheses. [1] Average quoted dollar spread. [2] Average percent (per dollar) quoted spread. [3] Average dollar effective spread. [4] Average dollar effective spread weighted by transaction value. [5] Average percent (per dollar) effective spread. [6] Average percent effective spread weighted by transaction value. [7] Average dollar depth, where depth is measured as the average of the dollar depth at ask and the dollar depth at bid. [8]Average number of transactions per day. [9]Average daily volume measured by number of shares traded in millions. [10]Average daily dollar volume. [11]Average daily number of buyer-initiated trades. [12]Average daily dollar volume of buyer-initiated trades. [13]Average daily number of seller-initiated transactions. [14]Daily dollar volume of seller-initiated trades. [15]Average dollar volume per trade. † Corresponds to the pre-announcement window, which covers 45 trading days that ends 20 days before the announcement. †† Corresponds to the announcement window, which consists of the announcement day, one day before and the day after. ‡ Corresponds to the post-effective window, which covers 45 trading days that start 20 days after the effective date. ‡‡ Corresponds to the effective window, which includes the effective day, one day before and the day after. The pre-announcement window is used as the benchmark. The univariate or matched sample tests compare each of the 3 remaining windows to the benchmark window. Both the matched t-tests and the Wilcoxon signed ranks tests are used for this purpose. For percentage variables like percentage quoted spread or percentage effective spread, the null that the difference is zero is tested, while for level variables like quoted spread, depth or number of trades, the test is if the ratio is different from one. Multivariate tests for the equality of the windows are also reported in this table under the column pre-ann. For this purpose, the Wilk's lambda from the repeated ANOVA analysis is used to test for no change in the mean variables, and the Friedman test is used to test median rank. [a, b] and [c] correspond to significance levels of 1, 5 and 10%, respectively.

Table 13. Change in limit orders for targets

Panel A. NASDAQ-listed targets									
		nb trades				nb shares			
Sample	Statistic	bid pre	bid post	ask pre	ask post	bid pre	bid post	ask pre	ask post
All	Mean	5.345	10.521	4.564	5.867	4.901	10.920	4.265	5.004
	Median	4.830	8.923	4.258	5.405	4.369	8.581	3.983	4.569
	Mean dif		5.176[a]		1.303[a]		6.019[a]		0.738[a]
	Median dif		3.787[a]		1.025[a]		3.772[a]		0.235[b]
Cash	Mean	5.117	14.924	4.492	6.246	4.966	16.195	4.058	5.166
	Median	4.830	13.556	4.029	6.023	4.437	15.486	3.942	4.660
	Mean dif		9.807[a]		1.754[a]		11.229[a]		1.109[b]
	Median dif		8.707[a]		1.650[a]		9.755[a]		0.473[c]
Shares	Mean	5.248	6.980	4.807	5.509	4.702	6.870	4.723	4.973
	Median	4.827	5.858	4.405	4.986	4.418	5.466	4.423	4.631
	Mean dif		1.731[a]		0.702[c]		2.168[a]		0.249
	Median dif		1.033[a]		0.106		1.143[a]		-0.105
Panel B. NYSE-listed targets									
		nb trades				nb shares			
Sample	Statistic	bid pre	bid post	ask pre	ask post	bid pre	bid post	ask pre	ask post
All	Mean	5.377	10.663	6.970	5.461	4.355	11.784	5.744	5.286
	Median	4.236	8.039	6.911	5.054	3.142	7.688	5.150	4.728
	Mean dif		5.287[a]		-1.509[a]		7.429[a]		-0.458
	Median dif		2.612[a]		-1.801[a]		3.311[a]		-0.999[b]
Cash	Mean	5.706	14.382	6.534	5.826	5.064	17.177	5.546	5.447
	Median	4.511	12.024	6.287	5.263	3.925	11.684	5.256	4.812
	Mean dif		8.676[a]		-0.708		12.113[a]		-0.099
	Median dif		7.665[a]		-1.395[b]		8.971[a]		-0.815
Shares	Mean	5.290	8.295	7.195	5.009	3.848	5.773	5.764	5.450
	Median	4.926	5.780	7.055	4.322	3.298	3.592	5.300	4.112
	Mean dif		3.005[c]		-2.186[a]		1.925		-0.313
	Median dif		0.859[c]		-2.256[a]		0.812		-0.994

Two windows are investigated in this table. The pre-announcement window consists of 45 trading days that ends 20 days before the announcement date. The announcement window includes the announcement day, one day before and the day after. Results are reported for the entire sample regardless of the method of payment and for two sub-samples based on whether the method of payment is cash or shares. The limit trade execution as a proportion of total trade execution is investigated, using either the number of trades or the number of shares traded. Bid pre (ask pre) corresponds to limit trades executed at the bid (ask) during the pre-announcement window. Bid post (ask post) corresponds to limit trades executed at the bid (ask) during the announcement window. The mean and median statistics for each event window are reported in the table, along with the mean and median difference for each proportion to test for changes around the tender offer announcement. The matched t-test (Wilcoxon signed rank test) is used to test if the mean (median) change from the pre-announcement to the announcement window is significant. [a], [b] and [c] correspond to significance levels of 1, 5 and 10%, respectively.

Table 14. Change in limit orders for acquirers

NASDAQ-listed acquirers		nb trades								nb shares							
Sample	**Statistic**	**bid w1**	**bid w2**	**bid w3**	**bid w4**	**ask w1**	**ask w2**	**ask w3**	**ask w4**	**bid w1**	**bid w2**	**bid w3**	**bid w4**	**ask w1**	**ask w2**	**ask w3**	**ask w4**
All	Mean	4.298	3.809	3.611	3.519	4.202	3.856	4.135	4.069	3.848	3.349	3.356	3.311	3.758	3.313	3.840	3.809
	Median	3.806	3.126	3.058	3.033	3.994	3.584	3.532	3.460	3.287	2.611	2.436	2.541	3.539	3.003	2.987	2.823
	Mean dif	0.891^{a,d}	-0.490^{a}	-0.687^{a}	-0.779^{a}	0.960^{b,d}	-0.346^{a}	-0.067	-0.132	0.946^{a,d}	-0.499^{a}	-0.492^{b}	-0.537^{b}	0.944^{a,d}	-0.445^{a}	0.082	0.051
	Median dif		-0.394^{a}	-0.630^{a}	-0.734		-0.279	-0.363	-0.529		-0.344	-0.676	-0.695		-0.257	-0.318	-0.493
Cash	Mean	3.806	3.150	3.212	3.187	3.756	3.367	3.876	3.199	3.277	2.731	3.284	3.151	3.395	3.010	3.867	3.308
	Median	3.465	2.838	2.834	2.878	3.532	3.228	3.318	2.881	2.957	2.379	2.392	2.473	3.230	2.716	2.669	2.424
	Mean dif	0.865^{b,d}	-0.656^{a}	-0.593^{b}	-0.618^{b}	0.908^{c,d}	-0.389^{c}	0.120	-0.557^{b}	0.912^{c,e}	-0.545^{b}	0.007	-0.125	0.951	-0.385	0.473	-0.086
	Median dif		-0.233	-0.451	-0.540		-0.157	-0.607	-0.676		-0.056	-0.337	-0.565		-0.151	-0.055	-0.355
Shares	Mean	4.903	4.650	4.213	4.073	4.743	4.471	4.634	5.009	4.353	4.228	3.892	3.414	4.335	3.806	4.596	4.624
	Median	4.181	3.716	3.688	3.519	4.301	3.930	4.583	4.155	3.859	2.718	2.913	2.854	3.864	3.158	3.853	3.643
	Mean dif	0.869^{b,e}	-0.253	-0.690^{b}	-0.830^{a}	0.944	-0.272	-0.109	0.265	0.861^{b,f}	-0.124	-0.461	-0.938^{a}	0.884^{b}	-0.529^{b}	0.261	0.289
	Median dif		-0.346^{c}	-0.541^{a}	-0.715^{a}		-0.234	-0.144	-0.257		-0.340^{c}	-0.643^{b}	-0.688^{a}		-0.383^{b}	-0.305	-0.489

NYSE-listed acquirers		nb trades								nb shares							
Sample	**Statistic**	**bid w1**	**bid w2**	**bid w3**	**bid w4**	**ask w1**	**ask w2**	**ask w3**	**ask w4**	**bid w1**	**bid w2**	**bid w3**	**bid w4**	**ask w1**	**ask w2**	**ask w3**	**ask w4**
All	Mean	4.299	3.585	3.796	3.452	6.387	6.037	6.427	6.281	3.122	2.593	2.715	2.749	5.229	4.589	5.018	4.961
	Median	3.824	3.593	3.625	3.378	5.994	5.862	5.759	5.561	2.565	2.452	2.317	2.119	4.895	4.257	4.418	4.458
	Mean dif	0.884^{a,d}	-0.714^{a}	-0.503^{a}	-0.847^{a}	0.975	-0.350^{a}	0.040	-0.107	0.919^{a,d}	-0.529^{a}	-0.406^{b}	-0.372^{b}	0.937^{b}	-0.640^{a}	-0.211	-0.268
	Median dif		-0.054^{a}	-0.448^{a}	-0.524^{a}		-0.088^{a}	-0.250^{b}	-0.265^{c}		-0.181^{a}	-0.459^{a}	-0.495^{a}		-0.267^{a}	-0.372^{b}	-0.449^{b}
Cash	Mean	4.071	3.581	3.768	3.566	6.435	5.997	5.837	5.892	3.021	2.596	2.679	2.975	5.175	4.561	4.628	4.673
	Median	3.796	3.544	3.663	3.536	6.004	5.766	5.349	5.328	2.530	2.426	2.199	2.150	4.869	4.231	4.067	4.167
	Mean dif	0.934^{c,f}	-0.490^{a}	-0.303^{b}	-0.504^{b}	0.936^{c,d}	-0.438^{c}	-0.597	-0.542^{b}	0.930^{c,d}	-0.425^{b}	-0.342	-0.045	0.931^{c}	-0.614	-0.548	-0.502
	Median dif		-0.022^{b}	-0.205^{b}	-0.307^{b}		-0.120	-0.643	-0.470^{b}		-0.142^{c}	-0.476	-0.407^{c}		-0.153^{c}	-0.648	-0.448
Shares	Mean	4.271	3.629	3.740	3.552	6.228	5.755	8.196	5.494	2.906	2.491	2.493	2.282	4.945	4.306	6.152	4.143
	Median	3.917	3.564	3.330	3.354	6.264	5.590	8.446	5.384	2.670	2.525	2.625	1.906	5.078	4.190	5.514	4.246
	Mean dif	0.731	-0.643	-0.532^{b}	-0.719^{b}	0.604^{b,e}	-0.473	1.968	-0.734	0.760	-0.415	-0.413	-0.624^{a}	0.533^{a,d}	-0.639^{b}	1.207	-0.802
	Median dif		-0.278^{c}	-0.753^{a}	-0.522^{a}		-0.518	1.819	-0.681		-0.341^{c}	-0.361^{b}	-0.435^{a}		-0.641^{b}	0.958	-0.897

Mean and median limit trade executions as a proportion of total trade executions are reported and tested for four event windows, using the numbers of trades and shares traded as the metric, for the entire sample undifferentiated and differentiated by listing venue and method of payment. Bid wi (ask wi) corresponds to limit trades executed at the bid (ask) during the window i. The mean and median matched differences for windows 2 to 4 relative to benchmark window 1 are reported and tested. The mean (median) equality between the specified window and benchmark window is examined using the matched t-stat (Wilcoxon signed ranks test). The multivariate test results that the parameters are equal for the four windows are reported under the w1 column. These tests use the Wilks' lambda from repeated ANOVA and the Friedman non parametric statistics. ^{a}, ^{b} and ^{c} correspond to significance levels of 1, 5 and 10%, respectively, for the univariate tests. ^{d}, ^{e} and ^{f} correspond to significance levels of 1, 5 and 10%, respectively, for the multivariate tests. Event window 1 is the pre-announcement or benchmark window that covers 45 trading days and ends 20 days before the announcement date. Window 2 is the post-effective window that covers 45 trading days beginning with day 20 after the effective date. Window 3 is the announcement window that includes the announcement day, one day before and the day after. Window 4 is the effective window that includes the effective day, one day before and the day after.

Table 15. Spread decomposition components for NASDAQ-listed targets

Model, payment method	π		\$ temporary		\$ permanent		% temporary		% permanent	
NW, all	0.748	0.828[a]	0.119	0.083[a]	0.051	0.027[a]	2.156	1.323[a]	0.775	0.328[a]
	(0.769)	(0.838[a])	(0.097)	(0.065[a])	(0.028)	(0.010[a])	(1.590)	(0.735[a])	(0.533)	(0.172[a])
NW, cash	0.746	0.831[c]	0.112	0.065[a]	0.048	0.020[a]	2.280	1.051[a]	0.802	0.256[a]
	(0.769)	(0.784[c])	(0.099)	(0.054[a])	(0.031)	(0.010[a])	(1.769)	(0.660[a])	(0.664)	(0.168[a])
NW, shares	0.753	0.832[a]	0.121	0.099[a]	0.048	0.024[a]	2.045	1.530[a]	0.749	0.380[a]
	(0.770)	(0.845[a])	(0.108)	(0.078[a])	(0.030)	(0.011[a])	(1.492)	(1.007[a])	(0.444)	(0.190[a])
Masson, all	0.791	0.755[b]	0.132	0.085	0.038	0.025	2.282	1.450[a]	0.649	0.425[c]
	(0.783)	(0.747[a])	(0.102)	(0.055[a])	(0.025)	(0.019[b])	(1.678)	(0.685[a])	(0.461)	(0.261[a])
Masson, cash	0.782	0.742	0.122	0.071	0.038	0.014	2.393	1.484	0.689	0.353[a]
	(0.766)	0.669a	(0.102)	(0.045[a])	(0.028)	(0.017)	(1.991)	(0.581[a])	(0.531)	(0.261[a])
Masson, shares	0.799	0.764	0.136	0.089[a]	0.033	0.034[c]	2.176	1.439[a]	0.618	0.472[b]
	(0.790)	(0.785)	(0.106)	(0.08[a])	(0.027)	(0.019)	(1.523)	(0.848[a])	(0.398)	(0.286)
GH, all	0.848	0.812[b]	0.093	0.056[a]	0.018	0.014	1.797	1.000[a]	0.310	0.192[a]
	(0.850)	(0.869)	(0.079)	(0.042[a])	(0.013)	(0.007[a])	(1.296)	(0.527[a])	(0.225)	(0.106[a])
GH, cash	0.837	0.762[a]	0.086	0.043[a]	0.018	0.014	1.848	0.733[a]	0.338	0.174[a]
	(0.841)	(0.844)	(0.078)	(0.033[a])	(0.013)	(0.008[a])	(1.527)	(0.441[a])	(0.295)	(0.116[a])
GH, shares	0.863	0.860	0.096	0.066[a]	0.017	0.011[a]	1.746	1.134[a]	0.283	0.210[a]
	(0.857)	(0.876)	(0.083)	(0.06[a])	(0.013)	(0.007[a])	(1.253)	(0.714[a])	(0.179)	(0.088[c])
LSB, all	0.874	0.834[a]	0.147	0.087[a]	0.023	0.023	2.566	1.392[a]	0.365	0.259[a]
	(0.879)	(0.878[c])	(0.115)	(0.067[a])	(0.015)	(0.010[a])	(1.873)	(0.79[a])	(0.269)	(0.146[a])
LSB, cash	0.866	0.825[b]	0.138	0.068[a]	0.022	0.017	2.680	1.085[a]	0.402	0.221[a]
	(0.872)	(0.881)	(0.112)	(0.056[a])	(0.016)	(0.009[a])	(2.221)	(0.637[a])	(0.345)	(0.116[a])
LSB, shares	0.884	0.833[b]	0.147	0.097[a]	0.022	0.027	2.466	1.614[a]	0.328	0.296
	(0.887)	(0.875[a])	(0.124)	(0.085[a])	(0.015)	(0.011)	(1.674)	(0.93[a])	(0.213)	(0.168)
MRR, all	0.701	0.642[b]	0.076	0.039[a]	0.037	0.028[a]	1.492	0.813[a]	0.664	0.343[a]
	(0.706)	(0.751)	(0.069)	(0.033[a])	(0.027)	(0.012[a])	(1.070)	(0.403)	(0.458)	(0.182)
MRR, cash	0.676	0.518[a]	0.069	0.022[a]	0.036	0.030[a]	1.514	0.495[a]	0.706	0.346[a]
	(0.686)	(0.705[c])	(0.069)	(0.019[a])	(0.028)	(0.015[a])	(1.149)	(0.298[a])	(0.638)	(0.218[a])
MRR, shares	0.736	0.758[a]	0.080	0.058[a]	0.035	0.019[a]	1.462	0.952[a]	0.619	0.339[a]
	(0.728)	(0.803[b])	(0.070)	(0.047[a])	(0.027)	(0.012[a])	(1.054)	(0.578[a])	(0.404)	(0.141[a])

This table reports mean and median statistics (latter in parentheses) and tests of their significance for π or the temporary component as a percentage of the total spread, \$ temp (perm) or the dollar temporary (permanent) component of the bid-ask spread, % temp (perm) or the proportional per-dollar temporary (permanent) component of the bid-ask spread for five spread decomposition models (NW, Masson, GH, LSB and MRR). The estimates are for the entire sample and for the sub-samples differentiated by method of payment for NASDAQ-listed targets and for two windows. The pre-announcement window consists of 45 trading days that end 20 days before the announcement date, and the announcement window includes the announcement day, one day before and the day after. For each of the five parameters, the left (right) column corresponds to the pre-announcement (announcement) window. We report significance levels of the tests of changes in the parameters values pre and post announcement. The parametric matched t-test and the non-parametric Wilcoxon signed ranks test are used to test for the change in the mean and median, respectively, of each of the parameter estimates. For parameters measured in percentages (dollars), the test is for the difference (ratio) between the announcement and pre-announcement windows. [a, b] and [c] correspond to significance levels of 1, 5 and 10%, respectively.

Table 16. Spread decomposition components for NYSE-listed targets

Model, payment method	π		\$ temporary		\$ permanent		% temporary		% permanent	
NW, all	0.366	0.548^{a}	0.045	0.049	0.088	0.050^{a}	0.448	0.326^{b}	0.711	0.379^{a}
	(0.363)	(0.467^{a})	(0.044)	(0.047)	(0.073)	(0.044^{a})	(0.205)	(0.178^{a})	(0.380)	(0.177^{a})
NW, cash	0.337	0.648^{a}	0.046	0.057	0.104	0.045^{a}	0.529	0.397^{c}	0.976	0.444^{a}
	(0.322)	(0.503^{b})	(0.043)	(0.052)	(0.091)	(0.039^{a})	(0.319)	(0.295)	(0.672)	(0.284^{a})
NW, shares	0.386	0.455^{a}	0.046	0.046	0.080	0.056^{a}	0.268	0.208	0.462	0.319^{a}
	(0.394)	(0.458^{b})	(0.048)	(0.051)	(0.067)	(0.057^{a})	(0.168)	(0.157^{b})	(0.278)	(0.167^{a})
Masson, all	0.590	0.690^{a}	0.075	0.085^{a}	0.058	0.033^{a}	0.690	0.478^{a}	0.469	0.232^{a}
	(0.583)	(0.636^{a})	(0.071)	(0.063^{a})	(0.052)	(0.032^{a})	(0.343)	(0.235^{a})	(0.232)	(0.117^{a})
Masson, cash	0.569	0.669^{b}	0.082	0.067^{a}	0.068	0.034^{a}	0.847	0.553^{a}	0.657	0.288^{a}
	(0.550)	(0.607^{a})	(0.074)	(0.063^{b})	(0.061)	(0.032^{a})	(0.575)	(0.313^{a})	(0.459)	(0.170^{a})
Masson, shares	0.589	0.712^{a}	0.072	0.151	0.053	0.033^{a}	0.431	0.371^{a}	0.299	0.169^{a}
	(0.608)	(0.625^{a})	(0.069)	(0.070)	(0.053)	(0.033^{a})	(0.259)	(0.216^{b})	(0.210)	(0.104^{a})
GH, all	0.629	0.669^{a}	0.043	0.044	0.028	0.0234^{a}	0.473	0.3332^{a}	0.207	0.146^{a}
	(0.628)	(0.744^{b})	(0.042)	(0.038)	(0.023)	(0.015)	(0.200)	(0.144)	(0.117)	(0.064^{b})
GH, cash	0.604	0.673^{c}	0.046	0.050	0.034	0.028^{b}	0.569	0.422^{a}	0.305	0.205^{a}
	(0.602)	(0.734^{c})	(0.044)	(0.050)	(0.028)	(0.015^{b})	(0.358)	(0.253^{b})	(0.191)	(0.095^{a})
GH, shares	0.647	0.651^{a}	0.043	0.043	0.027	0.020^{a}	0.264	0.225	0.130	0.093^{a}
	(0.650)	(0.754^{a})	(0.043)	(0.048)	(0.019)	(0.013^{a})	(0.178)	(0.147^{c})	(0.091)	(0.048^{a})
LSB, all	0.678	0.818^{a}	0.085	0.0737^{b}	0.048	0.0249^{a}	0.770	0.495^{a}	0.390	0.2095^{a}
	(0.686)	(0.830^{a})	(0.079)	(0.074)	(0.033)	(0.006)	(0.395)	(0.295^{b})	(0.190)	(0.022)
LSB, cash	0.613	0.769^{b}	0.087	0.067	0.063	0.034^{a}	0.905	0.524^{a}	0.599	0.317^{a}
	(0.584)	(0.887^{b})	(0.078)	(0.064^{c})	(0.060)	(0.010^{a})	(0.661)	(0.349^{a})	(0.368)	(0.052^{a})
LSB, shares	0.735	0.805^{b}	0.089	0.076	0.037	0.026^{a}	0.503	0.394^{c}	0.227	0.133^{c}
	(0.766)	(0.947^{a})	(0.085)	(0.088)	(0.026)	(0.005^{a})	(0.372)	(0.299^{b})	(0.106)	(0.015^{a})
MRR, all	0.463	0.437	0.032	0.034	0.043	0.035^{b}	0.405	0.266^{b}	0.312	0.258
	(0.459)	(0.592^{b})	(0.033)	(0.034^{a})	(0.034)	(0.025^{a})	(0.154)	(0.128^{b})	(0.179)	(0.097^{a})
MRR, cash	0.425	0.277	0.033	0.033	0.051	0.034^{a}	0.466	0.297	0.461	0.407
	(0.444)	(0.546)	(0.033)	(0.039^{a})	(0.048)	(0.029^{a})	(0.208)	(0.211^{b})	(0.308)	(0.204^{c})
MRR, shares	0.495	0.634^{a}	0.034	0.043	0.040	0.033	0.215	0.199	0.199	0.111^{b}
	(0.499)	(0.647^{a})	(0.035)	(0.045^{a})	(0.029)	(0.019^{a})	(0.133)	(0.128)	(0.134)	(0.076^{a})

This table reports mean and median statistics (latter in parentheses) and tests of their significance for π or the temporary component as a percentage of the total spread, \$ temp (perm) or the dollar temporary (permanent) component of the bid-ask spread, % temp (perm) or the proportional per-dollar temporary (permanent) component of the bid-ask spread for five spread decomposition models (NW, Masson, GH, LSB and MRR). The estimates are for the entire sample and for the sub-samples differentiated by method of payment for NYSE-listed targets and for two windows. The pre-announcement window consists of 45 trading days that end 20 days before the announcement date, and the announcement window includes the announcement day, one day before and the day after. For each of the five parameters, the left (right) column corresponds to the pre-announcement (announcement) window. We report significance levels of the tests of changes in the parameters values pre and post announcement. The parametric matched t-test and the non-parametric Wilcoxon signed ranks test are used to test for the change in the mean and median, respectively, of each of the parameter estimates. For parameters measured in percentages (dollars), the test is for the difference (ratio) between the announcement and pre-announcement windows. $^{a, b}$ and ^{c} correspond to significance levels of 1, 5 and 10%, respectively.

Table 17. Spread decomposition components for NASDAQ-listed acquirers

	π				$ temp.				$ perm.				% temp.				% perm.			
NW, all	0.814	0.815	0.817	0.806	0.134[a]	0.091[a]	0.119[a]	0.106[a]	0.041[a]	0.031[b]	0.034[c]	0.033	1.072[c]	0.954[a]	1.019	1.005	0.356	0.320	0.353	0.379
	(0.814)	(0.809)	(0.822)	(0.808)	(0.108[a])	(0.075[a])	(0.093[a])	(0.083[a])	(0.025[a])	(0.017[a])	(0.019[a])	(0.019[a])	(0.719[a])	(0.570[a])	(0.673[a])	(0.635[a])	(0.193)	(0.137[b])	(0.159)	(0.146)
NW, cash	0.781	0.785	0.779	0.772	0.144[a]	0.114[b]	0.124	0.130	0.055	0.039[c]	0.046	0.047	0.912	0.79[c]	0.790	0.827	0.390	0.308	0.406	0.433
	(0.792)	(0.796)	(0.811)	(0.811)	(0.110[a])	(0.086[a])	(0.097[b])	(0.093[a])	(0.033)	(0.025[a])	(0.024)	(0.024)	(0.628[b])	(0.512[b])	(0.586)	(0.622)	(0.196)	(0.134[b])	(0.172)	(0.170)
NW, shares	0.849	0.849	0.871[c]	0.835	0.121[a]	0.076[a]	0.105	0.082[a]	0.025[b]	0.015[a]	0.019	0.021	1.076	1.079	1.128	1.100	0.256	0.292	0.269	0.348
	(0.847)	(0.847)	(0.854)	(0.831)	(0.090[a])	(0.062[a])	(0.092[a])	(0.076[a])	(0.015[b])	(0.012[a])	(0.015[b])	(0.013[b])	(0.661[b])	(0.624)	(0.622)	(0.542[c])	(0.123)	(0.094)	(0.096)	(0.108)
Masson, all	0.871	0.863	0.903	0.869	0.15[a]	0.105[a]	0.139[a]	0.119[a]	0.025[b]	0.018	0.026	0.019	1.138[c]	1.002[a]	1.116	1.109	0.288	0.263	0.251	0.270
	(0.810)	(0.808)	(0.825)	(0.834)	(0.109[a])	(0.075[a])	(0.100[a])	(0.088[a])	(0.025[a])	(0.016[a])	(0.018)	(0.017[a])	(0.768[a])	(0.605[a])	(0.749[b])	(0.669[a])	(0.162[c])	(0.144[c])	(0.137[a])	(0.147[c])
Masson,cash	0.941	0.912[a]	0.971	0.902	0.188[a]	0.138[a]	0.177[b]	0.163[c]	0.011	0.014	0.030	0.014	1.090	0.868	1.021	1.019	0.202	0.228[b]	0.174	0.238
	(0.810)	(0.808)	(0.801)	(0.822)	(0.119[a])	(0.096[a])	(0.101[a])	(0.105[a])	(0.025)	(0.022)	(0.024)	(0.021)	(0.763[b])	(0.556[a])	(0.644)	(0.669)	(0.133)	(0.119)	(0.155)	(0.155)
Masson,shares	0.859	0.832[a]	0.866	0.857	0.121[a]	0.074[a]	0.102[b]	0.083[a]	0.025[c]	0.017[a]	0.022	0.020	1.055	1.055	1.074	1.181	0.273	0.303	0.320	0.259
	(0.826)	(0.813[c])	(0.838)	(0.839)	(0.085[a])	(0.065[a])	(0.085[a])	(0.073[a])	(0.019)	(0.013[b])	(0.015)	(0.009[b])	(0.681[c])	(0.608)	(0.661)	(0.540)	(0.121)	(0.147)	(0.106)	(0.142)
GH, all	0.854[b]	0.829[a]	0.833[b]	0.831[a]	0.105[a]	0.07[a]	0.092[a]	0.079[a]	0.019[a]	0.015[a]	0.019	0.016[b]	0.853[b]	0.744[a]	0.812	0.793	0.153	0.153	0.178	0.181
	(0.846[a])	(0.834[a])	(0.844[a])	(0.842[a])	(0.084[a])	(0.058[a])	(0.072[a])	(0.062[a])	(0.015[a])	(0.012[a])	(0.013[c])	(0.012[a])	(0.577[a])	(0.458[a])	(0.536[a])	(0.487[a])	(0.105)	(0.091)	(0.092)	(0.088)
GH, cash	0.851	0.807[c]	0.812[c]	0.821	0.112[a]	0.084[a]	0.091[a]	0.092[a]	0.023	0.020[c]	0.023	0.020	0.716[c]	0.605[b]	0.576[b]	0.598[c]	0.144	0.135	0.134	0.132
	(0.828[b])	(0.815[a])	(0.819[b])	(0.814[b])	(0.083[a])	(0.062[a])	(0.069[a])	(0.068[a])	(0.018)	(0.016[a])	(0.015)	(0.017)	(0.507[a])	(0.389[a])	(0.417[b])	(0.484[b])	(0.100)	(0.089)	(0.089)	(0.084)
GH, shares	0.86[b]	0.844[a]	0.848	0.841[b]	0.097[a]	0.058[a]	0.084	0.064[b]	0.017[b]	0.012[a]	0.015	0.012[b]	0.865	0.849	0.900	0.885	0.154	0.163	0.19[c]	0.196
	(0.863[b])	(0.841[a])	(0.871)	(0.855[b])	(0.074[a])	(0.050[a])	(0.072[a])	(0.061[a])	(0.011[a])	(0.009[a])	(0.012)	(0.010[a])	(0.540[b])	(0.508)	(0.539)	(0.412[b])	(0.087)	(0.088)	(0.080)	(0.079)
LSB, all	0.892[a]	0.880[a]	0.872[a]	0.874[a]	0.154[a]	0.105[a]	0.133[a]	0.120[a]	0.021[b]	0.017	0.021[b]	0.018	1.255[b]	1.090[a]	1.176[a]	1.186	0.165	0.167	0.195	0.198[c]
	(0.889[a])	(0.879[a])	(0.883[a])	(0.881[a])	(0.115[a])	(0.081[a])	(0.102[a])	(0.094[a])	(0.015[a])	(0.011[a])	(0.014)	(0.012)	(0.822[a])	(0.629[a])	(0.753[a])	(0.723[a])	(0.108[b])	(0.092)	(0.106)	(0.099)
LSB, cash	0.886[a]	0.862[a]	0.851[a]	0.861[a]	0.173[a]	0.127[a]	0.142[b]	0.151[c]	0.026	0.025	0.028[b]	0.026	1.118[c]	0.935[b]	1.004[a]	1.069	0.157	0.162	0.192	0.190
	(0.883[c])	(0.869[a])	(0.868[a])	(0.869[a])	(0.132[a])	(0.103[a])	(0.107[a])	(0.115[a])	(0.017)	(0.017)	(0.017[b])	(0.018)	(0.692[a])	(0.535[a])	(0.68[a])	(0.728)	(0.111)	(0.085)	(0.115)	(0.115)
LSB, shares	0.898[a]	0.894	0.88[a]	0.886[c]	0.129[a]	0.078[a]	0.108[a]	0.09[a]	0.017[a]	0.011[a]	0.016	0.012	1.175	1.147	1.199[a]	1.262	0.157	0.167	0.198	0.187
	(0.895[c])	(0.885[c])	(0.887[b])	(0.893)	(0.095[a])	(0.070[a])	(0.087[a])	(0.078[a])	(0.012[a])	(0.009[a])	(0.013)	(0.009[a])	(0.747[b])	(0.652)	(0.686[a])	(0.611[c])	(0.084)	(0.080)	(0.089)	(0.084)
MRR, all	0.874[a]	0.915[a]	0.892[a]	0.907[a]	0.090[a]	0.057[a]	0.074[a]	0.063[a]	0.036[a]	0.028[a]	0.033	0.030[b]	0.716[b]	0.609[a]	0.633[c]	0.546	0.296	0.292	0.294	0.271
	(0.901[a])	(0.930[a])	(0.908[a])	(0.920[a])	(0.071[a])	(0.047[a])	(0.062[a])	(0.054[a])	(0.029[a])	(0.023[a])	(0.021[c])	(0.022[a])	(0.473[a])	(0.397[a])	(0.411[a])	(0.338)	(0.189)	(0.164)	(0.169)	(0.144)
MRR, cash	0.864[a]	0.895[a]	0.889[a]	0.893[a]	0.095[a]	0.067[a]	0.070[a]	0.069[a]	0.042	0.038	0.040	0.037	0.597	0.484[b]	0.451[c]	0.406	0.275	0.259	0.243	0.218
	(0.896[a])	(0.921[a])	(0.907[b])	(0.908[a])	(0.076[a])	(0.047[a])	(0.06[a])	(0.055[a])	(0.032[c])	(0.032)	(0.026)	(0.031)	(0.453[a])	(0.322[a])	(0.331[c])	(0.294)	(0.178)	(0.158)	(0.155)	(0.145)
MRR, shares	0.884[a]	0.93[a]	0.898[a]	0.921[a]	0.085[a]	0.048[a]	0.072	0.055[a]	0.030[a]	0.022[a]	0.029	0.024[b]	0.732	0.707	0.735	0.612	0.293	0.309	0.348	0.279
	(0.913[a])	(0.938[a])	(0.912[a])	(0.925[a])	(0.067[a])	(0.042[a])	(0.062[a])	(0.055[a])	(0.020[a])	(0.015[a])	(0.018[c])	(0.017[a])	(0.520[a])	(0.455)	(0.445)	(0.337)	(0.158)	(0.156)	(0.137)	(0.135)

This table reports mean and median parameter estimates (latter in parentheses) and tests of their significance for five spread decomposition models (NW, Masson, GH, LSB and MRR) for NASDAQ-listed acquirers for four windows. The five parameters are π or the temporary component as a percentage of the total spread, $ temporary (permanent) or the dollar temporary (permanent) component of the bid-ask spread, and % temporary (permanent) or the proportional per-dollar temporary (permanent) component of the bid-ask spread. The estimates are for the entire sample and for sub-samples differentiated by method of payment. The pre-announcement or benchmark window consists of 45 trading days that end 20 days before the announcement date. The post-effective window covers the 45 trading days that begin 20 days after the effective date. The announcement window includes the announcement day, one day before and the day after. The effective window includes the effective day, one day before and the day after. For each of the five parameters, the columns from left to right represent the pre-announcement, the post-effective, the announcement and the effective windows, respectively. The significance levels for univariate tests of changes or ratios of the parameter estimates for windows subsequent to the first versus the first are reported. The parametric matched t-test and the non-parametric Wilcoxon signed rank test are used to examine the mean and median difference (ratio) between the announcement and pre-announcement windows for parameters measured in percentages (dollars). Multivariate tests of the equality of the parameter estimates across the four windows are reported under the column that corresponds to the pre-announcement window. The multivariate tests consist of Wilk's lambda from the repeated ANOVA analysis to test for no change in the means and the Friedman test for the median ranks. [a], [b] and [c] correspond to significance levels of 1, 5 and 10%, respectively.

Table 18. Spread decomposition components for NYSE-listed acquirers

	π				$ temp.				$ perm.				% temp.				% perm.			
NW, all	0.401^{a}	0.413	0.407	0.416	0.043^{a}	0.033	0.042	0.036	0.069^{a}	0.050^{a}	0.064^{b}	0.054^{a}	0.189^{b}	0.145^{a}	0.191	0.166	0.307^{b}	0.221^{a}	0.284	0.241^{a}
	(0.409)	(0.423^{b})	(0.418)	(0.425)	(0.041^{a})	(0.03^{a})	(0.038^{c})	(0.031^{a})	(0.065^{a})	(0.044^{a})	(0.058^{a})	(0.045^{a})	(0.145^{a})	(0.107^{a})	(0.133^{c})	(0.122^{a})	(0.229)	(0.158^{a})	(0.206^{a})	(0.155^{a})
NW, cash	0.409	0.418	0.418	0.425	0.041^{a}	0.033	0.040	0.037	0.065^{a}	0.049^{a}	0.060	0.054^{a}	0.177^{a}	0.139^{a}	0.170	0.155^{b}	0.280^{a}	0.206^{a}	0.272	0.241^{a}
	(0.415)	(0.427^{b})	(0.426)	(0.44^{c})	(0.039^{a})	(0.029^{a})	(0.037)	(0.032^{b})	(0.059)	(0.044^{a})	(0.055^{b})	(0.046^{a})	(0.140^{b})	(0.108^{a})	(0.132)	(0.129^{b})	(0.214)	(0.159)	(0.190)	(0.147^{a})
NW, shares	0.387	0.391	0.379	0.409	0.046^{a}	0.031^{a}	0.039^{b}	0.037	0.076^{a}	0.053^{a}	0.064^{a}	0.054^{a}	0.153^{a}	0.102^{a}	0.122^{a}	0.119^{b}	0.247^{a}	0.173^{a}	0.202^{a}	0.174^{a}
	(0.370)	(0.395)	(0.374)	(0.412)	(0.043^{a})	(0.028^{a})	(0.033^{b})	(0.03^{c})	(0.076^{b})	(0.044^{a})	(0.067^{a})	(0.045^{a})	(0.133^{b})	(0.092^{a})	(0.094^{a})	(0.085^{b})	(0.209)	(0.116^{a})	(0.177^{a})	(0.136^{a})
Masson, all	0.695	0.771^{a}	0.694	0.923^{b}	0.076^{a}	0.065^{a}	0.071^{a}	0.079	0.036^{a}	0.018^{a}	0.035	0.011^{a}	0.324^{a}	0.273^{a}	0.309	0.314	0.169^{a}	0.094^{a}	0.173	0.100^{a}
	(0.645)	(0.690^{a})	(0.655)	(0.681^{a})	(0.064^{a})	(0.051^{a})	(0.064^{a})	(0.054^{a})	(0.036^{a})	(0.02^{a})	(0.032^{b})	(0.023^{a})	(0.242^{a})	(0.195^{a})	(0.221^{a})	(0.209^{a})	(0.132)	(0.073^{a})	(0.105)	(0.08^{a})
Masson,cash	0.708^{b}	0.751^{b}	0.692	0.886	0.073^{b}	0.064^{a}	0.068^{b}	0.078	0.033^{a}	0.018^{b}	0.033	0.013^{b}	0.306^{b}	0.258^{a}	0.289	0.297	0.151^{a}	0.089^{a}	0.153	0.098^{b}
	(0.652)	(0.692^{a})	(0.671)	(0.679)	(0.063^{a})	(0.050^{a})	(0.061^{a})	(0.054^{a})	(0.033)	(0.020^{a})	(0.028)	(0.024^{b})	(0.228^{a})	(0.189^{a})	(0.213^{a})	(0.201^{a})	(0.113)	(0.070^{a})	(0.100)	(0.081^{a})
Masson,shares	0.638^{a}	0.746^{a}	0.692	0.722^{a}	0.076^{b}	0.06^{a}	0.067	0.065^{c}	0.046^{a}	0.024^{a}	0.036	0.026^{a}	0.244^{c}	0.197^{b}	0.206^{b}	0.206^{c}	0.152^{a}	0.079^{a}	0.118^{b}	0.090^{a}
	(0.620)	(0.693^{a})	(0.704)	(0.717^{a})	(0.075^{a})	(0.054^{a})	(0.066^{a})	(0.049^{b})	(0.054)	(0.019^{a})	(0.035^{c})	(0.020^{a})	(0.203^{c})	(0.176^{a})	(0.188^{a})	(0.169)	(0.133)	(0.052^{a})	(0.088^{a})	(0.061^{a})
GH, all	0.646	0.637	0.638	0.661	0.039^{a}	0.027^{a}	0.036	0.029^{a}	0.023^{a}	0.017^{a}	0.023	0.017^{a}	0.178^{a}	0.117^{a}	0.173	0.137^{a}	0.092^{a}	0.068^{a}	0.096	0.071^{a}
	(0.658^{a})	(0.627)	(0.654)	(0.677)	(0.036^{a})	(0.023^{a})	(0.033^{b})	(0.024^{a})	(0.018^{a})	(0.013^{a})	(0.017^{c})	(0.013^{a})	(0.121^{a})	(0.083^{a})	(0.118^{a})	(0.087^{a})	(0.063)	(0.045^{a})	(0.059^{b})	(0.044^{a})
GH, cash	0.645	0.636	0.643	0.675	0.036^{a}	0.026^{a}	0.034	0.029^{a}	0.021^{a}	0.016^{a}	0.020	0.018	0.161^{a}	0.109^{a}	0.152	0.126^{a}	0.085^{a}	0.065^{a}	0.084	0.075
	(0.658^{b})	(0.632)	(0.678)	(0.681)	(0.031^{a})	(0.023^{a})	(0.030)	(0.026^{a})	(0.018)	(0.013^{a})	(0.015^{b})	(0.013^{a})	(0.113^{a})	(0.083^{a})	(0.112^{c})	(0.088^{a})	(0.060)	(0.045^{a})	(0.057^{c})	(0.043^{a})
GH, shares	0.634^{b}	0.646	0.593^{c}	0.581	0.043^{a}	0.027^{a}	0.034^{a}	0.031^{c}	0.026^{a}	0.015^{a}	0.023	0.020	0.142^{a}	0.090^{a}	0.102^{a}	0.096^{b}	0.081^{a}	0.046	0.073	0.067
	(0.645^{b})	(0.623)	(0.599^{c})	(0.562)	(0.041^{a})	(0.025^{a})	(0.028^{a})	(0.022^{b})	(0.025^{a})	(0.015^{a})	(0.020)	(0.018^{c})	(0.115^{b})	(0.082^{a})	(0.082^{a})	(0.059^{b})	(0.075)	(0.039^{a})	(0.054^{c})	(0.045^{c})
LSB, all	0.742^{a}	0.775^{a}	0.708^{b}	0.714^{b}	0.079^{a}	0.061^{a}	0.070^{a}	0.061^{a}	0.033^{a}	0.022	0.036^{a}	0.029^{a}	0.346^{a}	0.264^{a}	0.319^{a}	0.277^{a}	0.149^{a}	0.102^{a}	0.159	0.132
	(0.760^{a})	(0.797^{a})	(0.735^{b})	(0.727^{b})	(0.074^{a})	(0.057^{a})	(0.064^{a})	(0.055^{a})	(0.025^{a})	(0.016^{a})	(0.025)	(0.021^{c})	(0.259^{a})	(0.208^{a})	(0.232^{a})	(0.196^{a})	(0.101^{b})	(0.054^{a})	(0.091^{c})	(0.079^{c})
LSB, cash	0.761^{a}	0.784^{c}	0.707^{a}	0.712^{a}	0.076^{a}	0.062^{a}	0.067^{a}	0.060^{a}	0.030^{a}	0.021	0.034^{a}	0.030	0.322^{a}	0.253^{a}	0.292	0.261^{a}	0.131^{a}	0.092^{a}	0.151^{c}	0.1365
	(0.779^{a})	(0.801^{b})	(0.749^{a})	(0.722^{a})	(0.068^{a})	(0.056^{a})	(0.063^{a})	(0.055^{a})	(0.023)	(0.014^{b})	(0.025^{a})	(0.021^{b})	(0.255^{a})	(0.203^{a})	(0.218^{a})	(0.205^{a})	(0.078)	(0.055)	(0.087)	(0.0783)
LSB, shares	0.722^{b}	0.807^{b}	0.707	0.707	0.087^{a}	0.065^{a}	0.071^{a}	0.064^{a}	0.035^{b}	0.019^{a}	0.034	0.027	0.282^{b}	0.213^{b}	0.215^{a}	0.202^{a}	0.117^{b}	0.062^{a}	0.115^{b}	0.091^{c}
	(0.728^{c})	(0.800^{b})	(0.721)	(0.704)	(0.087^{a})	(0.063^{b})	(0.065^{a})	(0.047^{a})	(0.031^{a})	(0.014^{a})	(0.033^{c})	(0.023^{c})	(0.222^{b})	(0.193^{b})	(0.192^{a})	(0.159^{b})	(0.101)	(0.039^{a})	(0.089^{b})	(0.065^{c})
MRR, all	0.472^{b}	0.433^{a}	0.460	0.506	0.029^{a}	0.017^{a}	0.026	0.020^{a}	0.035^{a}	0.027^{a}	0.036	0.027^{a}	0.143^{a}	0.08^{a}	0.128	0.101^{a}	0.142^{a}	0.109^{a}	0.153	0.110^{a}
	(0.468^{a})	(0.423^{a})	(0.492)	(0.496)	(0.025^{a})	(0.015^{a})	(0.021^{a})	(0.017^{a})	(0.029^{a})	(0.021^{a})	(0.025)	(0.021^{a})	(0.092^{a})	(0.051^{a})	(0.073^{a})	(0.053^{a})	(0.099)	(0.069^{a})	(0.087)	(0.07^{a})
MRR, cash	0.468^{a}	0.430^{a}	0.480	0.549	0.027^{a}	0.017^{a}	0.025	0.020^{b}	0.032^{a}	0.026^{a}	0.030	0.027	0.125^{a}	0.072^{a}	0.112	0.092^{b}	0.133^{a}	0.104^{a}	0.131	0.113
	(0.465^{a})	(0.405^{a})	(0.515)	(0.513)	(0.022^{a})	(0.015^{a})	(0.02^{b})	(0.018^{a})	(0.028^{c})	(0.021^{a})	(0.023^{b})	(0.02^{a})	(0.084^{a})	(0.051^{a})	(0.07^{b})	(0.06^{a})	(0.095)	(0.069^{a})	(0.081)	(0.070^{a})
MRR, shares	0.461^{b}	0.453	0.375^{a}	0.370	0.033^{a}	0.019^{b}	0.022^{b}	0.021	0.040^{a}	0.023^{a}	0.038	0.032	0.112^{a}	0.067^{b}	0.068^{a}	0.064^{b}	0.125^{a}	0.073^{a}	0.117	0.105
	(0.466^{a})	(0.420)	(0.38^{b})	(0.322)	(0.031^{a})	(0.019^{a})	(0.017^{b})	(0.012^{b})	(0.035^{a})	(0.022^{a})	(0.029)	(0.026^{b})	(0.092^{a})	(0.048^{b})	(0.042^{a})	(0.040^{a})	(0.110)	(0.061^{a})	(0.086)	(0.076^{c})

This table reports mean and median parameter estimates (latter in parentheses) and tests of their significance for five spread decomposition models (NW, Masson, GH, LSB and MRR) for NASDAQ-listed acquirers for four windows. The five parameters, four event windows and tests of significance are as defined in table 17.
$^{a, b}$ and ^{c} correspond to significance levels of 1, 5 and 10%, respectively.

Table 19. EKOP results for targets

Panel A. NASDAQ-targets											
		Pre-announcement					Announcement				
Sample	**Statistic**	α	δ	μ	ε	PIN	α	δ	μ	ε	PIN
All	Mean	0.445	0.533	57.239	149.560	0.238	0.614	0.686	139.465	465.552	0.198
	Median	(0.362)	(0.533)	(32.472)	(24.082)	(0.250)	(0.667)	(0.998)	(103.800)	(129.859)	(0.204)
	Mean D/R						0.169^{a}	0.154^{a}	7.645^{a}	8.037^{a}	-0.039^{a}
	Med. D/R						[0.115^{a}]	[0.238^{a}]	[2.534^{a}]	[4.265^{a}]	[-0.015^{a}]
Cash	Mean	0.384	0.546	57.004	73.754	0.259	0.649	0.871	114.216	242.842	0.239
	Median	(0.329)	(0.537)	(35.726)	(16.485)	(0.263)	(0.667)	(1.000)	(97.600)	(94.200)	(0.269)
	Mean D/R						0.266^{a}	0.324^{a}	4.083^{a}	7.767^{a}	-0.020^{a}
	Med. D/R						[0.208^{a}]	[0.380^{a}]	[2.331^{a}]	[4.522^{a}]	[0.000]
Shares	Mean	0.523	0.503	55.657	214.532	0.217	0.600	0.533	151.581	548.586	0.173
	Median	(0.411)	(0.524)	(30.667)	(53.145)	(0.215)	(0.643)	(0.667)	(119.700)	(162.016)	(0.181)
	Mean D/R						0.077	0.030	9.982^{a}	7.208^{a}	-0.044^{a}
	Med. D/R						[0.053^{c}]	[0.009]	[2.620^{a}]	[4.179^{a}]	[-0.021^{a}]

Panel B. NYSE-targets											
		Pre-announcement					Announcement				
Sample	**Statistic**	α	δ	μ	ε	PIN	α	δ	μ	ε	PIN
All	Mean	0.386	0.339	95.530	107.929	0.154	0.532	0.661	560.851	294.871	0.189
	Median	(0.357)	(0.283)	(51.796)	(54.239)	(0.151)	(0.333)	(0.998)	(156.925)	(151.750)	(0.173)
	Mean D/R						0.147^{a}	0.322^{a}	7.336^{a}	3.631^{a}	0.034^{b}
	Med. D/R						[0.061^{a}]	[0.419^{a}]	[2.508^{a}]	[2.845^{a}]	[0.043^{b}]
Cash	Mean	0.372	0.456	42.729	42.057	0.184	0.520	0.780	970.996	127.743	0.243
	Median	(0.337)	(0.446)	(36.812)	(30.654)	(0.178)	(0.333)	(1.000)	(140.400)	(66.400)	(0.275)
	Mean D/R						0.148^{a}	0.324^{a}	11.876^{a}	3.867^{a}	0.059^{b}
	Med. D/R						[0.066^{b}]	[0.399^{a}]	[3.030^{a}]	[2.845^{a}]	[0.098^{b}]
Shares	Mean	0.413	0.226	116.692	208.320	0.122	0.601	0.521	180.814	582.658	0.116
	Median	(0.398)	(0.218)	(80.601)	(120.385)	(0.116)	(0.333)	(0.787)	(208.900)	(328.075)	(0.095)
	Mean D/R						0.189^{b}	0.296^{a}	2.741^{b}	3.920^{a}	-0.006
	Med. D/R						[0.053^{c}]	[0.412^{b}]	[1.884^{b}]	[2.855^{a}]	[-0.002]

This table provides summary statistics for five parameter estimates for the EKOP model for two event windows for the entire sample of targets and for the sample differentiated by method of payment. The windows are as defined in table 11.
α is the probability of daily event occurrence; δ is the probability that the event, conditional on its occurrence, has a negative impact on the stock; μ is the trading intensity of the informed traders as measured by the number of trades conditional on the occurrence of an event; ε is the trading intensity of the uninformed traders, and PIN is the probability of informed trading. Mean D/R (med. D/R) refer to the mean (median) difference for the α, δ and PIN estimates and the ratio for the μ and ε parameters for the two windows. The statistical significance of the matched t-test statistic for the difference or ratio in the mean and the Wilcoxon signed rank test for the difference or ratio of the median are reported. ^{a}, ^{b} and ^{c} correspond to significance levels of 1, 5 and 10%, respectively.

Table 20. EKOP results for acquirers

	Pre-announcement					Post-effective					Announcement					Effective				
All	α	δ	μ	ε	PIN	α	δ	μ	ε	PIN	α	δ	μ	ε	PIN	α	δ	μ	ε	PIN
Panel A. NASD- listed Acquirers																				
All, mean	0.541	0.423	69.877	736.755	0.161	0.600	0.404	58.452	794.918	0.135	0.586	0.403	146.448	842.147	0.170	0.615	0.375	143.114	914.203	0.181
All, med.	0.417	0.445	44.678	101.696	0.182	0.471	0.415	36.148	144.369	0.145	0.666	0.052	57.400	135.998	0.157	0.667	0.113	52.229	127.989	0.156
All, Mean D/R	$0.955^{b,e}$	0.989	$0.950^{b,e}$	0.985	$0.872^{a,d}$	0.060^{b}	-0.020	2.754	1.559^{a}	-0.026^{a}	0.046	-0.021	4.877^{a}	1.505^{a}	0.008	0.074^{a}	-0.048	7.640^{a}	1.450^{a}	0.020^{a}
All, Med. D/R						0.000^{c}	0.000	0.854^{b}	1.194^{a}	0.000^{a}	0.009	-0.002	1.048	1.130	0.000	0.045^{a}	-0.003	0.890	1.098^{a}	0.000^{b}
Cash, mean	0.532	0.479	68.115	512.823	0.178	0.580	0.438	57.857	482.791	0.155	0.579	0.362	113.411	558.982	0.189	0.637	0.358	105.916	537.371	0.219
Cash, med.	0.428	0.450	52.293	62.479	0.184	0.460	0.437	41.401	80.063	0.159	0.639	0.003	57.098	99.750	0.170	0.667	0.026	41.300	97.542	0.203
Cash, Mean D/R	0.931	0.935	0.879^{b}	0.979	$0.820^{a,d}$	0.048	-0.041	4.827	1.483^{a}	-0.023^{b}	0.047	-0.117^{c}	4.784	1.482^{a}	0.011	0.105^{b}	-0.121^{b}	5.951^{c}	1.404^{a}	0.041^{a}
Cash, Med. D/R						0.000	0.000	0.904	1.224^{a}	-0.016^{b}	0.000	-0.122^{c}	1.016	1.037	0.000	0.016^{c}	-0.021^{c}	1.058	1.081^{b}	0.019^{b}
Shares, mean	0.570	0.404	77.638	1046.161	0.135	0.619	0.368	61.689	1028.727	0.114	0.630	0.448	197.903	1122.604	0.146	0.650	0.340	212.558	1110.795	0.143
Shares, med.	0.454	0.461	38.676	204.628	0.143	0.500	0.380	22.233	220.046	0.052	0.667	0.333	57.595	211.756	0.128	0.667	0.003	46.000	190.667	0.139
Shares, Mean D/R	0.960^{e}	0.941^{e}	0.943^{f}	0.981	0.908^{f}	0.049	-0.036	2.088^{b}	1.398^{a}	-0.022	0.060	0.044	5.869^{b}	1.379^{b}	0.011	0.080	-0.065	11.935^{b}	1.261^{b}	0.008
Shares, Med. D/R						0.004	-0.002	0.680	1.170^{c}	-0.000^{c}	0.001	0.000	0.977	1.120^{b}	0.000	0.050^{b}	-0.030^{c}	0.765	1.017	0.000
Panel B. NYSE- listed Acquirers																				
All, mean	0.438	0.286	106.222	282.541	0.128	0.485	0.214	113.631	359.703	0.131	0.649	0.232	114.332	342.950	0.160	0.684	0.246	118.339	370.225	0.154
All, med.	0.400	0.213	74.128	115.354	0.123	0.457	0.157	92.553	156.531	0.130	0.667	0.000	67.333	137.333	0.140	0.667	0.000	62.800	147.400	0.119
All, Mean D/R	$0.617^{a,d}$	$0.936^{b,d}$	0.993^{d}	$0.865^{a,d}$	$0.885^{a,d}$	0.047^{b}	-0.071^{a}	1.280^{a}	1.485^{a}	0.003	0.211^{a}	-0.053^{c}	2.465^{b}	1.257^{a}	0.032^{a}	0.246^{a}	-0.040^{b}	2.172^{c}	1.422^{a}	0.026^{a}
All, Med. D/R						0.046^{b}	-0.045^{a}	1.124^{b}	1.288^{a}	0.004	0.224	-0.100	0.850	1.149	0.018	0.229^{a}	-0.077^{b}	0.817^{b}	1.195^{a}	0.005^{b}
Cash, mean	0.459	0.275	108.742	335.384	0.129	0.471	0.240	113.341	393.152	0.129	0.671	0.261	108.337	402.415	0.157	0.654	0.274	123.643	415.071	0.148
Cash, med.	0.437	0.199	73.503	123.138	0.122	0.452	0.168	95.305	161.269	0.130	0.667	0.000	65.390	129.221	0.129	0.667	0.000	70.358	165.016	0.112
Cash, Mean D/R	$0.667^{a,d}$	0.983^{d}	0.984^{d}	$0.838^{a,d}$	$0.905^{b,f}$	0.012	-0.035	1.166^{b}	1.324^{a}	0.000	0.212^{a}	-0.014	2.641	1.120^{a}	0.028^{a}	0.196^{a}	-0.002	2.734^{c}	1.221^{a}	0.019^{c}
Cash, Med. D/R						0.049	-0.011^{c}	1.033	1.177^{a}	0.003	0.199	-0.078	0.836	1.102	0.013	0.180^{a}	-0.069	0.817	1.145^{a}	0.000
Shares, mean	0.437	0.282	113.828	293.153	0.115	0.488	0.179	129.600	484.890	0.118	0.664	0.137	148.195	332.995	0.149	0.693	0.299	94.517	456.698	0.114
Shares, med.	0.376	0.208	104.619	181.928	0.110	0.448	0.120	118.360	207.561	0.126	0.667	0.000	78.075	225.000	0.145	0.667	0.016	58.072	237.077	0.104
Shares, Mean D/R	$0.479^{a,e}$	$0.727^{b,f}$	0.773^{f}	$0.658^{c,f}$	$0.692^{c,f}$	0.051	-0.103^{b}	1.448^{c}	1.731^{a}	0.003	0.227	-0.146^{b}	1.248	1.323	0.034	0.256^{a}	0.017	0.983	1.742^{a}	-0.001
Shares, Med. D/R						0.073	-0.064^{c}	1.243^{b}	1.442^{a}	0.001^{c}	0.282	-0.157^{a}	0.989	1.260	0.027	0.318^{a}	-0.018	0.837	1.387^{a}	-0.005

This table provides summary statistics for five parameter estimates for the EKOP model for four event windows for the entire sample of targets and for the sample differentiated by method of payment. The windows are as defined in table 12. α is the probability of daily event occurrence; δ is the probability that the event, conditional on its occurrence, has a negative impact on the stock; μ is the trading intensity of the informed traders as measured by the number of trades conditional on the occurrence of an event; ε is the trading intensity of the uninformed traders, and PIN is the probability of informed trading. Mean D/R (med. D/R) refer to the mean (median) difference for the α, δ and PIN estimates and the ratio for the μ and ε parameters for the four windows. The statistical significance of the matched t-test statistic for the difference or ratio in the mean and the Wilcoxon signed rank test for the difference or ratio of the median for each window after the pre-announcement window relative to the pre-announcement window are reported in the column for the subsequent window. $^{a, b}$ and ^{c} correspond to significance levels of 1, 5 and 10%, respectively. The mean and median D/R statistics reported in the pre-announcement window columns correspond to the multivariate Wilk's lambda of equality of the appropriate parameter given the repeated measures design and the rank statistic of Friedman for differences in the four windows. $^{d, e}$ and ^{f} refer to significance levels of 1, 5 and 10%, respectively, for these multivariate tests.

Table 21. Garch estimation

Party	Venue	Parameter	Statistic				
			Mean	**s.d.**	**Median**	**t-stat.**	**Proportion**
Panel A: Mean equation							
Targets	**NASDAQ**	α (1000×)	0.071	11.020	0.894	0.091	0.221
		Up β	0.893	1.277	0.602	9.863[a]	0.342
		Down β	0.752	1.129	0.514	9.395[a]	0.332
		Up β^*	-0.452	2.529	-0.173	-2.521[b]	0.191
		Down β^*	-0.352	2.390	-0.192	-2.076[b]	0.221
		κ_1 (1000×)	67.372	98.110	57.970	9.687[a]	0.372
		κ_2 (1000×)					
Targets	**NYSE**	α (1000×)	1.957	11.166	1.108	1.846[c]	0.144
		Up β	0.472	0.885	0.260	5.611[a]	0.387
		Down β	0.386	0.623	0.319	6.519[a]	0.414
		Up β^*	-0.396	1.567	-0.057	-2.660[a]	0.198
		Down β^*	-0.399	2.948	0.000	-1.427	0.171
		κ_1 (1000×)	50.721	59.051	33.599	9.049[a]	0.270
		κ_2 (1000×)					
Acquirers	**NASDAQ**	α (1000×)	0.022	8.144	0.695	0.040	0.145
		Up β	1.356	1.442	1.009	13.980[a]	0.520
		Down β	1.265	1.084	1.015	17.349[a]	0.584
		Up β^*	0.039	1.546	0.015	0.379	0.195
		Down β^*	0.154	1.481	-0.020	1.545	0.163
		κ_1 (1000×)	-3.594	42.914	-0.078	-1.245	0.231
		κ_2 (1000×)	3.979	35.506	2.478	1.491	0.215
Acquirers	**NYSE**	α (1000×)	1.857	4.038	1.657	6.013[a]	0.205
		Up β	0.508	0.727	0.358	9.138[a]	0.474
		Down β	0.626	0.499	0.537	16.402[a]	0.614
		Up β^*	-0.029	1.111	0.005	-0.343	0.193
		Down β^*	0.119	0.892	0.075	1.741[c]	0.164
		κ_1 (1000×)	-0.523	27.023	-1.087	-0.253	0.228
		κ_2 (1000×)	0.890	17.768	1.049	0.588	0.210
Panel B. Variance equation							
Targets	**NASDAQ**	ω (1000x)	2.692	4.575	1.087	8.300[a]	0.704
		ϕ Arch	0.186	0.368	0.040	7.143[a]	0.236
		γ Leverage	0.287	0.965	0.060	4.194[a]	0.291
		ψ Garch	0.360	0.380	0.427	13.354[a]	0.588
		θ (1000x)	-1.317	3.626	-0.638	-5.122[a]	0.543
Targets	**NYSE**	ω (1000x)	1.998	10.027	0.487	2.099[b]	0.622
		ϕ Arch	0.213	0.409	0.093	5.472[a]	0.207
		γ Leverage	0.202	0.771	0.050	2.763[a]	0.153
		ψ Garch	0.282	0.347	0.405	8.562[a]	0.405
		θ (1000x)	0.760	5.078	-0.039	1.576	0.351
Acquirers	**NASDAQ**	ω (1000x)	1.245	1.965	0.549	9.420[a]	0.602
		ϕ Arch	0.127	0.243	0.070	7.761[a]	0.276
		γ Leverage	0.079	0.315	0.057	3.746[a]	0.199
		ψ Garch	0.449	0.455	0.480	14.662[a]	0.588
		θ (1000x)	-0.259	1.258	-0.058	-3.057[a]	0.226
Acquirers	**NYSE**	ω (1000x)	0.306	0.366	0.155	10.946[a]	0.626
		ϕ Arch	0.105	0.266	0.028	5.166[a]	0.292
		γ Leverage	0.082	0.383	0.060	2.781[a]	0.175
		ψ Garch	0.464	0.429	0.511	14.129[a]	0.626
		θ (1000x)	-0.020	0.407	-0.020	-0.636	0.234

Table 21. Continued.

The parameter estimates from fitting the following model are reported:

$$R_{i,t} = \alpha_i + \beta_i^{UP} \times R_{m,t}^{UP} + \beta_i^{DOWN} \times R_{m,t}^{DOWN} + \beta_i^{UP*} \times R_{m,t}^{UP} \times I_{a,t} + \beta_i^{DOWN*} \times R_{m,t}^{DOWN} \times I_{a,t} + \kappa_1 \times I_{announc,t} + \kappa_2 \times I_{effectiv,t} + \varepsilon_{i,t}$$

where $R_{i,t}$ is the excess return of stock i during day t, where the risk-free rate is proxied by the daily rate for three month treasury bills as published by the US Department of Treasury and daily stock returns are from the CRSP database, $R_{m,t}^{up}$ is the market excess return if positive, and is zero otherwise, where the value-weighted CRSP index which contains stocks from the NYSE/NASDAQ/AMEX exchanges is used, $R_{m,t}^{down}$ is the market excess return if negative, and is zero otherwise, $I_{a,t}$ is a dummy variable equal to 1 if after the announcement date, and is zero otherwise, $I_{announc,t}$ is a dummy variable equal to 1 for the day preceding, the day of and the day after the tender offer announcement, and is zero otherwise, $I_{effectiv,t}$ is a dummy variable equal to 1 for the day preceding, the day of and the day after the effective date of the acquisition, and is zero otherwise, and $\varepsilon_{i,t}$ is an error term with the usual assumed properties. A GARCH(1,1) model is fitted for the variance, which has the following form:

$$h_{i,t} = \varpi_i + \phi \times \varepsilon_{i,t-1}^2 + \gamma \times \varepsilon_{i,t-1}^2 \times I_{\varepsilon_{i,t-1}} + \psi \times h_{i,t-1} + \theta \times I_{a,t}.$$

The parameter θ captures the impact of the tender offer announcement (if any) on the return volatility. $I_{\varepsilon_{i,t-1}}$ is a dummy variable that is equal to 1 if $\varepsilon_{i,t-1} > 0$, and is zero otherwise.

Table 22. Logit results

Regression Run	Parameters									
	Intercept	**L(assets)**	**ΔPIN**	**GH**	**LSB**	**Nature**	**Cash**	**Shares**	**Listing**	**Logl**
(1)	-0.955		-0.493							-214.120
	(0.085[a])		(0.273[c])							(0.066)
(2)	-0.651	-0.049	-0.313							-180.403
	(0.283[a])	(0.044[c])	(0.628[c])							(0.064)
(3)	-1.338	0.002	-0.053			0.494			0.230	-176.34
	(0.464[a])	(0.055)	(0.627)			(0.176[a])			(0.226)	(0.072)
(4)	-1.455	0.003	-0.08			0.490	0.191	0.066	0.250	-135.210
	(0.486[a])	(0.055)	(0.627)			(0.177[a])	(0.097[c])	(0.238)	(0.229)	(0.076)
(5)	-0.978				-38.828					-192.147
	(0.086[a])				(19.226[b])					(0.062)
(6)	-0.676	-0.048			-35.769					-186.127
	(0.284[a])	(0.031)			(17.086[b])					(0.057)
(7)	-1.375	0.006			-22.2481	0.462			0.253	-177.432
	(0.467[a])	(0.055)			(11.398[c])	(0.180[a])			(0.226)	(0.0250)
(8)	-1.486	0.006			-20.529	0.461	0.182	0.075	0.271	-177.220
	(0.488[a])	(0.056)			(17.623)	(0.181[a])	(0.212)	(0.239)	(0.229)	(0.06279)
(9)	-0.973			-40.318						-207.173
	(0.086[a])			(18.459[b])						(0.071)
(10)	-0.665	-0.048		-28.704						-207.04
	(0.285[a])	(0.044)		(35.435)						(0.254)
(11)	-1.343	0.003		-9.082		0.486			0.233	-199.862
	(0.464[a])	(0.055)		(33.498)		(0.178[a])			(0.224)	(0.031)
(12)	-1.458	0.003		-6.205		0.485	0.187	0.067	0.253	-183.540
	(0.486[a])	(0.055)		(33.562)		(0.181[a])	(0.212)	(0.238)	(0.228)	(0.076)

The following logit model is estimated: $F(ABN_i = 1 \mid X_i, \theta) = \frac{\exp(X_i'\theta)}{1+\exp(X_i'\theta)}$ where ABN_i is one if the abnormal return for stock i is significant and zero otherwise. Abnormal returns are measured by κ_1 from table 21. X_i is a vector of the independent variables, and θ is the vector of parameters to estimate. The independent variables are L(assets) as given by the logarithm of the total assets from Compustat as of the end of the year preceding the announcement, ΔPIN as given by the PIN around the announcement less the PIN before the announcement as estimated by the EKOP model, GH and LSB are the difference between the proportional permanent cost between the value around the announcement and that pre-announcement as measured by the GH and the LSB models, respectively, nature is a dummy variable equal to one for targets and zero for acquirers, cash and shares refer to cash and share cash tender offers as measured by dummy variables, and listing that is a dummy variable equal to one for NASDAQ and zero for NYSE. Logl is the value of the log likelihood function. Below Logl is the log likelihood ratio test for the significance of all coefficients except the intercept. Standard errors are reported in the parentheses.

Table 23. Descriptive statistics

	All venues				AMEX			
	Total assets	**Trading vol.**	**Equity**	**Market cap**	**Total assets**	**Trading vol.**	**Equity**	**Market cap**
min	17.03	0.03	5.22	12.07	29.63	0.03	5.22	12.97
25% perc.	189.50	11.53	110.34	207.06	87.75	2.61	43.66	78.77
median	959.39	43.21	519.10	867.60	197.47	12.37	92.02	213.71
mean	13310.38	152.58	1810.41	3250.94	990.22	113.99	463.80	1315.76
75% perc.	6561.66	132.64	2039.60	3501.65	418.49	70.19	257.80	360.38
Max	376956.00	6101.72	17238.00	38485.12	11868.00	1183.91	5212.00	16995.79
SD	51061.97	545.30	2968.78	5674.58	2910.93	288.94	1276.59	4062.04
skewness	5.58	9.92	2.64	3.24	3.95	3.59	3.89	4.05
kurtosis	31.70	107.64	7.90	13.28	15.73	13.52	15.37	16.57
	NASDAQ				NYSE			
	Total assets	**Trading vol.**	**Equity**	**Market cap**	**Total assets**	**Trading vol.**	**Equity**	**Market cap**
min	17.03	0.15	5.36	12.07	117.13	1.42	78.03	219.50
25% perc.	82.17	3.93	35.49	78.10	2495.63	51.97	838.56	1845.30
median	220.47	14.10	152.63	224.63	6705.16	110.25	2069.03	3616.66
mean	493.96	29.73	282.16	501.42	27404.52	266.48	3412.64	6084.89
75% perc.	586.24	24.94	436.26	725.47	13378.93	252.52	4306.93	7248.22
Max	2874.51	400.12	1428.44	3259.77	376956.00	6101.72	17238.00	38485.12
SD	645.56	58.78	341.28	639.92	71830.46	762.78	3598.52	6950.29
skewness	2.21	5.10	1.77	2.19	3.73	7.34	1.78	2.43
kurtosis	5.16	30.59	2.87	5.87	13.34	56.66	3.26	7.45

"All venues" corresponds to all cross-listed shares in our sample. AMEX, NASDAQ and NYSE correspond to the samples of Canadian companies cross-listed on the AMEX, the NASDAQ and the NYSE, respectively. Market cap is the total market capitalization. Total assets (data item 6 in S&P Compustat database) and total capitalization (data item 24 times data item 25 in Compustat) are as the end of the calendar year 2002 and are in Canadian millions of dollars. The trading volume is the number of shares traded on the TSX for the calendar year 2002 and corresponds to data item 28 from the Compustat database. Equity is in millions of Canadian dollars.

Table 24. Sector distribution

NAICS	Sector	Companies
21	Mining	25
22	Utilities	2
23	Construction	1
31-33	Manufacturing	56
42	Wholesale trade	5
45	Retail trade	1
48	Transportation	5
51	Information	21
52	Finance and insurance	8
53	Real Estate and Rental and Leasing	2
54	Professional, Scientific, and Technical Services	2
56	Administrative and Support, Waste Management and Remediation Services	1
62	Health Care and Social Assistance	3
71	Arts, Entertainment, and Recreation	1
72	Accommodation and Foodservices	2
	TOTAL	135

NIACS refers to North American Industry Classification System. This is the classification system that replaced the Standard Industrial Classification (SIC) system in 1997.

Table 25. Trading activity measures for Canadian shares cross-listed on US exchanges

	Dollar volume		Shares volume		Nb. of trades		Dollar volume buy		Dollar volume sell		Nb. Trade buy		Nb. Trade sell	
All	US	Canada	US	Canada	US	Canada	US	Canada	US	Canada	US	Canada	US	Canada
min	0.0028	0.0031	0.0008	0.0002	0.0217	0.0120	0.0006	0.0003	0.0013	0.0005	0.0042	0.0017	0.0113	0.0080
25% p	0.0904	0.4370	0.0120	0.0427	0.2239	0.5534	0.0443	0.2001	0.0470	0.2126	0.1063	0.2573	0.1168	0.2685
median	0.4867	2.7153	0.0479	0.1662	0.7410	1.7029	0.2530	1.3563	0.2329	1.2672	0.3732	0.8485	0.3883	0.8044
mean	5.0188	11.4271	0.3857	0.5373	3.0338	4.1881	2.7863	5.9245	2.2325	5.5025	1.6054	2.1554	1.4284	2.0327
75% p	2.6576	11.9538	0.2346	0.4908	2.4237	5.0679	1.4888	6.1960	1.2876	5.7842	1.2993	2.5724	1.1451	2.5407
Max	104.0012	152.8856	28.0786	23.6620	44.4429	84.1707	61.0630	71.4520	46.4357	81.4336	23.2585	43.3851	23.1541	40.7856
SD	13.1026	19.8044	1.6162	1.4680	6.0291	7.5174	7.3497	10.2827	5.7725	9.5663	3.1415	3.8392	2.9015	3.7147
AMEX listed														
min	0.0045	0.0034	0.0013	0.0009	0.0217	0.0230	0.0021	0.0026	0.0020	0.0005	0.0103	0.0123	0.0113	0.0080
25% p	0.0484	0.0491	0.0223	0.0129	0.1727	0.1220	0.0259	0.0294	0.0215	0.0199	0.0881	0.0623	0.0846	0.0572
median	0.3545	0.3194	0.0632	0.0601	0.7100	0.6596	0.1832	0.2002	0.1781	0.1519	0.3767	0.2989	0.3406	0.3596
mean	0.7612	1.9824	0.3143	0.4419	1.1670	1.4932	0.4039	1.0438	0.3573	0.9386	0.6199	0.7864	0.5468	0.7068
75% p	1.0677	1.0979	0.3509	0.2693	1.6500	1.3931	0.5484	0.6521	0.5225	0.5527	0.8199	0.7492	0.7252	0.6257
Max	3.6836	14.9396	2.1759	4.9401	5.8663	12.8598	2.0024	8.1612	1.7529	6.7784	3.1673	6.8988	2.6988	5.9610
SD	0.9544	3.9328	0.5244	1.0323	1.3707	2.4064	0.5140	2.0638	0.4445	1.8768	0.7388	1.2938	0.6370	1.1160
NASDAQ listed														
min	0.0044	0.0031	0.0008	0.0002	0.0217	0.0120	0.0006	0.0003	0.0013	0.0027	0.0042	0.0020	0.0121	0.0100
25% p	0.0304	0.1343	0.0058	0.0161	0.1147	0.2494	0.0130	0.0662	0.0155	0.0740	0.0543	0.1151	0.0562	0.1174
median	0.1568	0.4819	0.0262	0.0465	0.3805	0.6679	0.0685	0.2266	0.0813	0.2617	0.1754	0.3127	0.1983	0.3339
mean	2.1730	2.1253	0.1654	0.1298	2.6900	1.5104	1.1362	1.0686	1.0368	1.0567	1.3790	0.7601	1.3110	0.7503
75% p	0.6866	1.5693	0.1096	0.1024	1.7026	1.3226	0.3359	0.7148	0.3644	0.8295	0.8839	0.6482	0.8424	0.6794
Max	53.0404	39.3616	2.4343	1.8296	44.4429	17.8568	28.3290	20.4432	24.7114	18.9184	23.2585	8.7138	21.1844	9.1430
SD	6.2971	4.9910	0.3896	0.2793	6.3501	2.7539	3.3460	2.5811	2.9618	2.4191	3.3062	1.4045	3.0479	1.3531
NYSE listed														
min	0.0028	0.0094	0.0010	0.0013	0.0294	0.0271	0.0014	0.0007	0.0014	0.0043	0.0075	0.0017	0.0161	0.0129
25% p	0.3536	4.8407	0.0203	0.2021	0.4665	2.1947	0.1752	2.2339	0.1709	2.4473	0.2318	1.0983	0.2305	1.1170
median	1.0621	10.7192	0.0612	0.4239	1.0078	4.2902	0.5173	5.2420	0.4870	5.2554	0.5263	2.2195	0.4771	2.1275
mean	8.1604	20.6497	0.5685	0.8670	3.7297	6.8374	4.5878	10.7276	3.5726	9.9222	2.0067	3.5277	1.7230	3.3097
75% p	7.7576	30.2509	0.3121	0.9221	4.5555	7.8380	4.4095	15.5319	3.3704	14.0296	2.4670	4.3829	2.0363	3.5332
Max	104.0012	152.8856	28.0786	23.6620	43.2007	84.1707	61.0630	71.4520	46.4357	81.4336	20.0432	43.3851	23.1541	40.7856
SD	17.0762	24.2295	2.2257	1.9367	6.3414	9.5571	9.6152	12.5699	7.4841	11.7302	3.2972	4.8665	3.0660	4.7460

Dollar volume, dollar volume buy, and dollar volume sell are in millions of dollars per day. Share volume is in millions of shares. Number of trades is in lots of 100. Only admissible trades are included to compute volume and number of trades. AMEX, NASDAQ and NYSE correspond to Canadian firms cross-listed on these exchanges and the TSX.

Table 26. Liquidity measures for Canadian shares cross-listed on US exchanges

	Dollar spread		Percent spread		Effective spread		Percent effective spread		Shares depth		Dollar depth	
All	US	Canada	US	Canada	US	Canada	US	Canada	US	Canada	US	Canada
min	0.0116	0.0110	0.0888	0.1143	0.0113	0.0151	0.0697	0.1314	0.2605	0.2615	1.1646	2.1116
25% p	0.0507	0.0704	0.3347	0.3356	0.0424	0.0645	0.2585	0.3100	0.9449	1.4171	7.0325	14.3547
median	0.0747	0.1172	0.7631	0.7229	0.0576	0.0999	0.6023	0.6178	1.3064	2.0017	15.0867	35.2444
mean	0.0995	0.1553	1.4051	1.4294	0.0761	0.1259	1.0839	1.1400	2.3136	2.5884	19.7992	44.8685
75% p	0.1111	0.1838	1.9420	1.7053	0.0835	0.1453	1.4541	1.3921	1.8046	2.7169	26.9804	65.2690
Max	0.6432	1.0821	8.5563	13.8959	0.4965	0.7969	6.9907	14.7567	162.2760	53.8131	190.6634	175.2999
SD	0.0913	0.1413	1.5366	1.9433	0.0678	0.1020	1.1856	1.4450	7.9997	3.4637	17.7788	37.1819
AMEX listed												
min	0.0171	0.0131	0.3161	0.2543	0.0113	0.0151	0.2097	0.2223	0.6609	0.8826	2.3320	5.0191
25% p	0.0340	0.0485	1.1811	1.0304	0.0235	0.0409	0.9367	0.9584	1.5625	1.7811	6.5157	9.3933
median	0.0687	0.1146	2.0853	1.7394	0.0471	0.0851	1.4514	1.4991	2.8087	2.2343	10.3498	14.0319
mean	0.0777	0.1525	2.4537	2.8875	0.0580	0.1175	1.7636	2.2848	5.0889	4.6990	13.7637	22.0024
75% p	0.1167	0.1810	3.5207	3.6274	0.0924	0.1560	2.3179	2.7995	5.8799	3.9108	17.7370	22.1548
Max	0.1887	0.5127	6.6385	13.0431	0.1604	0.5424	5.4710	14.7567	23.8618	24.1532	56.4375	114.0553
SD	0.0491	0.1425	1.5753	2.8769	0.0395	0.1065	1.1495	2.3551	5.6423	5.3300	11.5532	23.8188
NASDAQ listed												
min	0.0188	0.0226	0.1577	0.2428	0.0165	0.0203	0.1685	0.2751	0.2605	0.2615	1.1646	2.1116
25% p	0.0573	0.0962	0.9447	0.9687	0.0476	0.0848	0.7686	0.7663	0.8241	1.2004	4.0766	8.5724
median	0.0920	0.1644	1.6520	1.4698	0.0761	0.1273	1.3409	1.1555	1.0642	1.4633	7.3508	16.7371
mean	0.1409	0.2097	2.1976	2.1703	0.1104	0.1639	1.7601	1.6904	1.2019	1.6464	8.9618	20.8013
75% p	0.1704	0.2248	2.8639	2.4945	0.1316	0.1759	2.4514	2.1334	1.4218	1.9276	13.0945	28.4278
Max	0.6432	1.0821	8.5563	13.8959	0.4965	0.7969	6.9907	8.5477	5.2705	4.8455	28.9857	89.8335
SD	0.1311	0.1856	1.7808	2.1713	0.0959	0.1337	1.3849	1.4837	0.6498	0.7093	6.0313	15.6776
NYSE listed												
min	0.0116	0.0110	0.0888	0.1143	0.0120	0.0159	0.0697	0.1314	0.3195	0.7257	2.2719	5.3719
25% p	0.0498	0.0643	0.2287	0.2215	0.0400	0.0617	0.1827	0.2144	1.0098	1.7827	16.7350	41.6778
median	0.0700	0.0978	0.3819	0.3602	0.0531	0.0878	0.2861	0.3285	1.4018	2.3622	26.0339	62.7409
mean	0.0733	0.1150	0.5622	0.5297	0.0545	0.0991	0.4149	0.4573	2.5028	2.8050	29.3826	68.3636
75% p	0.0927	0.1423	0.6563	0.5960	0.0659	0.1212	0.4855	0.5004	1.8228	2.9752	38.5860	91.1984
Max	0.1836	0.3901	3.1431	5.2032	0.1211	0.3860	2.1562	4.9663	162.2760	53.8131	190.6634	175.2999
SD	0.0316	0.0727	0.5432	0.5788	0.0209	0.0530	0.3830	0.4652	10.8179	3.8983	19.5380	36.3624

Dollar quoted and effective spreads are in local currency. Percent spread and percent effective spread are both expressed as percentages. Share depth is in thousands of shares. Dollar depth is in thousands of dollars. Dollar amounts are in Canadian dollars for the Canadian market and in US dollars for the US market.

Table 27. Differences in trading activity and liquidity significance

	ALL			AMEX			NASDAQ			NYSE		
Variable	*Mean*	*t-stat*	*p-value*	*Mean*	*t-stat*	*p-value*	*Mean*	*t-stat*	*p-value*	*Mean*	*t-stat*	*p-value*
Δpct spd	0.0002	0.4559	0.3420	0.0043	1.8412	0.0160	-0.0003	-0.2269	0.5510	-0.0003	-1.4364	0.9060
Δpct eff spd	0.0006	1.5492	0.0450	0.0052	2.7275	0.0000	-0.0007	-1.0255	0.8310	0.0004	2.1158	0.0030
%depth shares	1.5263	20.7426	0.0000	1.0343	0.6505	0.0000	1.4423	16.7186	0.0000	1.7037	17.5135	0.0000
%volume share	9.6056	10.2620	0.0000	1.4688	2.3622	0.0000	6.2575	4.8459	0.0000	14.0019	9.3582	0.0000
%nb trades	4.0241	12.1846	0.0000	1.4440	2.3020	0.0000	2.5001	5.2569	0.0000	5.7636	11.5826	0.0000
%nb trades buy	4.1034	11.7807	0.0000	1.4199	2.1190	0.0000	2.6838	4.7036	0.0000	5.7889	11.4549	0.0000
%nb trades sell	4.0315	12.3171	0.0000	1.4813	2.5130	0.0000	2.4690	5.7741	0.0000	5.7928	11.4918	0.0000

All, AMEX, NASDAQ and NYSE correspond respectively to the entire sample of Canadian shares cross-listed on all the US exchanges, and to the shares cross-listed on the AMEX, NASDAQ and NYSE only. "Pct spd" is the percentage quoted spread. "Pct eff spd" is the percentage effective spread. "Depth shares" is the quoted depth in shares at the admissible bid and ask. "Volume shares" is the daily admissible traded volume in number of shares. "Nb trades" is the daily number of admissible trades. "Nb trades buy (sell)" is the daily number of admissible buyer (seller) initiated trades where the Lee and Ready algorithm is applied to sign the trades. For the spread variables, the difference as measured by the value for Canada less that for the US are investigated. For the remaining five variables, the ratio of the Canada/US values are investigated. For each variable, the variable is regressed on a column of ones to determine the mean and the deviations from the mean. Resamples of B times are obtained from these residuals and then the bootstrap regressions are re-run to generate the distribution of the t-statistics of the intercept under the null. For the first two variables, the null is that the intercept is zero. For the last five variables, the null is that the intercept is one. The p-value is the bootstrapped p-value. B, or the number of bootstrapped samples, is determined by the three-step method of Andrews and Bushinsky (2000). Samples of 999 observations also are used as an alternative choice for the number of bootstrapped samples.

Table 28. Determinants of trading costs for cross-listed shares

	{1}	{2}	{3}	{4}	{5}	{6}	{7}	{8}	{9}	{10}	{11}	{12}	{13}	{14}	{15}	{16}
Intercept	0.119	0.123	0.045	0.047	0.084	0.086	0.033	0.040	0.092	0.094	0.048	0.054	0.056	0.058	0.029	0.035
	[8.801]	[8.481]	[6.252]	[6.459]	[9.757]	[9.581]	[6.038]	[6.540]	[7.072]	[6.686]	[5.389]	[4.571]	[8.677]	[10.139]	[5.931]	[7.904]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
10^{+3}*Ln(assets)	1.574		0.912		0.947		0.251		-1.341		-1.462		-1.127		-1.306	
	[2.043]		[1.231]		[1.907]		[0.447]		[-1.734]		[-1.933]		[-2.528]		[-2.858]	
	(0.043)		(0.221)		(0.059)		(0.656)		(0.085)		(0.056)		(0.013)		(0.005)	
10^{+3}*Ln(MC)		3.249		0.776		1.193		-0.987		-2.896		-2.683		-2.246		-2.492
		[1.658]		[0.552]		[1.067]		[-1.043]		[-1.913]		[-1.942]		[-4.298]		[-4.661]
		(0.100)		(0.582)		(0.288)		(0.299)		(0.058)		(0.054)		(0.000)		(0.000)
volat Can	0.213	0.234	0.412	0.416	0.139	0.143	0.266	0.237								
	[2.586]	[2.417]	[4.066]	[3.194]	[2.715]	[2.459]	[4.148]	[3.005]								
	(0.011)	(0.017)	(0.000)	(0.002)	(0.008)	(0.015)	(0.000)	(0.003)								
volat us									0.150	0.136	0.283	0.263	0.208	0.192	0.280	0.251
									[1.931]	[1.729]	[3.680]	[3.386]	[4.440]	[4.165]	[5.757]	[5.142]
									(0.056)	(0.086)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
10^{+3}*Ln(vol Can)	-8.326	-9.415			-5.724	-5.939										
	[-8.062]	[-4.971]			[-9.427]	[-5.742]										
	(0.000)	(0.000)			(0.000)	(0.000)										
10^{+3}*Ln(nb T. Can)			-9.964	-9.953			-6.433	-5.607								
			[-8.572]	[-5.473]			[-8.782]	[-5.369]								
			(0.000)	(0.000)			(0.000)	(0.000)								
10^{+3}*Ln(Vol US)									-5.571	-4.876			-3.413	-2.876		
									[-8.067]	[-6.951]			[-10.123]	[-7.508]		
									(0.000)	(0.000)			(0.000)	(0.000)		
10^{+3}*Ln(nb T. US)											-7.614	-6.876			-4.324	-3.585
											[-7.823]	[-6.892]			[-10.028]	[-7.187]
											(0.000)	(0.000)			(0.000)	(0.000)
10^{+3}*AX	-5.811	-7.359	-1.338	-3.026	-3.801	-4.981	-0.509	-2.149	53.057	49.634	54.495	51.562	2.628	1.350	3.543	2.047
	[-1.144]	[-1.709]	[-0.267]	[-0.730]	[-1.336]	[-1.948]	[-0.178]	[-0.846]	[4.849]	[4.949]	[5.184]	[5.278]	[1.342]	[0.828]	[1.733]	[1.191]
	(0.255)	(0.090)	(0.790)	(0.467)	(0.184)	(0.054)	(0.859)	(0.399)	(0.000)	(0.000)	(0.000)	(0.000)	(0.182)	(0.409)	(0.086)	(0.236)
10^{+3}*NSQ	-5.137	-5.883	-2.880	-4.047	-2.407	-3.280	-0.616	-2.020	1.776	0.311	2.835	1.778	2.774	2.086	3.618	2.756
	[-1.834]	[-2.366]	[-1.004]	[-1.597]	[-1.422]	[-2.176]	[-0.330]	[-1.224]	[0.535]	[0.079]	[0.821]	[0.447]	[1.696]	[1.377]	[2.069]	[1.693]
	(0.069)	(0.020)	(0.317)	(0.113)	(0.157)	(0.031)	(0.742)	(0.223)	(0.594)	(0.937)	(0.413)	(0.656)	(0.092)	(0.171)	(0.041)	(0.093)
Adjusted R^2	0.686	0.688	0.670	0.667	0.751	0.748	0.700	0.702	0.673	0.671	0.694	0.691	0.730	0.741	0.725	0.738

The following regression is run:

$$spread_i = \alpha_1 + \beta_1 \times size + \beta_2 \times volat_i + \beta_3 \times vol_i + \alpha_2 \times AX_i + \alpha_3 \times NSQ_i + \varepsilon_i$$

Table 28. Continued.

The dependent variable is the quoted spread on the Canadian exchange for models 1-4, the proportional effective spread on the Canadian exchanges for models 5-8, the quoted spread on the US exchanges for models 9-12, and the proportional effective spread on the US exchanges for models 13-16. The sample contains 130 observations on Canadian shares cross-listed on the US market. Ln(assets) is the natural logarithm of total assets as determined from the S&P Compustat database in Canadian dollars. Ln(MC) is the natural logarithm of the market capitalization computed as the number of shares outstanding multiplied by the price per share, as in Table 23. Volat Can (US) is the standard deviation of the daily returns from Canadian (US) closing prices during the period under study. Ln(Vol Can) and Ln(Vol US) correspond to the natural logarithms of the average daily trading volumes on the Canadian exchange and the US exchanges, respectively. The former is in Canadian dollars and the latter is in US dollars. Ln(nb T. Can) and Ln(nb T. US) correspond respectively to the natural logarithms of the average daily number of trades on the Canadian exchange and the US exchanges for the cross-listed shares. AX and NSQ are dummy variables equal to one when the US listing venue is respectively AMEX and NASDAQ. The coefficients $\beta_1, \beta_3, \alpha_1$ and α_2 are multiplied by 1000. White corrected t-statistics are reported in the brackets and the corresponding p-values are reported in the parentheses.

Table 29. Limit executions as proportions of total executions

Sample		Canada						US					
	Statistics	*Nb. bid*	*Nb. ask*	*Nb. all*	*Vol. bid*	*Vol. ask*	*Vol. all*	*Nb. bid*	*Nb. ask*	*Nb. all*	*Vol. bid*	*Vol. ask*	*Vol. all*
All	min	0.4286	0.5146	0.6039	0.1146	0.1431	0.1684	0.1839	0.1176	0.1905	0.0264	0.0715	0.0635
	25% p	0.7253	0.7560	0.7451	0.4707	0.5296	0.5040	0.3527	0.3594	0.3668	0.2605	0.2743	0.2741
	median	0.7586	0.7887	0.7737	0.5589	0.6157	0.5838	0.4078	0.4188	0.4160	0.3299	0.3540	0.3408
	mean	0.7524	0.7836	0.7684	0.5552	0.6141	0.5789	0.4093	0.4183	0.4146	0.3357	0.3505	0.3427
	75% p	0.7832	0.8173	0.7951	0.6477	0.7042	0.6689	0.4626	0.4721	0.4633	0.3989	0.4193	0.4028
	Max	1.0000	1.0000	0.9787	1.0000	1.0000	0.9467	0.7065	0.6948	0.6648	1.0000	0.7015	0.6515
	SD	0.0554	0.0537	0.0443	0.1473	0.1400	0.1316	0.0839	0.0857	0.0793	0.1117	0.1061	0.0987
AMEX	min	0.6190	0.6053	0.7055	0.2189	0.1580	0.2534	0.2300	0.2423	0.2376	0.2130	0.2007	0.2045
	25% p	0.7440	0.7806	0.7730	0.5628	0.6454	0.6205	0.3428	0.3558	0.3467	0.3148	0.3124	0.3249
	median	0.7789	0.8189	0.7908	0.6668	0.7271	0.7039	0.4468	0.4472	0.4425	0.3978	0.3758	0.3833
	mean	0.7774	0.8096	0.7969	0.6557	0.7152	0.6806	0.4360	0.4362	0.4358	0.3948	0.3972	0.3949
	75% p	0.8081	0.8460	0.8163	0.7269	0.7881	0.7355	0.5128	0.5061	0.5156	0.4811	0.4770	0.4636
	Max	1.0000	0.9115	0.9787	1.0000	1.0000	0.9467	0.6197	0.6948	0.6648	0.6440	0.7015	0.6515
	SD	0.0613	0.0544	0.0461	0.1405	0.1345	0.1177	0.1085	0.1066	0.1042	0.0992	0.1078	0.0970
NASDAQ	min	0.4286	0.5146	0.6039	0.1204	0.1431	0.1729	0.1839	0.1176	0.1905	0.0264	0.0715	0.0635
	25% p	0.7086	0.7339	0.7276	0.4593	0.5079	0.4749	0.3350	0.3355	0.3456	0.2402	0.2398	0.2508
	median	0.7463	0.7685	0.7585	0.5505	0.6334	0.5921	0.3913	0.3912	0.3913	0.3185	0.3156	0.3177
	mean	0.7397	0.7631	0.7505	0.5603	0.6148	0.5778	0.3945	0.3915	0.3937	0.3259	0.3222	0.3234
	75% p	0.7734	0.7960	0.7801	0.6819	0.7395	0.6861	0.4515	0.4444	0.4377	0.3922	0.3920	0.3876
	Max	1.0000	1.0000	0.8795	1.0000	1.0000	0.9001	0.6800	0.6800	0.6343	1.0000	0.6471	0.6452
	SD	0.0630	0.0611	0.0479	0.1679	0.1635	0.1507	0.0860	0.0918	0.0802	0.1267	0.1150	0.1056
NYSE	min	0.4444	0.6557	0.6316	0.1146	0.2608	0.1684	0.2236	0.2153	0.2323	0.0855	0.1654	0.1570
	25% p	0.7305	0.7710	0.7587	0.4697	0.5263	0.4986	0.3679	0.3963	0.3859	0.2614	0.2959	0.2863
	median	0.7624	0.7947	0.7804	0.5432	0.5986	0.5675	0.4098	0.4342	0.4248	0.3260	0.3653	0.3506
	mean	0.7562	0.7931	0.7753	0.5279	0.5899	0.5559	0.4142	0.4343	0.4254	0.3292	0.3608	0.3450
	75% p	0.7829	0.8193	0.7986	0.6026	0.6565	0.6251	0.4526	0.4759	0.4664	0.3943	0.4214	0.4025
	Max	0.8552	1.0000	0.8555	0.9157	1.0000	0.8786	0.7065	0.6136	0.6598	0.6766	0.6383	0.6156
	SD	0.0444	0.0410	0.0347	0.1197	0.1083	0.1061	0.0734	0.0693	0.0680	0.0977	0.0925	0.0891

A modified version of the Greene (1997) algorithm is used to infer executions against limit orders. Statistics on executions against limit orders for all trades and for signed trades are reported separately, where the Lee and Ready (1991) algorithm is used to distinguish buyer and seller initiated trades. Sales (buys) are assumed to be executed against ask (bid) or selling (buying) limit orders. Executions against limit orders are reported as a fraction of total executions. Two measures for executions are used; namely, the number of trades (Nb.) and the number of shares traded (Vol.). Results are for the entire 41 days period centered on the earnings announcement dates.

Table 30. Limit executions as proportions of total executions around earnings announcements

Sample		Canada						US					
	Statistics	*Nb. bid*	*Nb. ask*	*Nb. all*	*Vol. bid*	*Vol. ask*	*Vol. all*	*Nb. bid*	*Nb. ask*	*Nb. all*	*Vol. bid*	*Vol. ask*	*Vol. all*
All	min	0.0000	0.3333	0.0000	0.0000	0.0488	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	25% p	0.6977	0.7368	0.7364	0.4537	0.5378	0.4791	0.3226	0.3119	0.3333	0.2249	0.2315	0.2456
	median	0.7491	0.7917	0.7670	0.6007	0.6842	0.6169	0.4000	0.4106	0.4048	0.3205	0.3333	0.3370
	mean	0.7444	0.7863	0.7626	0.5832	0.6523	0.5959	0.4035	0.4023	0.4041	0.3420	0.3485	0.3473
	75% p	0.7966	0.8375	0.7996	0.7370	0.7906	0.7262	0.4737	0.4849	0.4667	0.4286	0.4598	0.4371
	Max	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9000	1.0000	1.0000	0.8947
	SD	0.1005	0.0973	0.0761	0.2122	0.1983	0.1851	0.1441	0.1504	0.1118	0.1763	0.1799	0.1469
AMEX	min	0.0000	0.3333	0.4000	0.0000	0.0930	0.0851	0.0000	0.1600	0.1765	0.0000	0.0155	0.1238
	25% p	0.7164	0.7754	0.7560	0.5848	0.6373	0.6206	0.3141	0.2857	0.3125	0.2748	0.2676	0.2575
	median	0.7763	0.8477	0.7967	0.7023	0.7405	0.7256	0.4052	0.4162	0.4149	0.3724	0.3899	0.3959
	mean	0.7631	0.8240	0.7931	0.6822	0.7390	0.7064	0.4221	0.4191	0.4108	0.3980	0.3945	0.3849
	75% p	0.8554	0.8998	0.8471	0.8033	0.8734	0.8080	0.4766	0.5189	0.4936	0.5097	0.4873	0.4902
	Max	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.7018	1.0000	1.0000	0.6857
	SD	0.1608	0.1412	0.1078	0.2063	0.1972	0.1775	0.1821	0.1619	0.1250	0.1949	0.1765	0.1394
NASDAQ	min	0.0000	0.3333	0.0000	0.0000	0.0706	0.0000	0.0000	0.0000	0.0323	0.0000	0.0000	0.0081
	25% p	0.6747	0.7124	0.7105	0.4430	0.5334	0.4707	0.2977	0.2500	0.3000	0.2080	0.1828	0.2237
	median	0.7273	0.7747	0.7527	0.6218	0.7161	0.6483	0.4000	0.3671	0.3812	0.3235	0.2860	0.3190
	mean	0.7285	0.7739	0.7429	0.5979	0.6794	0.6055	0.3922	0.3583	0.3788	0.3329	0.3087	0.3260
	75% p	0.7795	0.8374	0.7886	0.7623	0.8314	0.7467	0.5000	0.4551	0.4561	0.4166	0.4171	0.4120
	Max	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.6949	1.0000	1.0000	0.8947
	SD	0.1122	0.1158	0.0925	0.2297	0.2256	0.2039	0.1598	0.1751	0.1181	0.1805	0.1978	0.1426
NYSE	min	0.5348	0.5000	0.5963	0.0190	0.0488	0.0330	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	25% p	0.7148	0.7546	0.7463	0.4487	0.5193	0.4673	0.3365	0.3705	0.3701	0.2292	0.2535	0.2512
	median	0.7522	0.7932	0.7718	0.5550	0.6354	0.5801	0.4005	0.4303	0.4191	0.3094	0.3586	0.3413
	mean	0.7521	0.7868	0.7703	0.5490	0.6116	0.5629	0.4077	0.4316	0.4215	0.3358	0.3678	0.3546
	75% p	0.7971	0.8264	0.7976	0.6790	0.7248	0.6718	0.4621	0.4913	0.4715	0.4118	0.4698	0.4504
	Max	1.0000	1.0000	0.8769	1.0000	1.0000	0.9655	1.0000	1.0000	0.9000	1.0000	0.9200	0.8500
	SD	0.0658	0.0609	0.0428	0.1911	0.1645	0.1600	0.1197	0.1164	0.0999	0.1666	0.1604	0.1500

A modified version of the Greene (1997) algorithm is used to infer executions against limit orders. Statistics on executions against limit orders for all trades and for signed trades are reported separately, where the Lee and Ready (1991) algorithm is used to distinguish buyer and seller initiated trades. Sales (buys) are assumed to be executed against ask (bid) or selling (buying) limit orders. Executions against limit orders are reported as a fraction of total executions. Two measures for executions are used; namely, the number of trades (Nb.) and the number of shares traded (Vol.). Results are for the three-day period centered on the earnings announcement dates.

Table 31. EKOP results for inter-day data.

		US venues					Canada				
Sample	*Statistic*	α	δ	μ	ε	*PIN*	α	δ	μ	ε	*PIN*
All	min	0.0000	0.0000	0.0000	0.0000	0.0000	0.0004	0.0000	0.0000	0.0000	0.0000
	25% p	0.2281	0.1790	11.2086	7.9545	0.1322	0.2095	0.2221	11.8768	19.0008	0.1134
	median	0.3458	0.3773	29.3964	28.9761	0.1896	0.3487	0.4373	47.3636	60.5044	0.1696
	mean	0.3586	0.4081	55.0772	141.0732	0.2090	0.3607	0.4446	74.3468	197.5747	0.1827
	75% p	0.4580	0.5986	74.2955	99.8571	0.2772	0.4832	0.6597	119.3873	218.9543	0.2346
	Max	1.0000	1.0000	331.7267	2348.6626	1.0000	1.0000	1.0000	344.7966	4210.1842	1.0000
	SD	0.2233	0.2858	66.1369	310.1766	0.1367	0.2394	0.2920	75.9688	407.2418	0.1393
AMEX	min	0.0155	0.0000	0.0000	0.2824	0.0000	0.0106	0.0000	0.0000	0.0000	0.0000
	25% p	0.2058	0.1860	5.8864	4.6471	0.1418	0.2342	0.1416	2.8840	1.6835	0.1679
	median	0.3186	0.4484	27.4433	25.7233	0.1979	0.3301	0.4350	24.4883	21.9570	0.2259
	mean	0.3411	0.4231	45.2633	47.1329	0.2075	0.4268	0.4338	44.4274	60.3750	0.2720
	75% p	0.4187	0.6022	56.3787	64.2565	0.2512	0.5353	0.6684	72.3465	49.0581	0.3090
	Max	1.0000	1.0000	250.5050	296.9101	0.7407	1.0000	1.0000	201.2895	636.6282	1.0000
	SD	0.2252	0.2923	53.1554	60.9826	0.1303	0.2987	0.3257	50.2916	112.5416	0.2144
NASDAQ	min	0.0027	0.0000	0.0000	0.0000	0.0000	0.0004	0.0000	0.0000	0.3330	0.0000
	25% p	0.1881	0.2656	8.0859	3.7587	0.1830	0.1791	0.3203	14.5390	8.9836	0.1614
	median	0.2826	0.4991	24.3040	12.9688	0.2740	0.3155	0.5261	38.4588	25.5339	0.2098
	mean	0.3298	0.4747	47.1333	120.4331	0.2706	0.3344	0.5204	56.4309	69.5791	0.2280
	75% p	0.4088	0.6937	67.4076	63.7760	0.3593	0.4230	0.6959	75.0730	56.4269	0.2910
	Max	1.0000	1.0000	299.4353	2227.8574	1.0000	1.0000	1.0000	344.7966	877.3289	0.6250
	SD	0.2410	0.2920	58.5576	308.9371	0.1643	0.2254	0.2766	61.3738	138.0762	0.1230
NYSE	min	0.0000	0.0000	0.0000	0.7860	0.0000	0.0011	0.0000	0.0000	0.2061	0.0000
	25% p	0.2642	0.1433	16.0798	18.6571	0.1147	0.2374	0.1686	16.5612	95.2142	0.0760
	median	0.3871	0.3116	32.9773	44.4690	0.1627	0.3911	0.3644	85.5563	189.0592	0.1276
	mean	0.3865	0.3501	64.1185	182.6332	0.1593	0.3646	0.3860	96.7933	337.7278	0.1223
	75% p	0.4901	0.5127	84.0854	199.2263	0.1984	0.5135	0.5582	154.1950	373.6982	0.1706
	Max	1.0000	1.0000	331.7267	2348.6626	0.4760	1.0000	1.0000	329.1722	4210.1842	0.8755
	SD	0.2046	0.2672	73.6283	342.5322	0.0836	0.2303	0.2819	85.3537	536.8170	0.0930

This table presents the EKOP model estimates by maximizing expression 3 for the US and the Canadian based trades, respectively. The sample is separated into three sub-samples to conform to the following three cross-listing venues: the AMEX, the NASDAQ and the NYSE. The estimation is based on interdaily observations of buyer and seller initiated trades. α is the probability of daily event occurrence; δ is the probability that the event, conditional on its occurrence, has a negative impact on the stock; μ is the trading intensity of the informed traders as measured by the number of trades conditional on the occurrence of an event; ε is the trading intensity of the uninformed traders; and PIN is the probability of informed trading.

Table 32. Simulated p-values for EKOP inter-day results

Sample	Statistic	α	δ	μ	ε	PIN
All	Mean	0.0021	0.0365	2.5967	4.4494	-0.0263
	Median	0.0055	0.0061	1.1537	1.6349	-0.0234
	t-stat	0.1582	2.6816	8.6409	11.9517	-4.4075
	p-value	0.4280	0.0020	0.0000	0.0000	0.0000
AMEX	Mean	0.0857	0.0107	1.4585	1.4049	0.0644
	Median	0.0199	-0.0059	0.7984	1.3423	0.0244
	t-stat	1.9549	0.2405	1.4423	2.0842	2.7624
	p-value	0.0190	0.4050	0.0290	0.0140	0.0020
NASDAQ	Mean	0.0057	0.0458	1.9503	3.0452	-0.0424
	Median	0.0106	0.0002	1.5469	1.1567	-0.0375
	t-stat	0.2683	2.1128	4.2721	5.6046	-3.9623
	p-value	0.3980	0.0140	0.0000	0.0000	0.0000
NYSE	Mean	-0.0228	0.0359	3.3905	6.3689	-0.0371
	Median	0.0057	0.0180	1.2622	3.2537	-0.0288
	t-stat	-1.2474	1.9036	7.5761	11.0442	-6.6692
	p-value	0.8890	0.0320	0.0000	0.0000	0.0000

α is the probability of event occurrence; δ is the probability that the event, conditional on its occurrence, has a negative impact on the stock; μ is the trading intensity of the informed traders as measured by the number of trades conditional on the occurrence of an event; ε is the trading intensity of the uninformed traders; and PIN is the probability of informed trading . The matched differences between Canadian and US based trades are computed for the α, δ and PIN parameters. The ratios are computed for the μ and ε trading intensity parameters. The reported p-values are the bootstrap statistics under the null that the difference is zero for α, δ and PIN, and the ratio is one for μ and ε.

Table 33. Regime switching estimates

	$10^4 \times c_0$		$10^6 \times c_1$		$10^6 \times c_2$		$10^6 \times c_3$		$10^4 \times z_0$		$10^6 \times z_1$	
Statistic	Canada	US	Canada	US	Canada	US	Canada	US	Canada	US	Canada	US
Min	3.1616	-7.5360	-82.9358	-28.3423	-19.6045	-5.4253	-2.6603	-17.2917	-4.9529	-689.2872	-726.4505	-5000.1583
25%	6.6315	3.3311	-7.7685	0.0520	-3.5242	0.1212	-0.0392	0.0538	18.6726	17.9055	-23.4901	-7.9852
Median	11.3276	7.3022	-1.8315	1.9076	-1.7035	0.8577	-0.0012	0.2786	59.8971	42.0794	-0.4004	11.3764
Mean	19.5970	23.1497	-5.8499	2.4053	-2.7203	1.2417	0.1155	0.6240	110.0495	120.2338	21.4732	86.6784
75%	21.5618	21.7049	0.1999	5.8469	-0.6707	1.8349	0.0144	0.6968	138.6433	133.8085	17.7747	38.9271
Max	263.0903	469.6151	8.0643	27.1362	3.6956	25.3221	11.7556	26.4806	1151.2003	2464.5576	3315.0590	15342.9017
SD	27.3989	49.6286	12.3754	8.1057	3.2623	2.6688	1.2720	3.0620	152.2355	285.1025	334.6197	1428.9854
t-stat	8.5231	5.5585	-5.6329	3.5360	-9.9366	5.5443	1.0816	2.4284	8.6142	5.0254	0.7647	0.7228
Median**		2.0627		-4.8606		-3.1914		-0.2487		2.2432		-9.4057
Mean*		-3.8044		-8.3001		-3.9799		-0.5078		-11.8417		-65.0207
t-stat		-1.7061		-6.6680		-10.6131		-1.8123		-0.5437		-0.5234
p-value		0.0902		0.0000		0.0000		0.0721		0.5875		0.6015
Wilcoxon		2.2330		7.0468		9.9302		7.0262		0.4528		1.8173
p-v alue		0.0255		0.0000		0.0000		0.0000		0.6507		0.0692

	$10^6 \times z_2$		$10^6 \times z_3$		p_{11}		p_{22}		p_1	
Statistic	Canada	US	Canada	US	Canada	US	Canada	US	Canada	US
Min	-3.7135	-12.4621	-48.3663	-44.5644	0.0000	0.0000	0.0334	0.0000	0.0014	0.0061
25%	-0.4596	0.2377	-1.7281	-0.2817	0.9140	0.9168	0.1236	0.1772	0.8395	0.8980
Median	1.0869	5.0896	-0.3003	2.0911	0.9596	0.9570	0.1575	0.2428	0.9545	0.9484
Mean	6.8451	27.4280	-2.1752	8.7311	0.7798	0.8258	0.3074	0.3334	0.7761	0.8234
75%	3.2834	24.5767	0.0031	9.9461	0.9740	0.9750	0.2311	0.3308	0.9697	0.9676
max	179.5766	894.8992	7.7640	223.3726	0.9980	0.9991	0.9986	0.9947	0.9978	0.9990
SD	25.1639	89.0060	6.8754	27.2352	0.3696	0.3019	0.3258	0.2797	0.3522	0.3177
t-stat	3.2415	3.6721	-3.7700	3.8202	25.1397	32.5899	11.2417	14.2019	26.2601	30.1387
Median**		-7.6144		-2.7771		-0.0001		-0.0630		0.0051
Mean*		-23.7751		-10.9094		-0.0472		-0.0248		-0.0474
t-stat		-2.4260		-4.3806		-1.0710		-0.6356		-1.9461
p-value		0.0165		0.0000		0.2860		0.5261		0.0535
Wilcoxon		5.8223		6.2215		0.4425		2.2845		0.1173
p-v alue		0.0000		0.0000		0.6581		0.0223		0.9066

Prices are assumed to follow the motion equation (19): $dp_t = I_t \times Z_t \times s_t + I_t \times C_t - I_{t-1} \times C_{t-1} + e_t$, where I_t is the usual trade indicator variable, Z_t is the information asymmetry trading cost, C_t is the temporary trading cost, s_t is a state variable and e_t is the innovation induced by new public information. The state variable is one (state one) when the trader is privately informed and zero (state two) if not. Both trading cost components are assumed to be linearly dependent on the trading volume. The change in price would be given by the state variable as:

If state 1: $dp_t = \alpha_1 + c_0 \times dI_t + c_1 \times d(I_t.V_t.DS_t) + c_2 \times d(I_t.V_t.DM_t) + c_3 \times d(I_t.V_t.DL_t) + e_t$

If state 2: $dp_t = \alpha_2 + c_0 \times dI_t + c_1 \times d(I_t.V_t.DS_t) + c_2 \times d(I_t.V_t.DM_t) + c_3 \times d(I_t.V_t.DL_t)$
$+ z_0 \times I_t + z_1 \times I_t.V_t.DS_t + z_2 \times I_t.V_t.DM_t + z_3 \times I_t.V_t.DL_t + e_t$

Estimation is based on maximizing equation (21): $\underset{\theta}{Max}\sum_{t=1}^{T} Log\left[1'(\xi_{t|t-1} * \eta_t)\right]$.

Two vector parameter sets $\theta = \left(\alpha_1, c_0, c_1, c_2, c_3, z_0, z_1, z_2, z_3, \alpha_2, \sigma^2, p_{11}, p_{22}\right)$ are estimated for the Canadian and the US trades of the Canadian listed companies. P_{11} and P_{22} are respectively the transition probabilities of state one and two. Lim state 1 is the limiting probability of state 1 and is given by $P_1 = \frac{1 - P_{22}}{2 - P_{11} - P_{22}}$. * and ** indicate the mean and the median respectively of the matched difference between Canadian and US estimates on the cross-section.
Since observations are dependent by nature, the p-values are simulated under the null of equality.

Table 34. Probability of informed trading from the regime switching model

	announcement		exclude announcement	
	PI Canada	*PI US*	*PI Canada*	*PI US*
min	0.0000	0.0000	0.0000	0.0000
25% quartile	0.0238	0.0236	0.0251	0.0306
median	0.0436	0.0559	0.0438	0.0482
mean	0.2070	0.1418	0.2066	0.1976
75% quartile	0.0956	0.0898	0.0926	0.1067
max	1.0000	1.0000	0.9983	0.9954
SD	0.3392	0.2352	0.3391	0.3215
Test	***(i)***	***(ii)***	***(iii)***	***(iv)***
Mean*	0.0652	0.0091	0.0004	-0.0558
t-stat	1.7207	0.2075	0.1171	-3.1069
p-value	0.0740	0.8380	0.9180	0.0120
Median**	-0.0048	-0.0042	0.0002	-0.0002
wilcoxon	0.0967	0.3443	0.5128	0.7852
p-value	0.9230	0.7306	0.6081	0.4323

PI is the probability of trading against informed trading. It is computed by summing the smoothed vector of the state variable $\xi_{t|T}$ generated by using the Kim (1993) algorithm, and then dividing by the number of trades over each period. The state vector drives the motion of the share price through equation (19): $dp_t = I_t \times Z_t \times s_t + I_t \times C_t - I_{t-1} \times C_{t-1} + e_t$ where I_t is the usual trade indicator variable, Z_t is the information asymmetry trading cost, C_t is the temporary trading cost, s_t is a state variable, and e_t is the innovation induced by new public information. The state variable is one (state one) when the trader is privately informed and zero (state two) if not. Both trading cost components are assumed to be linearly dependent on the trading volume. The change in price is given by the state variable as:

If state 1: $dp_t = \alpha_1 + c_0 \times dI_t + c_1 \times d(I_t.V_t.DS_t) + c_2 \times d(I_t.V_t.DM_t) + c_3 \times d(I_t.V_t.DL_t) + e_t$

If state 2: $dp_t = \alpha_2 + c_0 \times dI_t + c_1 \times d(I_t.V_t.DS_t) + c_2 \times d(I_t.V_t.DM_t) + c_3 \times d(I_t.V_t.DL_t)$
$+ z_0 \times I_t + z_1 \times I_t.V_t.DS_t + z_2 \times I_t.V_t.DM_t + z_3 \times I_t.V_t.DL_t + e_t$

Estimation is based on maximizing equation (21): $\underset{\theta}{Max}\sum_{t=1}^{T} Log\left[1'(\xi_{t|t-1} * \eta_t)\right]$.

Smoothed state vector $\xi_{t|T}$ is given by $\xi_{t|t} * \left(P'.\left[\xi_{t+1|T} (\div) \xi_{t+1|t}\right]\right)$ where P is the transition matrix. The four tests correspond to (i) the difference between the PI from the Canadian trades less the PI from the US trades for the earnings announcement three days periods; (ii) the difference between the PI from the Canadian trades less the PI from the US trades for the periods excluding the earnings announcement three days periods; (iii) the difference between the PI for the earnings announcement days less the PI for the periods excluding the earnings announcement windows for the Canadian trades; and (iv) the difference between the PI for the earnings announcement days less the PI for the periods excluding the earnings announcement windows for the US trades. * and ** correspond respectively to the mean and median of these differences, and they are tested for equality with zero. Because of the dependent nature of the observations, the p-values are computed by bootstrapping from the estimates.

Table 35. Spread components from the regime switching model

Panel A. Spread and spread components from Canadian trades														
	Earnings announcement							*Non announcement days*						
Statistic	(1-π)	Dollar			percent			(1-π)	dollar			percent		
		total	temporary	permanent	total	temporary	permanent		total	temporary	permanent	total	temporary	permanent
Min	0.0025	0.0074	-0.0142	0.0001	0.0028	-0.0095	0.0000	0.0303	0.0032	-0.0057	0.0000	0.0016	-0.0013	0.0000
25%	0.0809	0.0295	0.0242	0.0061	0.1368	0.0271	0.0062	0.0987	0.0293	0.0230	0.0040	0.0394	0.0297	0.0043
Median	0.1333	0.1568	0.0946	0.0684	0.2297	0.1645	0.0812	0.1452	0.1402	0.1033	0.0352	0.1594	0.1093	0.0422
Mean	0.2544	0.1980	0.1675	0.0304	0.2948	0.1721	0.1227	0.3583	0.1630	0.1160	0.0370	0.2533	0.2039	0.0494
75%	0.2344	0.3970	0.2459	0.0635	0.4428	0.2127	0.1292	0.2832	0.2760	0.2336	0.0579	0.3737	0.3298	0.0766
Max	1.2764	6.5413	6.5250	0.1302	2.6483	2.6417	0.2634	7.8442	1.6228	1.6061	0.3156	1.3045	1.2912	0.2632
SD	0.3366	0.7263	0.7252	0.0069	0.3395	0.3287	0.2332	1.0470	0.2210	0.2192	0.1452	0.2668	0.2455	0.0401

Panel A. Spread and spread components from US trades														
	Earnings announcement							*Non announcement days*						
Statistic	(1-π)	dollar			Percent			(1-π)	dollar			percent		
		total	temporary	permanent	total	temporary	permanent		total	temporary	permanent	total	temporary	permanent
min	-0.0070	0.0038	0.0017	-0.2098	0.0010	0.0002	-0.0217	0.0055	0.0031	0.0024	-0.0985	0.0009	0.0001	-0.0091
25%	0.0811	0.0402	0.0365	0.0351	0.0528	0.0008	0.0044	0.0837	0.0459	0.0073	0.0360	0.0086	0.0012	0.0077
median	0.1356	0.1428	0.0729	0.0490	0.1815	0.1519	0.0403	0.1398	0.1347	0.0813	0.0592	0.1680	0.1220	0.0563
mean	0.3122	0.1519	0.0723	0.0690	0.2062	0.1635	0.0427	0.2888	0.1437	0.0676	0.0791	0.2193	0.1537	0.0656
75%	0.3978	0.1798	0.1017	0.1495	0.5696	0.2041	0.0558	0.1983	0.3604	0.1321	0.1199	0.4341	0.1944	0.0810
max	0.9867	4.0445	0.2371	3.9762	1.2248	0.2371	0.2013	6.6275	4.8989	0.1499	4.8239	1.2790	0.9470	0.1748
SD	0.2838	0.5589	0.1304	0.5478	0.1357	0.2106	0.0345	0.7286	0.6861	0.0256	0.6750	0.2338	0.1754	0.0123

The table reports results for half-spreads and half-spread components. Spreads and spread components are derived from the Glosten and Harris (1988) model using a regime-switching framework. Dollar spreads are multiplied by 10 and the proportional spreads are in percentages. The state vector drives the motion of the share price through equation (19): $dp_t = I_t \times Z_t \times s_t + I_t \times C_t - I_{t-1} \times C_{t-1} + e_t$, where I_t is the usual trade indicator variable, Z_t is the information asymmetry trading cost, C_t is the temporary trading cost, s_t is a state variable, and e_t is the innovation induced by new public information. The state variable is one (state one) when the trader is privately informed and zero (state two) if not. Both trading cost components are assumed to be linearly dependent on the trading volume. The change in price would be given by the state variable as:

If state 1: $dp_t = \alpha_1 + c_0 \times dI_t + c_1 \times d(I_t.V_t.DS_t) + c_2 \times d(I_t.V_t.DM_t) + c_3 \times d(I_t.V_t.DL_t) + e_t$

If state 2: $dp_t = \alpha_2 + c_0 \times dI_t + c_1 \times d(I_t.V_t.DS_t) + c_2 \times d(I_t.V_t.DM_t) + c_3 \times d(I_t.V_t.DL_t)$
$+ z_0 \times I_t + z_1 \times I_t.V_t.DS_t + z_2 \times I_t.V_t.DM_t + z_3 \times I_t.V_t.DL_t + e_t$

where V_t is the share volume for trade at time t.

Estimation is based on maximizing equation (21): $\underset{\theta}{Max}\sum_{t=1}^{T} Log\left[1'(\xi_{t|t-1} * \eta_t)\right]$. The quoted implied half-spread is equal to $S_t = \hat{C}_t + \hat{Z}_t$ with the half temporary component given by $\hat{C}_t = \hat{z}_0 + \hat{c}_1 \times V_t \times DS_t + \hat{c}_2 \times V_t \times DM_t + \hat{c}_3 \times V_t \times DL_t$ and the half permanent component given by $\hat{Z}_t = \hat{c}_0 + \hat{z}_0 + \hat{z}_1 \times V_t \times DS_t + \hat{z}_2 \times V_t \times DM_t + \hat{z}_3 \times V_t \times DL_t$. The fitted values $\hat{c}_0$, $\hat{c}_1$, $\hat{c}_2$, $\hat{c}_3$, $\hat{z}_0$, $\hat{z}_1$, $\hat{z}_2$ and $\hat{z}_3$ are the estimates whose cross-sectional statistics appears in table 33. (1-π) is the proportion of the implied spread that is attributed to the permanent component, and it is expressed as a percentage.

Table 36. Statistical tests

	Panel A. Announcement dates: Canada - US					
	Percent			*Dollar*		
	Total	Temporary	Permanent	Total	Temporary	Permanent
mean	0.0887	0.0091	0.0794	0.0464	0.0952	0.0004
t-stat	1.7146	1.7539	2.3778	2.2218	2.7583	2.1977
p-value	0.0790	0.0530	0.0040	0.0260	0.0000	0.0400
median	0.0491	0.0139	0.0500	0.0213	0.0218	0.0199
wilcoxon	3.7101	5.7740	3.0678	4.6488	7.7884	4.1211
p-value	0.0002	0.0000	0.0022	0.0000	0.0000	0.0000
	Panel B. No announcement dates: Canada - US					
	Percent			*Dollar*		
	Total	Temporary	Permanent	Total	Temporary	Permanent
mean	0.0342	0.0504	-0.0163	0.1930	0.0496	-0.0422
t-stat	3.7353	0.8555	3.7181	3.2039	11.8246	3.0950
p-value	0.0010	0.4250	0.0010	0.0170	0.0000	0.0200
median	-0.0103	-0.0124	-0.0149	0.0051	0.0221	-0.0264
wilcoxon	6.3014	4.0556	6.2475	5.3373	12.3934	4.5172
p-value	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000
	Panel C. Canada: announcement dates – no announcement dates					
	Percent			*Dollar*		
	Total	Temporary	Permanent	Total	Temporary	Permanent
mean	0.0417	-0.0322	0.0733	0.0354	0.0515	0.0032
t-stat	2.4800	-0.0700	2.4785	2.5823	0.3320	1.5931
p-value	0.0320	0.9290	0.0320	0.0350	0.7580	0.219
median	0.0709	0.0554	0.0394	0.0166	-0.0092	0.0341
wilcoxon	1.4875	1.1596	2.1977	2.3057	1.1596	2.2333
p-value	0.1369	0.2462	0.0310	0.0211	0.2462	0.0255
	Panel D. US: announcement dates – no announcement dates					
	Percent			*Dollar*		
	Total	Temporary	Permanent	Total	Temporary	Permanent
mean	0.0212	0.0321	-0.0152	0.0033	-0.0152	-0.0202
t-stat	1.5408	2.1000	-1.5295	1.5130	-1.4817	-2.5355
p-value	0.3280	0.0370	0.3300	0.1470	0.1520	0.0350
median	0.0212	0.0321	-0.0152	0.0033	-0.0152	-0.0202
wilcoxon	1.0155	1.2089	1.9895	0.5324	2.4228	2.5444
p-value	0.3099	0.2267	0.0659	0.5873	0.0154	0.0109

This table present results of paired matched sample tests of half spreads and components. We compare the announcement three day period to the non announcement 38 day period. We also compare the estimates from the US and the Canadian trades. P-values are computed using a bootrapping method under the null that the mean or the median is zero. Total, temporary and permanent correspond to the half implied spread, the temporary fixed and the permanent variable parts of the half spread. Spreads and spread components are derived from the Glosten and Harris (1988) model using a regime-switching framework. The state vector drives the motion of the share price through equation (9): $dp_t = I_t \times Z_t \times s_t + I_t \times C_t - I_{t-1} \times C_{t-1} + e_t$ where I_t is the usual trade indicator variable, Z_t is the information asymmetry trading cost, C_t is the temporary trading cost, s_t is a state variable, and e_t is the innovation induced by new public information. The state variable is one (state one) when the trader is privately informed and zero (state two) if not. Both trading cost components are assumed to be linearly dependent on the trading volume. The change in price would be given by the state variable as:

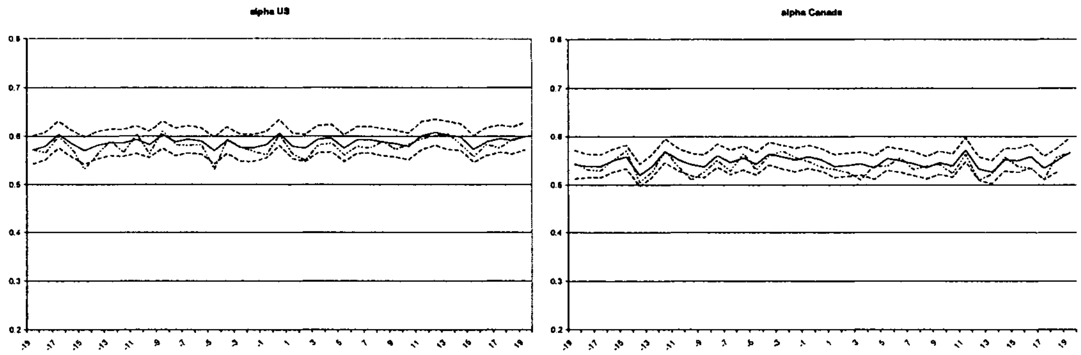
If state 1: $dp_t = \alpha_1 + c_0 \times dI_t + c_1 \times d(I_t.V_t.DS_t) + c_2 \times d(I_t.V_t.DM_t) + c_3 \times d(I_t.V_t.DL_t) + e_t$

If state 2: $$dp_t = \alpha_2 + c_0 \times dI_t + c_1 \times d(I_t.V_t.DS_t) + c_2 \times d(I_t.V_t.DM_t) + c_3 \times d(I_t.V_t.DL_t) + z_0 \times I_t + z_1 \times I_t.V_t.DS_t + z_2 \times I_t.V_t.DM_t + z_3 \times I_t.V_t.DL_t + e_t$$

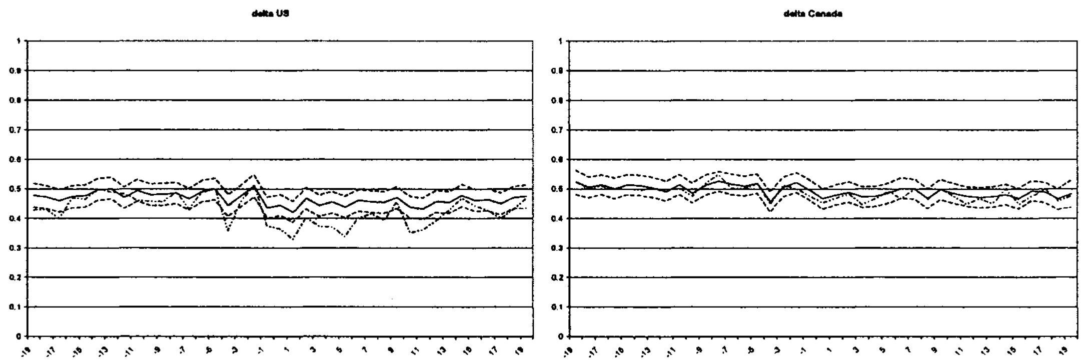
where V_t is the share volume for trade at time t.

Estimation is based on maximizing equation (21): $\underset{\theta}{Max}\sum_{t=1}^{T} Log\left[1'(\xi_{t|t-1} * \eta_t)\right]$. The quoted implied half-spread is equal to $S_t = \hat{C}_t + \hat{Z}_t$ with the half temporary component given by $\hat{C}_t = \hat{z}_0 + \hat{c}_1 \times V_t \times DS_t + \hat{c}_2 \times V_t \times DM_t + \hat{c}_3 \times V_t \times DL_t$, and the half permanent component given by $\hat{Z}_t = \hat{c}_0 + \hat{z}_0 + \hat{z}_1 \times V_t \times DS_t + \hat{z}_2 \times V_t \times DM_t + \hat{z}_3 \times V_t \times DL_t$. The fitted values $\hat{c}_0$, $\hat{c}_1$, $\hat{c}_2$, $\hat{c}_3$, $\hat{z}_0$, $\hat{z}_1$, $\hat{z}_2$ and $\hat{z}_3$ are the estimates whose cross-sectional statistics appears in table 33.

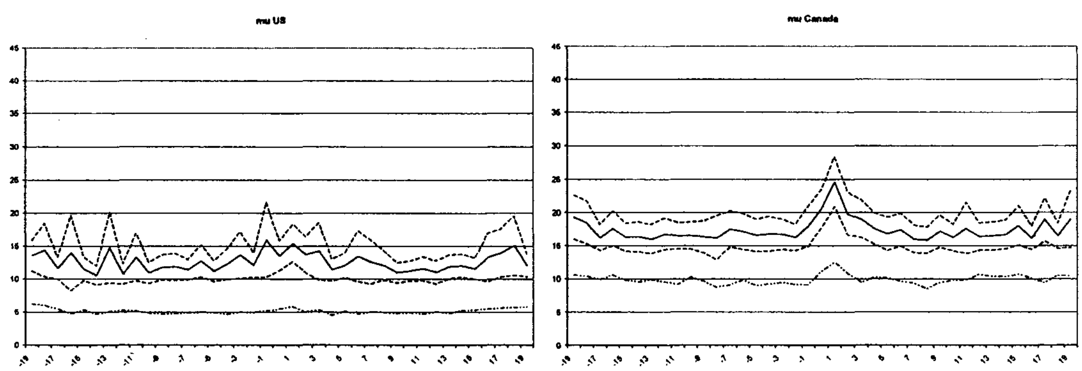
Figure 1. Time series of intraday EKOP estimates



Panel A. α estimates

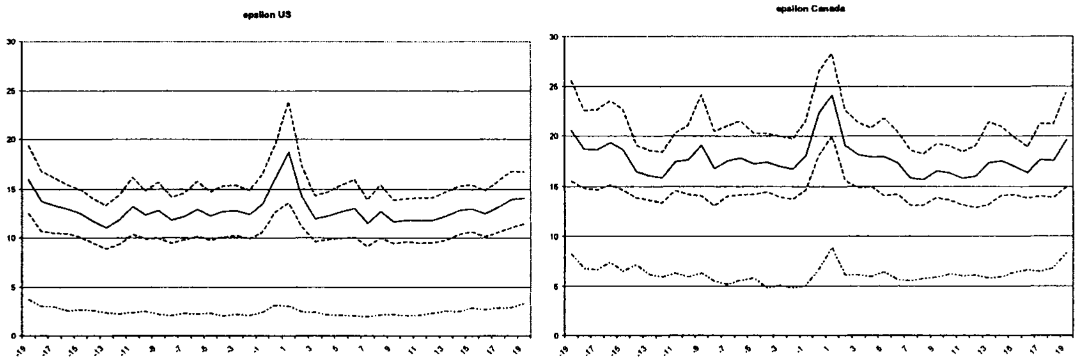


Panel B. δ estimates

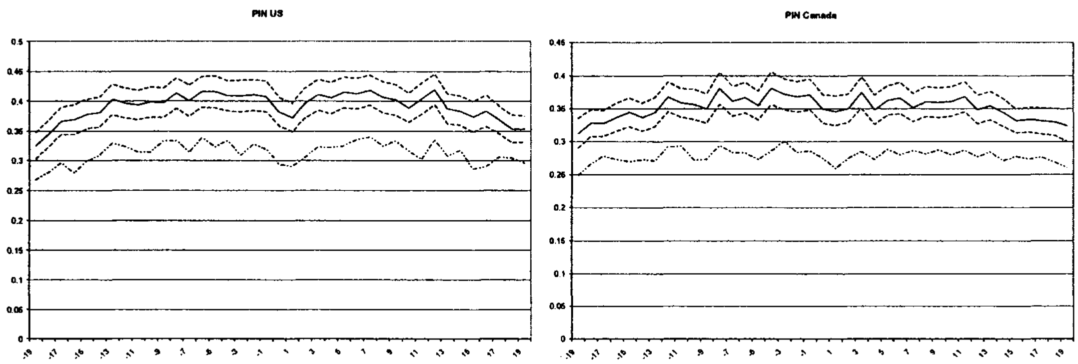


Panel C. μ estimates

Figure 1 continued



Panel D. ε estimates



Panel E. PIN estimates

The above graphs show the time series of the EKOP estimates. For each observation, intradaily estimates of EKOP are conducted by maximizing expression 3 using intradaily samples of trades. Daily estimates of the five parameters α, δ, μ, ε and PIN are obtained. Cross-sectional averages are then computed using event days. α is the probability of event occurrence; δ is the probability that the event, conditional on its occurrence, has a negative impact on the stock; μ is the trading intensity of the informed traders as measured by the number of trades conditional on the occurrence of an event; ε is the trading intensity of the uninformed traders; and PIN is the probability of informed trading.