A Market Microstructure Perspective on the Price Formation of Cross-Listed Stocks

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Abstract

Over the past two decades, globalization in capital markets has led to the growth of equity listings in more than one market. Such growth has heightened the levels of competition among stock exchanges, especially in terms of attracting more foreign listings and the associated business opportunities. Hence, finding ways to achieve a competitive advantage over other markets is becoming more crucial for exchanges. This has emphasized the need to understand how prices are formed in multiple markets. In that respect, this thesis intends to add to the understanding of the price formation process for stocks with foreign listings through three empirical studies. In terms of application, this thesis focuses on Canadian stocks which are listed on the Toronto Stock Exchange (TSX) and cross-listed on the New York Stock Exchange (NYSE).

The first essay contributes to our understanding of the impact of news arrival on price discovery. It employs macroeconomic news announcements as proxies for new information and examines the impact of these announcements on price discovery of cross-listed stocks. This study reveals that price discovery shifts significantly from Canada to the U.S. during days with a macroeconomic news announcement, regardless of the origin of the news. This finding shows that markets differ in terms of information processing capability, particularly with regard to the processing of market-wide information.

The second essay examines the dynamics of price discovery for cross-listed stocks. We model the interactions between daily price discovery measures, trading volume, bid-ask spread, and algorithmic trading activity using a vector autoregression, taking into account lagged and contemporaneous relations among the variables. We observe

that price discovery exhibits a trend and persistence over time. Improvements in liquidity increase an exchange's contribution to price discovery, while at the same time, an increase in price discovery leads to better liquidity. We also find that algorithmic trading activity is negatively related to price discovery of cross-listed stocks, which we attribute to the crowding out effect as arbitrageurs make use of computers to trade aggressively and compete for arbitrage opportunities that exist in their respective markets. As a consequence, high-frequency trading by these arbitrageurs push away informed investors, who are disadvantaged in terms of speed.

The third essay assesses how information is incorporated into prices in multiple markets. We develop a general model to assess how quotes in dual markets react to information coming from quotes and trades. We further develop this model to extract an implied model for the spreads, the efficient price, and the relative premium between the two markets. We observe that quotes of cross-listed stocks are linked directly to each other. We find evidence of intermarket competition between liquidity providers as indicated by significant impacts of bid-ask spreads on quotes in both markets. We also find that while prices adjust primarily to trades in their respective market, there is some impact by trades from another market. This finding suggests that there is some degree of informational segmentation between markets. On the whole, the above findings describe the mechanisms of how information is incorporated into prices for dually-listed stocks.

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Attestation of Authorship

I, Ivan Mulyadi Indriawan, hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning.

Signed:

Date:

Acknowledgements

When I first embarked on my Ph.D. journey, I had no idea how short three years would be in the scheme of academic research. Nevertheless, the journey has come to an end and I hereby present to you my Ph.D. thesis. I would not have completed this thesis without the support and involvement of some people, whom I would like to thank.

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Chapter 1

Introduction

Market microstructure is the area of finance concerned with the trading processes of securities in financial markets. It studies how security prices are formed from investors' demands into order submissions and ultimately into transactions (Madhavan, 2000). As such, research in this area covers the different aspects of trades such as: transaction costs, prices, quotes, and volume. Market microstucture research helps explain why prices exhibit particular time-series properties, thus enhancing our ability to understand the returns to financial assets and the process underlying such price formation. As market microstructure explains the behavior of prices and markets, it has immediate application in the regulation of markets, and in the design and formulation of new trading mechanisms, making trade more efficient.

One interesting aspect of microstructure research is its evolution. Interests in market microstructure are driven by rapid structural, technological, and regulatory changes affecting securities markets worldwide. The proliferation of new financial instruments, the growth of electronic trading, and the growth in foreign listings are transforming the landscape of financial markets, thus, emphasizing the relative importance of microstructure research.

During the past two decades, globalization in capital markets has made trading and owning securities from around the world easier. Equity listings in more than one market are becoming an increasingly important strategic issue for companies looking for direct access to foreign capital markets.[1] As more companies become global, the international integration of capital markets has led to unprecedented levels of competition among stock exchanges. In this intermarket competition between exchanges, the winners are the exchanges that manage to attract more foreign listings and the associated trading volume and business opportunities.

The importance of foreign listings for exchanges has emphasized the need to understand the price formation process for stocks in a multi-market context. In the case of stocks that are listed and traded in multiple markets, information may come from any of the markets. Investors too, have the option to trade in a market they prefer. Consequently, prices of stocks are determined by information entering the market as well as trading activity in these markets. However, we often observe that investors have a preference to trade in one market over the other. Understanding how prices are determined and the mechanisms underlying security trades in these markets are crucial in determining which factors contribute to the competitiveness of a market.

The topic examined in this thesis is primarily based on the process of price formation in multiple markets. Why this particular focus? For market participants, the focus emphasizes the importance of information in decision making. New information forms the basis for liquidity providers to adjust their expectations on an asset's fundamental value, and to update their prices. Investors too, revise their expectations based on the information they obtain, and subsequently, trade in the cheapest and the most liquid trading venue. Furthermore, exchanges and regulators continuously strive to find ways to achieve competitive advantage over other exchanges and markets. In that respect, the findings in this thesis indicate areas where exchange officials and market regulators should focus on in order to adjust and introduce new trading rules, keeping markets competitive.

[1] See for example, Pagano et al. (2002), Karolyi (2006), Fernandes and Ferreira (2008), and Halling et al. (2008) for evidences of cross-listings.

As a starting point for this thesis, Chapter 2 presents a primer on market microstructure with an emphasis on how prices are determined in a market. The chapter starts with a discussion on market frictions and how they cause prices observed in the market to differ from their true values. We then introduce the notion of price discovery, which concerns the process of how different information sources contribute to the evolution of an asset's fundamental value. Price discovery reflects the competitiveness of a market to incorporate information into prices, and indicates in which market investors prefer to trade. This chapter also assesses the importance of information coming from trades, and how such information affects prices in terms of quote midpoints, and induces asymmetric responses from the bid and ask prices.

Given the importance of information for security prices, our first objective is to examine the role of information arrival on price discovery. One important source of new information is the release of macroeconomic news. These news announcements provide indications for the near-term policy changes that will subsequently be used by investors to price securities. Since macroeconomic news announcements are prescheduled, the timing of such releases is known, and investors may choose to trade on this information in one or another market. This may lead to a temporal shift in price discovery between markets which is related to the arrival of information from macroeconomic news announcements. In Chapter 3, we take the above predictions and examine the impact of macroeconomic news announcements on the price discovery of cross-listed stocks. Specifically, we analyze the impact of macroeconomic news releases on the level of price discovery between two markets by comparing the price discovery between days with and without news releases. By assessing a market's contribution to price discovery, we gain additional insight on the information processing capacity of a market.

Examining Canadian stocks which are cross-listed in the U.S., we observe that price discovery shifts towards the U.S. market during days with macroeconomic news announcements, regardless of the origin of the news. This finding indicates that some markets are better at processing information than others. It also implies that information induces a shift in price discovery from one market to another, hence, indicating dynamics in price discovery.

While the dynamics of price discovery provides additional insight to the literature, it raises several questions which have yet to be addressed, such as: does price discovery persist once gained by a particular market? Is price discovery beneficial for a market? How does a market improve its contribution to price discovery? Existing literature has not fully addressed these issues because studies tend to measure price discovery at one point in time over a period. As such, extant studies tend to assess cross-sectional differences in price discovery and determinants of those differences, rather than the dynamics of price discovery over time.[2]

In Chapter 4, we address the above questions by examining the dynamics of price discovery. We first compute daily measures of price discovery from January 2004 to January 2011. By doing so, we are able to assess the evolution and persistence in price discovery which have not been explored previously. We then show how changes in price discovery over time can be attributed to various factors. For instance, investors have the tendency to trade in the cheaper and more liquid market. Such liquidity-motivated trading may cause information clustering in a market, which may lead to a shift in price discovery. Furthermore, the automation of trading activity helps investors scan public information faster and trade on this information. Such speed and intensity of trading activity may also lead to changes in price discovery between markets. Based on these expectations, we analyse the bi-directional relations between price discovery and other market quality measures such as liquidity and algorithmic trading activity. Thus, our analyses also shed light on what drives

[2]Extant studies find that the home market tends to lead in terms of price discovery because it is the market where most information about the company is generated (see e.g. Lieberman et al.,1999; Hupperets and Menkveld, 2002; Grammig et al., 2005). However, these studies assume that the information processing capacity of a market does not change over time.

a market's contribution to price discovery, and on the importance of price discovery for a market.

To further improve our understanding of price formation process, we assess the mechanisms of how information is incorporated into prices. Microstructure theories suggest that information can be inferred from trade-related activities, such as the direction of trade (Glosten and Milgrom, 1985; Jang and Venkatesh, 1991), trading volume (Easley and O'Hara, 1987; Barclay and Warner, 1993) and trade order flow (Kyle, 1985). These variables reflect information signals from various market participants. How these variables lead to updates in the market's expectation about the long-run value of a stock, reflects the mechanism by which information drives prices. As shown in Kavajecz and Odders-White (2001), Engle and Patton (2004), and Escribano and Pascual (2005), such mechanism is better observed from the dynamics of bid and ask prices, rather than the quote midpoint. That is because information causes asymmetric revisions of market quotes. Bid and ask prices do not respond symmetrically to buyer-initiated and seller-initiated trades.

Motivated by the above studies, we aim to improve the understanding of the price formation process for stocks with foreign listings. In Chapter 5, we assess the mechanism of how information gets incorporated into prices through studying quote dynamics in multiple markets. We incorporate various microstructure theories which have been shown to drive prices in a single market setting, and develop a general model for quote dynamics of stocks traded in dual markets. Specifically, we model the bid and ask quotes in two different markets simultaneously, and allow these quote revisions to be a function of quote-related information (e.g. the bid-ask spread and the difference in quoted depth), and trade-related information (e.g. trade direction, size, duration, and order flow). This model allows us to examine how information affects prices in dual markets, and to evaluate the degree of information spillover between markets. At the same time, the model can be used to assess the relevance of existing microstructure theories in explaining price dynamics in a multi-market setting. Our model can further be transformed into an implied vector autoregression (VAR) for the bid-ask spreads in the two markets, the midpoint of prices (the implied efficient price of the cross-listed stock) and the difference in midquotes across markets (the relative premium between markets). How information affects these variables reflects the mechanism of how information gets incorporated into prices for dually-listed stocks.

Overall, this thesis is intended to improve our understanding of stocks with foreign listings. The chapters in this thesis cover several empirical market microstructure issues regarding the price formation process in multiple markets, such as the impact of news arrival on price discovery, the determinants and trends in price discovery, and the role of information on quotes in multiple markets. To conclude, Chapter 6 highlights the importance of our results and their implications to practice and academia.

Chapter 2

A Primer on Market Microstructure

2.1 Introduction

This chapter presents a primer on market microstructure, with a focus on how prices are determined in a market. We discuss several market frictions that lead to trading costs and affect prices. We further develop a general framework on how prices in two different markets are linked. This framework becomes the basis of price discovery measures which forms an integral part of this thesis. We discuss how information can be inferred from trades and how prices respond to such information. Finally, as this thesis is directed towards understanding stocks with foreign listings, we discuss about the markets involved in our studies.

2.2 How Prices are Determined

One of the fundamental questions in finance is what determines a price? Economic theory suggests that price is the result of intersecting supply and demand curves for a particular good. The equilibrium price is achieved when the quantity supplied and quantity demanded at that price are equal. Using that as a basis, the early theory in market microstructure suggests that price formation process could be captured by a Walrasian auction. The mechanism starts with traders submitting their demands to the auctioneer. The auctioneer announces a potential trading price, and traders then revise their orders. This process is repeated until there is no further revision. Equilibrium is achieved at the price where the quantity supplied equals the quantity demanded.

The downside of this process is that while over time the quantity supplied might equal the quantity demanded, at any particular point in time such an outcome is not guaranteed. If the quantity supplied by traders who wish to sell immediately does not equal the quantity demanded by traders who wish to buy immediately, the imbalance of trade will make it impossible to find a market clearing price at a given time.

Demsetz (1968) argues that the lack of equlibrium could be overcome by paying a premium for immediate execution. If there is an excess demand by traders wanting to buy immediately, these traders either have to wait for more sellers to arrive, or they can offer a higher price to induce existing sellers to increase their supplies and transact now. This practise creates a difference between the fundamental value of an asset (i.e. the efficient price), and the price observed in the market. The difference in these prices is the cost of immediacy, and reflects the frictions that are present in the market. How prices are affected by different market frictions set the stage for the formal study of market microstructure.

2.2.1 Market Frictions and Trading Costs

In the field of market microstructure, we acknowledge that prices are affected by various market frictions. Understanding the role of frictions is a logical starting point for an exploration of how prices are actually determined. Here, we provide an overview of the frictions observed in financial markets.

Market frictions lead to various costs that liquidity providers must bear when matching buyers and sellers and providing immediacy in a market. In order to be compensated for these costs, a liquidity provider will post two different prices; the price at which he wants to buy (bid price), and the price at which he wants to sell (ask price). This creates a positive difference between the two prices called the spread. It represents the income the liquidity provider gains from a round trip transaction (a buy followed by a sell, or vice versa). The spread can therefore be seen as the compensation to the market maker for frictions. Hence, the lower the frictions, the smaller the trading costs, and subsequently, the narrower the spreads.

One type of friction comes from the sunk cost, which is a concept originally introduced by Benston and Hagerman (1974) based on Demsetz (1968). The sunk cost represents the fixed expenses in conducting a trade (such as labour, communication, clearing and record keeping expenses). Liquidity providers account for these expenses in the form of order processing cost, and is reflected in wider spreads. Due to order processing cost, the ask price that a liquidity provider offers to traders who wish to buy, is higher than the efficient price, while the bid price is lower than the efficient price. When only order processing costs are present, quotes are centred symmetrically around the true price. Liquidity providers do not adjust their bid and ask prices after the occurrence of a transaction and spreads remain fairly constant.

Another type of friction comes from the risk of carrying and managing inventories to meet the requirements of investors who demand immediacy. Stoll (1978) and Amihud and Mendelson (1980) argue that liquidity providers must be compensated for this risk. An unwanted inventory position poses a risk to the liquidity provider. He, therefore, quotes a wider spread compared to when he only faces order processing costs. Hence, another component of trading cost arises, which is known as the inventory cost. The inventory cost leads to dynamics in the quoted prices. For example, when a liquidity provider receives a sell order (i.e. a transaction at the bid price), his inventory position increases. When this position is unwanted, he will lower both his bid and ask prices so that less people sell and more people buy. By adjusting his bid and ask prices, a liquidity provider maintains a stable inventory position.

The last type of friction comes from information asymmetry. This concept has its roots in the study of Bagehot (1971) who makes a distinction in the market between informed and uninformed traders. The uninformed traders are those who have access to publicly available information and trade mainly for liquidity reasons. The informed traders, on the other hand, are either those who are able to react more timely to the release of new information, or those who simply have superior information. These traders buy when they know the current stock price is too low, and sell when they know it is too high. Trading with informed traders leads to losses for the liquidity providers. To remain solvent, liquidity providers offset those losses by making gains from the uninformed traders in the form of wider bid-ask spreads. This leads to the last component of trading cost known as the adverse selection cost. It reflects the compensation a liquidity provider must obtain for trading with the informed.

The discussion above show how frictions lead to various costs of trading and affect prices. Glosten and Harris (1988) show that these price impacts can be classified into transitory and permanent components. Order processing and inventory costs are considered transitory because they reflect temporary deviation in price needed to accomodate a trade, which are not related to the underlying value of the securities. The adverse selection cost, however, has permanent impact on prices because they result in liquidity providers revising their expectations on the fundamental value of the securities.

One of the instances where frictions lead to temporary and permanent price changes is during the arrival of new information. News arrivals, for example, induce more trades to occur in a market, leading the components of trading costs to change. Following the arrival of news, inventory cost may increase temporarily because liquidity providers need to fill up inventories in order to meet market demands. Information asymmetry between the informed and uninformed traders may also increase, leading to an increase in adverse selection cost and a permanent change in prices. The extent to which information affects the underlying value of an asset leads to the notion of price discovery. This will be discussed in the next section.

2.2.2 Price Discovery

Price discovery is a field in market microstructure that concerns itself with the process of how different information sources contribute to the evolution of the underlying value of an asset. Given that the amount of frictions differ between markets, information affects prices differently in these markets. Price discovery is relevant for stocks with foreign listings as it highlights the relative contribution of a market over another market to the evolution of the fundamental value of the stock. In this section, we introduce a model for prices, in which frictions can be considered. We then extend this model to account for prices in multiple markets. This sets the framework for measuring price discovery.

We start with the assumption that each asset has an efficient price. This unobserved efficient price represents the underlying value of an asset conditional on all available public information. Following Madhavan (2000), we assume that all investors share the same public information set, and prices are efficient in the sense that the current price reflects future price expectations conditional on the available information set. Consequently, the efficient (log) price, p_t, follows a random walk,

$$p_t = p_{t-1} + \eta_t, \tag{2.1}$$

where η_t is the innovation in public beliefs. The existence of market frictions (e.g. order processing cost, inventory holding cost, asymmetric information cost) leads to deviations from the efficient price, resulting in two different prices that market makers trade at. The observed transaction price, y_t, is equal to the efficient price and the friction component, ζ_t, which is positive (negative) for a buy (sell) transaction and zero for a transaction at the midpoint,

$$y_t = p_t + \zeta_t. \tag{2.2}$$

In the case of an asset trading in two different markets, the observed prices in both markets, share one common stochastic trend. Let $y_t = \begin{pmatrix} y_{1,t} & y_{2,t} \end{pmatrix}'$ be the price vector where $y_{1,t}$ and $y_{2,t}$ are the prices in the two markets. In a multivariate setting, this can be expressed as:

$$\begin{pmatrix} y_{1,t} \\ y_{2,t} \end{pmatrix} = \iota p_t + \begin{pmatrix} \zeta_{1,t} \\ \zeta_{2,t} \end{pmatrix}, \tag{2.3}$$

where ι is a (2×1) unit vector. This equation can be seen as the integrated process of random walk and news innovations plus the market frictions observed at time t. The study of price discovery relies on the assumption that when a single security trades in two different markets, prices in the two markets share a common efficient price, p_t. Since prices in both markets are driven by the same underlying fundamentals, the prices should be cointegrated. Therefore, the two $I(1)$ price series $y_{1,t}$ and $y_{2,t}$ are cointegrated with cointegrating vector, $\beta' = \begin{pmatrix} 1 & -1 \end{pmatrix}$. Subsequently, $\beta' y_t = y_{1,t} - y_{2,t}$, which is a stationary process will be the error correction term. The Engle–Granger Representation Theorem states that a cointegrated system can be expressed as an error-correction model of the following form,

$$\Delta y_t = c + \alpha \beta' y_{t-1} + \sum_{i=1}^{N} \Gamma_i \Delta y_{t-1} + \epsilon_t, \tag{2.4}$$

where Δy_t is the (2×1) vector of log returns, c is a vector of constants, α is a (2×1) vector that measures the speed of adjustment to the error-correction term, Γ_i are (2×2) matrices of autoregression (AR) coefficients, and ϵ_t is a (2×1) vector of innovations. The vector error correction model (VECM) above has two parts:

the first part, $\alpha\beta' y_{t-1}$, represents the long-run equilibrium between the price series, and the second part, $\sum_{i=1}^{N} \Gamma_i \Delta y_{t-1}$, represents the short-term dynamics induced by market imperfections.

The above VECM forms the basis for measuring price discovery. There are two main measures that are often used to investigate the mechanics of price discovery: the Gonzalo Granger (1995) Permanent-Transitory (PT) model, and Hasbrouck (1995) Information Share (IS). They are directly related, and the results of both models are primarily derived from the VECM. Despite this initial similarity, the IS and PT measure price discovery differently. The PT measure is concerned with the permanent shocks that result in a disequilibrium as markets process news at different speeds. Thus, the PT measures each market's contribution to the efficient price, where the contribution is defined to be a function of the market's error correction coefficients; in this case, the speed of adjustment coefficients, α. The IS, on the other hand, measures the proportion of variance contributed by one market with respect to the variance of the innovations in the common efficient price. This contribution is called the market's information share.

These two measures of price discovery form an integral part of this thesis. Essentially, these measures indicate which market contributes more to the formation of the underlying value of a cross-listed asset. The market which contributes more to price discovery incorporates new information into prices faster and has better information processing capacity than the other market. We argue that such contribution can be attributed to various factors. In Chapter 3, we conjecture that the arrival of new information may induce investors to trade in one or another market. This may lead to a temporal shift in price discovery. In Chapter 4, we evaluate how price discovery varies over time and what areas an exchange (or market) should focus on to improve price discovery.

2.2.3 Trades and Prices

In the previous section, we discuss the adverse selection component of trading costs. As liquidity providers lose on average to the informed traders, the spread reflects a balancing of losses to the informed with gains from the uninformed traders. The notion that asymmetric information is priced provide a fundamental insight into the nature of price formation.

The informed traders profit from trading if prices are not at full-information levels. During such times, any informed trader will prefer to trade as much and as often as possible. However, such behavior would quickly reveal the information of the informed trader. Liquidity providers would quickly adjust their prices to reflect this information. The ability to learn from trades means that the process by which information is impounded into prices could be addressed by analyzing how liquidity providers learn from trade-related activities.

Glosten and Milgrom (1985) use this insight and develop a pricing model of liquidity providers. They focus on the fact that in a competitive market, informed agents' trades will reflect their information, either selling if they know bad news or buying if they know good news. If a trader wants to sell to the market, it could signal either that he knows bad news, or he is uninformed and simply needs liquidity. Since the liquidity provider cannot tell which is the case, he protects himself by adjusting his beliefs about the value of the stock, conditional on the type of trade that occurs. Subsequently, his expectation of the asset's value changes, and so do his prices. Glosten and Milgrom (1985) demonstrate that, over time, the dominance of trades on one side of the market results in the liquidity provider eventually learning the informed traders' information. His prices will then converge to the expected value of the asset given this information.

If a market is efficient, the price of a security should reflect the value of its underlying assets. However, we often observe that large trades have persistent price impacts, with trade prices lower after large sales and higher after large purchases (see e.g. Dann, Mayers, and Raab, 1977; Holthausen et al., 1987). Easley and O'Hara (1987) examine how the ability to transact orders for large or small quantities provides the potential to address the effects of trade size on security prices. Informed traders are assumed to be risk neutral and trade to maximise their expected profits. Consequently, trade size induces an adverse selection problem, because at the same price, the informed trader always prefers to trade larger quantities. Since uninformed traders do not share this bias, a rational liquidity provider will interpret large orders as a signal of information-based trading and adjust prices accordingly. As a result, the liquidity provider's pricing strategies will depend on trade size, with large trades being made at less favorable prices.

Kyle (1985) shows that apart from the direction and volume of trade, information can also be inferred from an order flow. Liquidity providers set prices and trade the quantity which clears the market. Since they do not observe individual quantities traded by the informed and the uninformed separately, and do not have any other kind of special information, they set prices based on the observations of the current and past aggregate quantities traded by the informed and uninformed traders combined, known as the order flow.

The literature above demonstrates that trades convey new information that leads to updates in the market's expectation about the fundamental value of an asset. Such a relation has been modelled empirically. Perhaps the most influential model is that of Hasbrouck (1991), who jointly models the data generating processes of prices and trades. He suggests that midquote revisions and trades can be modeled as a vector autoregressive system. Such a model demonstrates the importance of trades for price revisions and depicts the transmission of information that is incorporated into prices.

2.2.4 Asymmetries in Bid and Ask Responses

Hasbrouck (1991) adds to our understanding of price dynamics and on how information from trades gets incorporated into security prices. However, since the quote dynamics are averaged through the quote midpoint, the model assumes that bid and ask prices respond symmetrically to trades. To learn more about price formation processes, we also need to evaluate the asymmetries in the dynamics of bid and ask prices. As discussed in Escribano and Pascual (2006), there is additional information gained from analyzing the dynamics of ask and bid prices jointly rather than averaging them through the quote midpoint.

Several empirical studies have shown that price responses to buyer- and seller-initiated trades may be asymmetric. For example, Jang and Venkatesh (1991) report that, in the NYSE, bid and ask quote revisions after trades are often observed to be asymmetrical. When a trade occurs at the ask (generally classified as a buy) the ask is more likely to be raised than the bid. Biais et al. (1991) shows that asymmetries between ask and bid quotes are not exclusive to the NYSE. Furthermore, the empirical work of Holthausen et al. (1987), Griffiths et al. (2000), Koski and Michaely (2000) suggest that buyer-initiated trades are more informative than seller-initiated trades. Hence, they conclude that the impact of a buyer-initiated trade may not simply be the reverse of the price impact of seller-initiated trade.

Buyer- and seller-initiated trades may not be equally informative for several reasons. First, buy orders are more informative than sell orders because short-selling restrictions may prevent the informed traders from exploiting negative information in the market (Kempf and Korn, 1999). Second, short-sale restrictions also mean that traders can choose among many potential assets to buy, but when they sell, they are limited to those assets they already own. Hence, the choice of a particular stock to buy, out of the numerous possibilities on the market, is likely to be more informationally motivated, while the choice to sell tends to be liquidity motivated (see e.g. Chan and Lakonishok, 1993; Keim and Madhavan, 1995).

Motivated by the evidence above, we propose that in order to further assess how prices are determined in multiple markets, we need to also examine the responses of bid and ask quotes to the arrival of information. In Chapter 5, we look at quote dynamics and assess how various information affects quote revisions in multiple markets. Empirically, we model quote revisions from dual markets simultaneously in a VAR setting. In doing so, we are not only able to analyze any asymmetries in the impacts of trades on the bid or the ask prices from multiple markets, but also analyze the degree of information spillover among these markets. Since the empirical part of this thesis focuses on cross-listed stocks, we will discuss the process of stock selections in the next section.

2.3 The Canadian and the U.S. Markets

In this thesis, we focus on Canadian stocks which are listed on the Toronto Stock Exchange (TSX) and cross-listed on the New York Stock Exchange (NYSE). These stocks are chosen because the nature of cross-listings of Canadian stocks in the U.S. offers several advantages. Before we compare the features of the TSX and the NYSE, we briefly describe the structure of the TSX and important changes that influenced the nature of how trading was conducted in both markets.

The TSX was incorporated in 1878. It had soon grown in size and in shares traded to become the second largest stock exchange in Canada after the Montreal Stock Exchange.[1] In 1977, the TSX introduced CATS (Computer Assisted Trading System), an automated trading system that started to be used for the quotation of less liquid equities. It was one of the first technologies allowing for a full automation of the price-setting process in a stock exchange. Following the success of CATS,

[1]Following the Canadian capital markets restructuring in 1999, the Montreal Stock Exchange became Canada's derivatives exchange while the Toronto Stock Exchange became Canada's sole exchange for the trading of senior equities.

the TSX closed its trading floor in April 1997, making it the second-largest stock exchange in North America to choose a floorless, electronic trading environment. Since then, the TSX operates an entirely electronic market with a centralized limit order book. As per June 2014, the TSX is the eighth largest exchange in the world by market capitalization, and the third largest single group of exchange after the NYSE and NASDAQ. Generally, the blue-chip Canadian firms are listed on both the TSX and NYSE. Among the foreign stocks listed in the United States, Canadian listings constitute the largest group of stocks from a single country.

2.3.1 Alternative Trading Systems, Consolidated Tape, and the Order Protection Rule

There were several important changes that influenced the nature of trading mechanism in the U.S. and Canada, such as the emergence of alternative trading systems (ATSs), the use of consolidated tape, and the Order Protection Rule (OPR). In this section, we explain these changes in both markets and their consequences for trading.

The presence of ATSs means that orders can be executed in various trading venues. For instance, stocks listed on the NYSE can be traded in the NYSE and in various regional exchanges such as the Boston Stock Exchange (BSE), Cincinnati Stock Exchange (CSE) and in an electronic communication network, BATS. In the U.S., ATSs have existed since the 1970s. In Canada, however, ATSs only started to emerge in mid-2007 with the arrival of alternative markets such as PURE trading, ALPHA trading, CHI-X and Omega. This means that the TSX was no longer the sole exchange for the trading of senior securities in Canada.

The development of ATSs emphasized the need to have a market integrator to interconnect data from the new markets. Without a connected data source, each exchange chooses a different data vendor to publish their data. It took a significant amount of time before data vendors had sufficient information from all markets to be able to publish any sort of combined quotations. Hence, there was a need to establish a consolidated quotation system which provides continuous, real-time data on trading volume and price from various exchanges. In the U.S., the consolidated tape system started in 1978, with NASDAQ being the information processor. The system provides its subscribers quotation information for stocks traded on the American Stock Exchange, NYSE, and other regional stock exchanges. In Canada, the Canadian Securities Administrators (CSA) selected the TMX group to fulfill the information processor role in 2009.[2] The consolidated tape functioned for the first time in Canada in mid-2010.

The consolidated tape system, however, would not work well if there was no binding trading rule in place to ensure orders were executed fairly. In the early days of competition, regulators required dealers to achieve the best price in filling client orders. In order to fulfill their best price obligation, a dealer was required to "make reasonable efforts" to achieve the best price. A lack of clarity around what constituted compliance with the rule meant that dealers could carry out orders at a non-optimal price even though a better price was available on the same exchange or other exchanges. This triggered a series of initiatives designed to modernize and strengthen the securities markets. In the U.S., the Securities and Exchange Commission (SEC) passed a set of rules called the Regulation National Market System (Reg. NMS). It was intended to help create a more integrated market through improved fairness in price execution, and to improve the displaying of quotes and access to market data. One of the most influential components of the Reg. NMS is the Order Protection Rule (OPR) which requires that marketplaces enforce policies to ensure consistent price quotation and prevent trading through a better priced order on another market. The OPR was implemented in the U.S. as part of the Reg. NMS which was adopted in stages from 2006 to 2007. In Canada, the OPR was introduced on Feb

[2]The TMX group is the parent company of the TSX.

1, 2011.

2.3.2 Market Features

The Canadian and the U.S. markets have properties which makes them distinctive from other market combinations for multi-market empirical studies. First, Canada and the U.S. markets have a highly integrated nature, which enables easy access for firms to list and also for investors to invest in the other country's exchanges. Many Canadian firms listed on the TSX also cross-list their stocks on the main U.S. exchanges such as the NYSE, NASDAQ, and AMEX. The extent of integration of the exchanges is shown by the fact that many of the cross-listed Canadian firms report their financial statements and pay dividends in US dollars.

Second, the U.S. and Canadian markets have the longest overlapping trading hour compared to any other market pairs. There is no time difference for the opening and closing trading time between TSX and NYSE (09.30am to 04:00pm EST). The importance of this is pointed out by Hupperets and Menkveld (2002), who find increased volume, volatility and spread during the overlapping trading hours that suggest the presence of informed trading, thus indicating differences in price discovery.

Third, as mentioned in Eun and Sabherwal (2003), Canadian securities are listed in the United States as ordinary shares, unlike securities from other countries which are usually listed as American Depositary Receipts (ADRs). The certificate for a Canadian stock traded in the United States is identical to the one traded in Canada, hence, there are no conversion fees. This suggests the U.S. and TSX prices of cross-listed stocks are likely to move more closely to each other than the prices of ADRs from other countries and their home-market securities.

Chapter 3

Macroeconomic News Announcements and Price Discovery[1]

3.1 Introduction

In today's globalized financial markets, financial assets such as stocks, often trade in multiple markets. In the case of cross-listed stocks, intermarket arbitrage should keep the prices in the different markets from drifting apart. When new information arrives it affects the price of the asset in both markets. However, both markets may react to the new information in a different way. This leads to the concept of price discovery, which examines how well these markets process the information and incorporate them into prices. Price discovery becomes particularly important when new information arrives, because this is the time when the information processing capacity of a market is most relevant, and reflects the competitiveness of that particular market.

One important point in time when new information arrives to the market is during the release of macro-economic news. These news announcements provide indications for the near-term policy changes that will subsequently be used by investors to price

[1] This chapter is based on Frijns, B., Indriawan, I., & Tourani-Rad, A. (2015). Macroeconomic News Announcements and Price Discovery: Evidence from Canadian–U.S. Cross-Listed Firms. *Journal of Empirical Finance*, Vol. 32, pp. 35-48.

securities. Since macroeconomic news announcements are pre-scheduled, the timing of such releases is known, and investors may choose to trade on this information in one or another market. This may lead to a temporal shift in price discovery between markets which is related to the arrival of information from macroeconomic news announcements. Although the impact of news announcements on security prices has been studied extensively (see Andersen et al., 2007; Love and Payne, 2008; and Nowak et al., 2011), and studies on price discovery of cross-listed securities are abundant (see Hupperets and Menkveld, 2002; Pascual et al., 2006; Chen and Choi, 2012), studies on the impact of news announcement on price discovery are rare, especially when considering a multi-market setting. However, we can expect a relationship between macroeconomic news announcements and price discovery, because when news gets released, they affect prices in one market which then leads to movements in prices in other markets. In addition, we may expect that the shift in price discovery is driven by the information processsing capacity of a market and should not be affected by the origin of the news (i.e. whether this information is produced in the home or in the foreign market).

In this chapter, we investigate whether information released during scheduled news announcements in one market leads to a shift in price discovery from one market to another. We test this conjecture by comparing the Hasbrouck (1995) Information Share (IS) and Gonzalo and Granger (1995) Permanent-Transitory (PT) decomposition measures during days with scheduled macroeconomic news announcements and days with no announcements. In particular, we assess Canadian stocks traded in Canada and the U.S. In doing so, we consider Canadian as well as U.S. macroeconomic news. Particularly, we examine the extent to which macroeconomic news announcements from either market contribute to the price discovery of Canadian stocks listed in these two markets.

Our work has a number of novel features compared with previous studies. First, our study is the first to analyze the impact of macroeconomic news on price discovery of cross-listed stocks. Second, we assess both Canadian and U.S. macroeconomic news, compared with previous studies which only looked at the impact of announcements in a single market. Third, we examine the relation between price discovery and macroeconomic news announcements over a long period of time, from 2004-2011.

Our analysis leads to several interesting findings. First, we observe that price discovery shifts significantly during macroeconomic news announcements. Second, the U.S. market becomes more dominant in terms of price discovery, regardless of the news country of origin. Third, we examine the relation between price discovery and market microstructure variables. After controlling for liquidity shocks, we find that the impact of news announcements still persists. Intraday analyses of price discovery on periods surrounding news releases further support these findings, particularly during Federal Funds Rate announcements. On the whole, our results suggest that the U.S. market is better at processing information from macroeconomic news announcements.

The remainder of this chapter is as follows. Section 3.2 discusses some of the relevant literature on price discovery of cross-listed stocks and its linkage with macroeconomic news announcements. Section 3.3 describes the framework in deriving the Vector Error Correction Model, as well as the Gonzalo and Granger (1995) permanent-transitory decomposition and Hasbrouck (1995) information share measures. Section 3.4 looks at the selection of sample companies, and macroeconomic news announcements. Section 3.5 reports the empirical findings. Finally, section 3.6 concludes.

3.2 Literature Review

The main objective of this study is to assess whether information from macroeconomic news releases contributes to the price discovery of stocks listed on multiple exchanges. As such, we connect two strands of literature; namely, the price discovery of cross-listed stocks and the impacts of macroeconomic news announcement on security prices. While each of these topics has been studied separately in the literature, the connection between them has received little attention.

Extant studies on price discovery suggest that the home market tends to lead price discovery for cross-listed stocks, and this can be attributed to several market characteristics. For instance, Lieberman, Ben-Zion, and Hauser (1999) investigate the dominant-satellite relation of stocks listed on two international markets, Tel-Aviv and New York. They find that arbitrage opportunities are generally not available and that usually, the domestic market emerges as the dominant one and the foreign market as the satellite one, particularly for international companies with large volume and stock-holding. Eun and Sabherwal (2003) examine price discovery for Canadian stocks that are cross-listed on the NYSE, AMEX, or NASDAQ in the U.S., and find that generally the Canadian market leads in terms of price discovery. They further observe that the U.S. share of price discovery is directly related to the U.S. share of trading, and inversely related to the ratio of bid-ask spreads. Pascual et al. (2006) study the price discovery process of the Spanish stocks listed on the Spanish Stock Exchange and cross-listed on the NYSE. They find that the home market leads in terms of price discovery which is attributable to its own trading activity. Frijns et al. (2010) examine the price discovery of Australian and New Zealand bilaterally cross-listed stocks, and find that in both cases the home market is dominant in terms of price discovery. However, they also observe that as firms grow larger and their cost of trading in Australia declines, the Australian market becomes more informative.

It has further been documented that the arrival of information contributes to the price discovery process between markets. Using volatility as a proxy for information on the Bund futures contract, Martens (1998) shows that during volatile periods, the share of volume in the London International Financial Futures Exchange decreases while the share in price discovery process increases; whereas in quiet periods, the Deutsche Terminbourse share of price discovery increases. Amin and Lee (2010) document that the option market's share of price discovery increases relative to the equity market's share prior to quarterly earnings announcements. This is mainly due to the fact that option traders initiate a greater proportion of long and short positions immediately before the dissemination of earnings news.

In this study, we use macroeconomic news announcements as a proxy for information arrival. Macroeconomic news conveys price-relevant information and its release time is predetermined. Security prices are affected by adjustments in expectations to the changing economic conditions driven by macroeconomic news announcements, such as GDP output, employment and inflation surprises, among others. Studies have shown that macroeconomic news announcements are linked to changes in security prices. Andersen et al. (2003), for instance, list 25 important macroeconomic variables and demonstrate the asset pricing impact (instantaneous response) of macroeconomic announcements on exchange rates. They find that high-frequency exchange rate dynamics are linked to economic fundamentals. A similar reaction is observed by Bernanke and Kuttner (2005) and Boyd et al. (2005) who analyze the stock markets, while Balduzzi et al. (2001) and Fleming and Remolona (1999) analyze the bond market.

Since price discovery concerns the process of how information gets incorporated into prices, changes in prices during macronews announcements could affect the level of price discovery. Indeed, several papers have investigated this link between price discovery and macroeconomic news announcements. For instance, Mizrach and Neely

(2008) examine price discovery in the U.S. Treasury futures market using data at the one minute frequency during macroeconomic announcements in the period from 1997 to 2000. They find weak evidence on the impact of announcements on price discovery. Only in one out of four cases when news is released does the futures market gain in terms of price discovery. They conclude that macroeconomic announcements rarely explain price discovery independently of liquidity. Stronger evidence is provided by Taylor (2011) who observes an increase in information asymmetry and price discovery around the release of key macroeconomic information. He assesses the level of price discovery for S&P 500 index constituents over the period January to December of 2002 at the one minute frequency. He finds that the E-mini futures market becomes more dominant during conditions of high liquidity and extreme information asymmetry, i.e. during macroeconomic news releases. Phylaktis and Chen (2010) investigate price discovery of the foreign exchange market during macroeconomic news announcements. They estimate price discovery over time for major trading banks in the U.K. and U.S. markets over the period January 1994 to December 1998. They find that the top 10 trading banks' information advantage becomes prevalent, and their contribution to price discovery increases during scheduled macroeconomic news.

Existing studies are limited to several asset classes, suchs as foreign exchange rates, index funds, and Treasury futures. However, one can also expect a strong relationship between stock prices and macroeconomic news because businesses are concerned about inflation, industrial production, and the unemployment rate which is conveyed in macroeconomic variables (McQueen and Roley, 1993). Existing studies are limited to a single market context, while in reality, news affect prices of stocks listed in multiple markets. These points combined, provide an opportunity to investigate how macroeconomic news announcements contribute to price discovery of cross-listed stocks.

3.3 Methodology

In this section, we first propose a model of stock price dynamics of cross-listed stocks which builds on a vector error-correction. Subsequently, we compute Gonzalo and Granger (1995) permanent-transitory decomposition and Hasbrouck (1995) information share to measure price discovery.

3.3.1 Error-Correction Model

The study of price discovery relies on the assumption that when a single security trades in two different markets, prices in the two markets share a common efficient price, p_t. Since prices in both markets are driven by the same underlying fundamentals, the prices should be cointegrated. Therefore, the two $I(1)$ observed transaction price series $y_{1,t}$ and $y_{2,t}$ are cointegrated with cointegrating vector, $\beta' = (1\ \text{-}1)$. Subsequently, $\beta' y_t = y_{1,t} - y_{2,t}$, is a stationary process known as the error-correction term. The Engle-Granger Representation Theorem states that a cointegrated system can be expressed as an error-correction model of the following form,

$$\Delta y_t = c + \alpha\beta' y_{t-1} + \sum_{i=1}^{N} \Gamma_i \Delta y_{t-i} + \epsilon_t, \tag{3.1}$$

where Δy_t is the (2×1) vector of log returns, c is a vector of constants, α is a (2×1) vector that measures the speed of adjustment to the error-correction term (i.e. $\alpha = \binom{\alpha^{US}}{\alpha^{CAN}}$), Γ_i are (2×2) matrices of AR coefficients, and ϵ_t is a (2×1) vector of innovations. The VECM has two parts: the first part, $\beta' y_{t-1}$, represents the long-run equilibrium between the price series. The second part, $\sum_{i=1}^{N} \Gamma_i \Delta y_{t-i}$, represents the short-term dynamics induced by market imperfections.

The VECM has been used extensively to study price discovery of a security traded in multiple markets. For example, Hasbrouck (1995) uses the VECM to estimate price discovery of stocks traded on the NYSE and U.S. regional exchanges. Werner and

Kleidon (1996) analyze market integration of British stocks cross-listed in the U.K. and U.S. markets. Huang (2002) studies the price discovery of quotes in NASDAQ market submitted by the electronic communication networks (ECNs) and by traditional market makers. Pascual et al. (2006) investigate the price discovery process of Spanish cross-listed stocks in the NYSE during the daily (two-hour) overlapping interval.

3.3.2 Price Discovery Measures

In this chapter, we use the VECM to compute the price discovery measures of Canadian stocks cross-listed in the U.S. We follow two approaches: the Gonzalo Granger (1995) permanent-transitory (PT) decomposition, and the Hasbrouck (1995) information share (IS) measures. They are directly related and the results of both models are primarily derived from the VECM.[2]

Gonzalo Granger (1995) Permanent-Transitory (PT) Decomposition

The PT measure is concerned with the permanent shocks that result in a disequilibrium as markets process news at different speeds. The PT measures each market's contribution to the common factor, where the contribution is defined to be a function of the market's error correction coefficients; in this case, the speed of adjustment coefficients, α. When a market dominates in terms of price discovery, its value of α will be small, indicating that this market does not correct in response to any differences in prices between markets. Conversely, when a market is a satellite market, its value of α will be large in absolute terms relative to the dominant market, indicating strong adjustment to price differences. If neither market is completely dominant,

[2] Baillie et al. (2002) explain that PT and IS provide similar results if the VECM residuals are uncorrelated. However, if substantial correlation exists, the two measures usually yield different results. While the PT measure is not affected by contemporaneous correlation in the residuals, the IS model is. Therefore it needs to be handled using Cholesky factorization, which requires that the prices be ordered. This makes the IS results to be variable order dependent and Hasbrouck (1995) suggests that different orders be used in order to calculate the upper and lower IS bounds before they are averaged to arrive at a final IS result.

the magnitude of α will indicate the relative dominance between the two. The PT can be computed using the following measure,

$$PT^{US} = \frac{\alpha^{CAN}}{\alpha^{CAN} + |\alpha^{US}|}, \tag{3.2}$$

where α^{US} is negative, and α^{CAN} is positive given our β definition of (1 -1)$'$. This ratio gives an indication of the degree of dominance of one market over the other. A higher value of this ratio reflects a greater feedback or contribution from the US. Therefore, a PT^{US} of zero would imply that the NYSE does not contribute to the price discovery of the stocks, whereas a PT^{US} greater than zero would imply feedback from the NYSE to the TSX.

Hasbrouck (1995) Information Share

Hasbrouck proposes an alternative measure for price discovery – the information share (IS). It measures the proportion of variance contributed by one market with respect to the variance of the innovations in the common efficient price. To assess this, note that we can rewrite Equation (3.1) as a vector moving average (Wold representation):

$$\Delta y_t = \Psi(L)e_t, \tag{3.3}$$

where $\Psi(L)$ is a matrix polynomial in the lag operator ($\Psi(L) = 1 + \psi_1 L + \psi_2 L^2 + \psi_3 L^3 + ...$). Following the Beveridge and Nelson (1981) decomposition, which states that every (matrix) polynomial has permanent and transitory structure, we can write Equation (3.3) in its integrated form as:

$$y_t = \Psi(1) \sum_{s=1}^{t} e_s + \Psi^*(L)e_t. \tag{3.4}$$

where $\Psi(1)$ is the sum of all moving average coefficients, and measures the long-run impact of an innovation to the level of prices. Since prices are cointegrated, $\beta' y_t$ is a stationary process, this implies that $\beta'\Psi(1) = 0$, i.e. the long-run impact is the same for all prices. If we denote $\psi = (\psi_1 \psi_2)$ as the common row vector in $\Psi(1)$, Equation (3.4) becomes:

$$y_t = \iota\psi \left(\sum_{s=1}^{t} e_s \right) + \Psi^*(L)e_t. \tag{3.5}$$

Hasbrouck (1995) states that the increment ψe_t in Equation (3.5) is the component of price change that is permanently impounded into the price and is presumably due to new information and decomposes the variance of the common factor innovations, i.e., $var(\psi e_t) = \psi\Omega\psi'$. The information share of a market is defined as the proportion of variance in the common factor that is attributable to innovations in that market. Since Hasbrouck (1995) uses the Cholesky factorization of $\Omega = MM'$ to handle contemporaneous correlation, where M is a lower triangular matrix, the information share of market i is represented as:

$$S_i = \frac{([\psi M]_i)^2}{\psi\Omega\psi'}. \tag{3.6}$$

We compute $\Psi(1)$ in Equation (3.5) by calculating the product of the orthogonal matrices of $\beta_\perp$ and $\alpha_\perp$ (see Baillie et al., 2002),

$$\begin{aligned} \Psi(1) &= \beta_\perp \Pi \alpha'_\perp, \\ \Pi &= (\alpha'_\perp (I - \sum_{j=1}^{k} A_j)\beta_\perp)^{-1}, \end{aligned} \tag{3.7}$$

where I is a (2×2) identity matrix, and Π is a scalar if there is only one common factor in the system. Since $\beta = (1\ \text{-}1)'$, we know that $\beta_\perp = (1\ 1)'$. Therefore,

$$\Psi(1) = \begin{bmatrix} \psi \\ \psi \end{bmatrix} = \Pi \begin{bmatrix} \gamma_1 & \gamma_2 \\ \gamma_1 & \gamma_2 \end{bmatrix} \tag{3.8}$$

Where γ_1 and γ_2 are the elements of $\alpha'_\perp$. The lower triangular matrix, M given by Cholesky factorization of Ω in Equation (3.6) can be expressed as:

$$M = \begin{bmatrix} m_{11} & 0 \\ m_{12} & m_{22} \end{bmatrix} = \begin{bmatrix} \sigma_1 & 0 \\ \rho\sigma_2 & \sigma_2(1-\rho^2)^{1/2} \end{bmatrix} \tag{3.9}$$

Using Equation (3.5), (3.8), and (3.9) we can rewrite the information share as:

$$\begin{aligned} S_1 &= \frac{(\gamma_1 m_{11} + \gamma_2 m_{12})^2}{(\gamma_1 m_{11} + \gamma_2 m_{12})^2 + (\gamma_2 m_{22})^2}, \\ S_2 &= \frac{(\gamma_2 m_{22})^2}{(\gamma_1 m_{11} + \gamma_2 m_{12})^2 + (\gamma_2 m_{22})^2}, \end{aligned} \tag{3.10}$$

where S_1 denotes the upper bound of the information share of market 1 and S_2 the lower bound of market 2. To get the lower bound for market 1 and the upper bound for market 2, we reverse the order of $\Psi(1)$ and M and recompute Equation (3.10). Subsequently, we compute the midpoints to obtain the IS value as suggested by Baillie et al. (2002).

3.4 Data Sources

3.4.1 Intraday Stock Returns Data

We collect data for 38 Canadian stocks which are traded on the TSX and the NYSE for the period January 1, 2004 to January 31, 2011 (1,727 trading days). For the U.S. market, we use the national best bid and ask quotes for stocks with the NYSE as primary listings and for the Canadian market, we use quotes posted at the TSX. The end of the sample is chosen to avoid confounding effects from the new Order Protection Rule in Canada which became effective on February 1, 2011 (see Clark, 2011). The stocks in our sample are simultaneously traded cross-listed pairs through the sample period. Data are collected from the Thomson Reuters Tick History (TRTH) database maintained by SIRCA.[3] We obtain intraday quotes sampled at a one-second frequency.[4] Since sometimes trading in one of the markets starts later than 9:30:00, we risk having missing data. Therefore, we omit the first five minutes of the trading day. This leaves us to 23,100 observations per trading day per company. Following Grammig et al. (2005), we use midpoints of quotes to study price discovery as these are less affected by the bid-ask bounce that is normally observed in transaction prices. We also obtain intraday Canadian - U.S. Dollar exchange rate quotes from TRTH and use the midpoint to convert prices into a common currency to facilitate the specification of the error-term and ensure the comparability of prices between the two markets, similar to Eun and Sabherwal (2003) and Chen and Choi (2012). Hence, our analyses in this chapter are based on the quote price series for each firm in the same currency, the U.S. dollar.[5]

Table 3.1 contains descriptive statistics for our sample consisting of 38 firms. We report the market capitalization, average daily trade, and average percentage bid-ask spread for each stock in both the U.S. and Canada. We also include the trading and spread ratio of the U.S. market relative to the Canadian market. Our sample covers a broad set of firms with market capitalization ranging from $558 million to

[3] Securities Industry Research Centre of Asia-Pacific.

[4] Fleming and Remolona (1999) indicate that more powerful tests of market efficiency can be carried out only by using intraday observations of financial asset prices. Eun and Sabherwal (2003) use quotes at 10-minute interval to assess price discovery in their study from February to July 1998, while 1-minute interval is employed in Chen and Choi (2012) in their study from January 1998 to December 2000. Riordan and Storkenmaier (2012) uses milisecond frequency to capture price discovery in their 2007 study, albeit their sample are the most actively traded companies making up the German main indexes. With these considerations, we postulate 1-second interval as the optimal sampling frequency.

[5] We also conducted the analysis in Canadian dollars and found no significant difference in results.

$66 billion. It covers the less liquid stock such as Kingsway Financial Services with average daily U.S. trades of 158 trades to a more liquid stock such as Barrick Gold with average daily trades of 33,331 trades, with a sample average of 7,110 trades. In Canada, the daily number of trades ranges from a minimum of 108 trades for MI Developments Inc. to a maximum of 10,213 trades for Suncor Energy, with a sample average of 4,179 trades. The trading ratio suggests that trading intensity is higher in the U.S. than in Canada as shown by a ratio of 63%. The highest trading ratio in the U.S. is Brookfield Office with 84% while the minimum is reported by TransAlta Corp with 11%. The average daily percentage spread in both markets is 0.12%, and the average spread ratio for the U.S. market as a proportion to the Canadian market is 50%, suggesting that the cost of trading, on average, is about the same in the U.S. and Canada.

We conduct the usual procedures of unit root and cointegration tests before estimating the PT and IS measures. To test for non-stationarity, we perform Augmented-Dickey Fuller tests using Akaike Information Criterion (AIC) to select optimal lag length. For all stocks, we cannot reject the presence of a unit root. Subsequently, we conduct Johansen's (1988) test for cointegration. In all tests, we reject the null of no cointegration in favour of the alternative of one cointegrating vector. Since the price series in our sample satisfy both conditions, we conclude that each pair of our sample stocks is cointegrated.

3.4.2 Macroeconomic News Announcements

Table 3.2 lists the names, sources, time of release and the frequency of all the macroeconomic news announcements considered in this study. We obtain the date, time and the actual figures for the macroeconomic news announcements from their respective websites as listed in the Appendix. For the Canadian market, we select 10 Canadian macroeconomic news releases (in line with studies such as Gravelle and Moessner, 2001; Doukas and Switzer, 2004). Real GDP, Capacity Utilization Rate,

Table 3.1: Sample of Canadian firms listed in Canada and the U.S.

This table provides a summary statistics of the 38 stocks in our sample. It reports the Market capitalization, the average daily trade, and the average percentage spread in the U.S. and Canada. Also reported are the trading ratio and the spread ratio of the U.S. market relative to the Canadian market.

	January 2004 - January 2011		Market Cap	Average Daily Trade			Average %Spread		
No.	Company	Symbol	($mil)	US	CAN	US/(US+CAN)	US	CAN	US/(US+CAN)
1	Agnico-Eagle Mines Limited	AEM	7,122	12,197	3,543	77%	0.07%	0.10%	41%
2	Agrium Inc.	AGU	8,784	11,923	4,180	74%	0.07%	0.10%	43%
3	Bank of Montreal	BMO	31,497	2,195	5,578	28%	0.09%	0.05%	63%
4	Bank of Nova Scotia	BNS	49,846	1,886	6,456	23%	0.09%	0.05%	65%
5	Barrick Gold	ABX	34,904	33,331	9,682	77%	0.04%	0.06%	43%
6	BCE Inc.	BCE	27,213	3,347	5,823	36%	0.07%	0.05%	56%
7	Brookfield Office	BPO	7,793	7,738	1,470	84%	0.10%	0.14%	41%
8	Cameco Corp.	CCJ	11,372	9,971	4,703	68%	0.08%	0.09%	49%
9	Canadian Imperial Bank Communication	CM	27,844	1,679	4,637	27%	0.10%	0.05%	65%
10	Canadian National Railway Company	CNI	27,396	6,165	4,264	59%	0.06%	0.06%	49%
11	Canadian Natural Resources Ltd.	CNQ	34,037	11,492	7,157	62%	0.06%	0.06%	49%
12	Canadian Pacific	CP	9,967	3,115	2,594	55%	0.08%	0.08%	50%
13	Celestica Inc.	CLS	1,826	3,734	1,588	70%	0.14%	0.16%	47%
14	CGI Group	GIB	3,738	581	1,479	28%	0.25%	0.17%	59%
15	COTT Corp.	COT	889	1,737	679	72%	0.28%	0.37%	43%
16	Enbridge Inc.	ENB	19,012	1,405	2,599	35%	0.10%	0.08%	55%
17	Encana Corp.	ECA	31,810	13,930	8,092	63%	0.05%	0.05%	48%
18	Enerplus Corp.	ERF	4,834	2,640	1,380	66%	0.11%	0.13%	45%
19	Gildan Activewear Inc.	GIL	3,060	2,987	1,436	68%	0.14%	0.16%	47%
20	Goldcorp Inc.	GG	24,539	30,137	9,517	76%	0.05%	0.07%	42%
21	Kingsway Financial Services Inc.	KFS	558	158	409	28%	0.49%	0.36%	58%
22	Kinross Gold Corp.	KGC	10,759	19,549	7,345	73%	0.11%	0.11%	50%
23	Manulife Financial Corp.	MFC	40,305	7,026	7,590	48%	0.06%	0.06%	52%
24	MI Developments Inc.	MIM	1,385	317	108	75%	0.21%	0.36%	37%
25	Nexen Inc.	NXY	12,615	8,974	5,645	61%	0.09%	0.09%	51%
26	Pengrowth Energy Corp.	PGH	3,156	3,081	1,250	71%	0.13%	0.17%	43%
27	Potash Corporation of Saskatchewan Inc.	POT	28,774	26,273	5,374	83%	0.05%	0.07%	42%
28	Precision Drilling Trust	PDS	2,307	3,980	1,936	67%	0.13%	0.13%	49%
29	Ritchie Brothers Auctioneers	RBA	2,262	1,252	281	82%	0.16%	0.36%	30%
30	Rogers Communication Inc.	RCI	16,220	2,016	3,980	34%	0.12%	0.09%	57%
31	Royal Bank of Canada	RY	66,555	3,849	8,094	32%	0.07%	0.05%	60%
32	Shaw Communications Inc.	SJR	7,803	945	2,011	32%	0.14%	0.12%	54%
33	Sun Life Financial	SLF	20,867	2,074	3,958	34%	0.10%	0.07%	57%
34	Suncor Energy Incorporated	SU	42,305	22,901	10,213	69%	0.05%	0.06%	48%
35	Talisman Energy Inc.	TLM	17,131	12,566	6,478	66%	0.08%	0.08%	49%
36	Toronto-Dominion Bank	TD	52,833	4,437	7,027	39%	0.07%	0.05%	59%
37	TransAlta Corp.	TAC	4,865	205	1,654	11%	0.20%	0.11%	64%
38	TransCanada Corp.	TRP	23,358	1,449	3,615	29%	0.08%	0.06%	58%
	Mean			7,454	4,311	63%	0.12%	0.12%	49%

and Current Account Balance are announced quarterly, Interest Rates are released every 6 weeks, while the rest are released monthly. As for the U.S. announcements, given the large number of data releases, we restrict our sample to the most relevant 22 items. This is in line with the literature in this area (see e.g. Balduzzi et al., 2001; Andersen et al., 2003, 2007). From these major announcements, the GDP related announcements are released quarterly, Fed Funds Rate is released every 6 weeks, and all the remaining announcements are released monthly.

3.5 Results

In this section, we present the results for the models proposed in Section 3.3. We divide our analyses into two subsections. The first subsection concerns the change in daily level of price discovery caused by macroeconomic news announcements. Specifically, we compute the IS and PT for stocks during announcement and non-announcement days over the sample periods. Then, we measure the difference between the two sets. We examine the absolute changes in price discovery as well as the directional changes. We further conduct a regression analysis and control for the possible impact of liquidity during announcement times. The second subsection concerns the change in intraday price discovery during announcement times. Using smaller intraday event windows on periods surrounding the announcements, we implement similar tests to the first subsection. These tests assess the impact of macroeconomic news announcements on price discovery, the direction of the news impact, the types of news (domestic vs foreign news), as well as the accuracy of the time and model specifications.

Table 3.2: Macroeconomic news releases (January 2004 - January 2011)

This table provides a summary of the macroeconomic news announcements used in the study, the total number of releases (Obs.), sources, the time of release using Eastern Standard Time (EST), and the frequency of releases. * indicates that U.S. Personal Income and U.S. Personal Consumption Expenditures have the same release dates. ** indicates that U.S. Business Inventories release times varies from 8:30am and 10:00am. *** indicates that U.S. Industrial Production and U.S. Capacity Utilization have the same release dates. Total U.S. and Canada announcements are adjusted for overlapping days.

No	Macroeconomic Announcement	Obs	Source	EST	Frequency
	CAN Announcements				
1	Real GDP	28	CANSIM	8:30	Quarterly
2	Capacity Utilization Rate	28	CANSIM	8:30	Quarterly
3	Current Account Balance	28	CANSIM	8:30	Quarterly
4	CPI	85	CANSIM	7:00	Monthly
5	Industrial Product Price	86	CANSIM	8:30	Monthly
6	Unemployment Rate	85	CANSIM	7:00	Monthly
7	Retail Sales	85	CANSIM	8:30	Monthly
8	Leading Indicators Index	85	CANSIM	8:30	Monthly
9	Housing Starts	57	CMHC	8:15	Monthly
10	Interest Rate	85	BoC	9:00	6-Week
	US Announcements				
11	GDP Advance	29	BEA	8:30	Quarterly
12	GDP Preliminary	28	BEA	8:30	Quarterly
13	GDP Final	28	BEA	8:30	Quarterly
14	Personal Income, Personal Consumption Expenditures*	85	BEA	8:30	Monthly
15	Trade Balance	85	BEA	8:30	Monthly
16	Nonfarm Payroll Employment	85	BLS	8:30	Monthly
17	PPI	85	BLS	8:30	Monthly
18	CPI	85	BLS	8:30	Monthly
19	Retail Sales	85	BC	8:30	Monthly
20	New Home Sales	85	BC	10:00	Monthly
21	Durable Goods Orders	85	BC	8:30	Monthly
22	Factory Orders	85	BC	10:00	Monthly
23	Business Inventories**	85	BC	8:30/10:00	Monthly
24	Construction Spending	85	BC	10:00	Monthly
25	Housing Starts	85	BC	8:30	Monthly
26	Consumer Confidence Index	85	CB	10:00	Monthly
27	Chicago PMI	85	CB	9:45	Monthly
28	Leading Indicators Index	85	CB	10:00	Monthly
29	Industrial Production, Capacity Utilization***	85	FRB	9:15	Monthly
30	Consumer Credit	85	FRB	15:00	Monthly
31	Government Budget	86	FMS	14:00	Monthly
32	Federal Funds Rate	57	FRB	14:15	6-Week
	Total US and Canada Announcements (adjusted)	1297			
	Total Non-Announcement Days	430			
	Total Sample Days	1727			

CANSIM = Statistics Canada
CMHC = Canada Mortgage and Housing Corporation
BoC = Bank of Canada
BES = Bureau of Economic Analysis
BLS = Bureau of Labour Statistics
BC = Bureau of the Census
CB = Conference Board
FRB = Federal Reserve Bank
FMS = Financial Management Service

3.5.1 Daily Price Discovery during Announcement and Non-Announcement Days

To illustrate the importance of macroeconomic news announcements in understanding the price discovery mechanism, we consider the relation between announcement vs non-announcement days and the price discovery measures of the stocks. We compute IS and PT daily. The VECM of Equation (3.1) is estimated by Ordinary Least Squares with optimal lag length suggested by AIC. We differentiate between the IS and PT on non-announcement days and specific announcement days. The difference in IS and PT indicates market reactions to price discovery imposed by news releases. We report the percentage change in IS and PT. Significance tests are based on t-statistics which are computed using paired-difference test, and controlled for possible heteroskedasticity using a Newey-West correction.

Absolute Difference Test

Price discovery may shift in either direction for stocks listed in multiple markets, especially when news may originate from either market. Therefore, the relative impact of news on price discovery is not obvious. As discussed in Eun and Sabherwal (2003), the TSX, as the home market stock exchange, is likely to contribute substantially to price discovery as it is in the security's home market where substantial information is expected to be produced. However, the dominance of the U.S. stock exchanges as among the largest and most liquid exchanges in the world also suggests that they are likely to contribute significantly to price discovery. Such conflicting arguments do not provide us with a clear prior hypothesis on the directional impact of news announcements. Therefore, we may observe price discovery shifts in either directions.

Table 3.3 reports the difference in price discovery between non-announcement and announcement days for the period January 2004 to January 2011. The figures re-

Table 3.3: Absolute change in price discovery during announcement days

This table provides the change in IS and PT for 38 Canadian cross-listed stocks during announcement days. The IS and PT are computed of daily averages, reported as the absolute percentage difference between IS and PT during announcement and non-announcement days, $\frac{|(IS(PT)_{Announcement} - IS(PT)_{Non-Announcement})|}{IS(PT)_{Non-Announcement}}$. The figures under "Total" denote the number of firms (out of 38 firms) showing significant shift in Price Discovery during announcement times at 5% significance level obtained using the bootstrap procedure. Figures in parentheses are the t-statistics. *** denotes significance at 1% level.

January 2004 - January 2011		Panel A: Information Share (IS)			Panel B: Component Share (PT)		
Price Discovery	**Time**	**Diff**	**t-stat**	**Total**	**Diff**	**t-stat**	**Total**
ALL Announcements		3.1%***	(17.1)	36.7	2.6%***	(18.73)	36.8
CAN Announcements		3.4%***	(8.94)	36.7	2.8%***	(9.87)	36.7
US Announcements		3.0%***	(14.91)	36.7	2.5%***	(16.15)	36.8
CAN Announcement							
CPI	7:00	2.9%***	(8.59)	35	2.5%***	(8.6)	36
Labour Force Survey	7:00	3.2%***	(12.76)	36	2.3%***	(11.25)	38
Housing Starts	8:15	2.2%***	(7.34)	35	1.8%***	(8.63)	36
Real GDP	8:30	4.5%***	(8.95)	38	3.6%***	(7.98)	36
Capacity Utilization Rate	8:30	6.0%***	(9.6)	38	4.4%***	(10.57)	38
Current Account Balance	8:30	4.2%***	(7.14)	36	3.6%***	(6.46)	37
Industrial Price Index	8:30	2.0%***	(10.54)	37	1.7%***	(8.63)	37
Retail Sales	8:30	3.7%***	(10.49)	38	3.4%***	(10.93)	36
Leading Indicators Index	8:30	2.8%***	(10.45)	37	2.3%***	(9.1)	36
Interest Rate	9:00	2.7%***	(6.44)	37	2.3%***	(6.88)	37
US Announcement							
GDP Advance	8:30	5.7%***	(8.09)	38	4.1%***	(7.09)	36
GDP Preliminary	8:30	3.9%***	(6.47)	34	3.4%***	(7.33)	38
GDP Final	8:30	3.7%***	(7.66)	37	3.4%***	(7.86)	36
Personal Income	8:30	2.6%***	(7.51)	38	1.7%***	(7.31)	37
Trade Balance	8:30	2.7%***	(8.48)	36	2.4%***	(8.96)	37
Nonfarm Payroll Employment	8:30	2.0%***	(7.13)	36	2.0%***	(8.44)	38
PPI	8:30	1.8%***	(6.62)	36	1.6%***	(7.17)	36
CPI	8:30	3.2%***	(7.17)	38	2.5%***	(7.58)	37
Retail Sales	8:30	1.8%***	(8.12)	36	1.6%***	(8.67)	37
Durable Goods Orders	8:30	2.8%***	(8.25)	36	2.1%***	(9.15)	36
Housing Starts	8:30	3.7%***	(9.54)	37	3.0%***	(11.94)	37
Industrial Production	9:15	3.7%***	(8.47)	38	2.9%***	(8.52)	37
Chicago PMI	9:45	2.5%***	(6.86)	38	2.0%***	(6.39)	34
New Home Sales	10:00	2.9%***	(8.35)	36	2.4%***	(7.58)	37
Factory Orders	10:00	2.2%***	(7.23)	38	1.8%***	(6.75)	35
Business Inventories	10:00	1.8%***	(10.2)	35	1.6%***	(8.39)	37
Construction Spending	10:00	4.3%***	(10.62)	38	3.8%***	(11.43)	38
Consumer Confidence Index	10:00	2.8%***	(6.33)	36	2.2%***	(6.72)	38
Leading Indicators Index	10:00	2.7%***	(8.04)	37	2.6%***	(9.84)	37
Government Budget	14:00	3.2%***	(7.82)	37	2.8%***	(9.16)	37
Federal Funds Rate	14:15	2.9%***	(9.52)	36	2.3%***	(9.01)	36
Consumer Credit	15:00	2.41%***	(9.82)	36	2.0%***	(9.75)	38

ported are the absolute percentage differences in IS and PT and their corresponding t-statistics. It also reports the number of firms which significantly cause shifts in

IS and PT.[6] On aggregate, macroeconomic news announcements cause a 3.1% shift in IS, and a 2.6% shift in PT, respectively. Canadian announcements contribute to 3.4% (2.8%) shifts in IS (PT), while U.S. announcements lead to 3.0% (2.5%) shifts. On average, more than 95% from a total of 38 firms in our sample react significantly to macroeconomic news announcements, causing significant shifts in both IS and PT.

Looking at individual announcements, we find significant shifts in price discovery during all announcements. The number of firms which show significant reactions is also very high. These results strongly suggest that macroeconomic news announcements affect the level of price discovery between Canada and the U.S.

Directional Difference Test

We examine the directional impact of news announcements on price discovery by computing the percentage difference in IS and PT during days with a specific announcement and non-announcement days. Table 3.4 reports the differences in price discovery during various announcement days and their corresponding t-statistics. It also reports the number of firms with significant reduction and increase in the IS and PT measures.

Panel A in Table 3.4 presents the changes in U.S. IS during the different announcement days. We observe that price discovery mainly shifts to the U.S. during days with macroeconomic news announcements. On average, macroeconomic news announcements cause a significant 1.1% increase in the U.S. IS, at 1% level significance, with an average of 24.3 firms significantly showing increases in IS and 12.3 firms show decreases. Canadian announcements contribute to a significant 1.5% increase in IS, and the U.S. announcements contribute to a 0.9% increase.

[6] We use Li and Maddala's (1997) stationary bootstrap method to resample the residuals. We first estimate the VECM model of Equation (3.1). The estimated parameters and residuals are stored. The resampled residuals are then inserted back into the VECM. The VECM is-re-estimated and the new IS and PT recalculated. We repeat the process 200 times.

Table 3.4: Change in price discovery during announcement days

This table provides the change in U.S. IS and PT for 38 Canadian cross-listed stocks during announcement days. The IS and PT are computed of daily averages, reported as the percentage difference between IS and PT during announcement and non-announcement days, $\frac{(IS(PT)_{Announcement} - IS(PT)_{Non-Announcement})}{IS(PT)_{Non-Announcement}}$. The figures under "-"("+") denote the number of firms (out of 38 firms) showing a decrease (increase) in U.S. Price Discovery during announcement times at 5% significance level obtained using the bootstrap procedure. Figures in parentheses are the t-statistics. *, **, and *** denotes significance at 10%, 5%, and 1% level, respectively.

January 2004 - January 2011		Panel A: Information Share (IS)				Panel B: Component Share (PT)			
US Price Discovery	**Time**	**Diff**	**t-stat**	**-**	**+**	**Diff**	**t-stat**	**-**	**+**
ALL Announcements		1.1%***	(3.45)	12.3	24.3	1.0%***	(3.73)	11.5	25.2
CAN Announcements		1.5%***	(2.39)	11.4	25.3	1.1%**	(2.16)	10.9	25.8
US Announcements		0.9%***	(2.49)	12.8	23.9	0.9%***	(2.97)	11.8	25.0
CAN Announcement									
CPI	7:00	2.4%***	(5.53)	5	30	1.9%***	(5.05)	6	30
Labour Force Survey	7:00	2.8%***	(7.78)	2	34	2.1%***	(7.86)	4	34
Housing Starts	8:15	0.5%	(1.17)	14	21	0.6%*	(1.66)	14	22
Real GDP	8:30	0.3%	(0.31)	17	21	0.0%	(-0.05)	16	20
Capacity Utilization Rate	8:30	4.7%***	(5.37)	6	32	3.6%***	(6.07)	4	34
Current Account Balance	8:30	-1.6%*	(-1.91)	22	14	-1.8%***	(-2.45)	21	16
Industrial Price Index	8:30	-0.3%	(-0.86)	21	16	0.0%	(-0.06)	20	17
Retail Sales	8:30	3.7%***	(10.11)	2	36	3.3%***	(9.92)	1	35
Leading Indicators Index	8:30	1.7%***	(3.92)	9	28	1.6%***	(4.31)	9	27
Interest Rate	9:00	0.5%	(0.87)	16	21	0.2%	(0.5)	14	23
US Announcement									
GDP Advance	8:30	-1.8%	(-1.56)	24	14	-1.6%*	(-1.83)	21	15
GDP Preliminary	8:30	0.4%	(0.48)	14	20	0.3%	(0.44)	18	20
GDP Final	8:30	1.0%	(1.33)	11	26	1.8%***	(2.76)	8	28
Personal Income	8:30	-2.2%***	(-5.26)	28	10	-1.3%***	(-4.68)	29	8
Trade Balance	8:30	1.7%***	(3.58)	6	30	1.8%***	(4.83)	4	33
Nonfarm Payroll Employment	8:30	1.4%***	(3.69)	8	28	1.7%***	(5.8)	7	31
PPI	8:30	0.5%	(1.23)	13	23	1.0%***	(3.31)	9	27
CPI	8:30	2.8%***	(5.33)	4	34	2.0%***	(4.89)	6	31
Retail Sales	8:30	0.4%	(1.06)	17	19	0.6%*	(1.95)	14	23
Durable Goods Orders	8:30	-1.0%*	(-1.76)	24	12	-0.8%**	(-2.12)	22	14
Housing Starts	8:30	3.2%***	(6.31)	3	34	2.6%***	(7.29)	4	33
Industrial Production	9:15	2.8%***	(4.8)	6	32	2.5%***	(5.9)	5	32
Chicago PMI	9:45	2.0%***	(4.63)	6	32	1.7%***	(4.68)	4	30
New Home Sales	10:00	2.0%***	(4.24)	6	30	2.0%***	(5.23)	6	31
Factory Orders	10:00	0.4%	(0.88)	18	20	0.4%	(0.92)	16	19
Business Inventories	10:00	0.5%	(1.64)	14	21	0.8%***	(2.75)	12	25
Construction Spending	10:00	-3.4%***	(-5.73)	32	6	-3.1%***	(-6.45)	33	5
Consumer Confidence Index	10:00	1.4%***	(2.42)	12	24	1.2%***	(2.63)	13	25
Leading Indicators Index	10:00	2.3%***	(5.74)	6	31	2.3%***	(6.85)	4	33
Government Budget	14:00	2.7%***	(5.43)	9	28	2.6%***	(7.28)	5	32
Federal Funds Rate	14:15	1.5%***	(2.81)	10	26	1.3%***	(3.32)	9	27
Consumer Credit	15:00	1.3%***	(3.19)	10	26	0.9%***	(2.56)	11	27

When we break down the different Canadian announcements, we find that five macroeconomic announcements: Consumer Price Index, Labour Force Survey, Capacity Utilization Rate, Retail Sales and Leading Indicator Index significantly increase the U.S. IS (decrease Canada IS). This is reflected in the number of firms which significantly increase the U.S. IS as opposed to those which reduce it, as reported in the third and fourth columns of Panel A. For example, the increase in IS during Consumer Price Index announcements is caused by 30 of the firms in our sample showing significant increase in IS whereas only 5 firms show significant decrease. Some of the largest increase in IS are during Canada Capacity Utilization Rate announcements with 4.7%, followed by Retail Sales announcements with 3.7%, and Labour Force Survey with 2.8%. This may indicate that these announcements lead to more concentrated and intensive reaction from U.S. market players. Canada Interest Rates announcements do not appear to be significant. One possible explanation may be the relative ease of predictability of the statistics by the market players, since there has not been a sufficient degree of divergence between Canadian and U.S. business cycles after the Bank of Canada began efforts to improve its monetary policy transparency in the early to mid-1990s.

As for the U.S. announcements, we observe that a large number of announcements significantly increase the U.S. IS. The Fed Funds Rate announcements, as one of the key macroeconomic variables, appear to lead to a significant increase in IS. Forward looking macroeconomic announcements such as Consumer Confidence Index, Chicago PMI, and Leading Indicator Index also report significant increase in IS. Housing Starts reports, which are used by analysts to help create estimates for other consumer-based indicators, is also significant. Another important macroeconomic variable is the Trade Balance. It has been documented that small open economies are affected by international economic developments, especially by large countries with which they have important relationships in international trade.[7] Therefore, it is not surprising if an open economy like Canada with a strong trade and capital market links with the United States is affected by developments in the U.S. economy.

[7] Campbell and Lewis (1998) show that Australian fixed-income markets are significantly affected by U.S. macroeconomic news.

Panel B of Table 3.4 reports the PT results. They are very similar to those of the IS results in Panel A. The correlation coefficient between the IS and PT measures is 0.978, which confirms our earlier finding. On average, macroeconomic announcements cause a significant 1.0% increase in PT, with a 1.1% increase contributed by the Canadian announcements and 0.9% increase by the U.S. announcements. Overall, price discovery shifts to the U.S. during macroeconomic news announcements. To further assess the robustness of our results, we conduct a regression analysis, controlling for possible exogenous variables as discussed in the next section.

Daily Regression Analysis

Jiang et al. (2011) suggest that liquidity shocks, such as changes in the bid-ask spread and market depth during macroeconomic news announcements have significant predictive power for changes in security prices. Moreover, Mizrach and Neely (2008) find that market liquidity contributes significantly to the level of IS and PT during announcement times. With these considerations, we construct a model using dummy variables as a proxy for announcement days to test for the impact of announcements, controlling for liquidity effect. In doing so, we first construct series using daily IS and PT, and estimate the following model:

$$\begin{aligned}\ln\left(\frac{PD_t^{US}}{1-PD_t^{US}}\right) &= c+\beta_1\left[\ln\left(\frac{N_t^{US}}{N_t^{US}+N_t^{CAN}}\right)\right]+\beta_2\left[\ln\left(\frac{S_t^{US}}{S_t^{US}+S_t^{CAN}}\right)\right] \\ &\quad +\beta_3 Time+\beta_4 D_t+\varepsilon_t \qquad (3.11)\end{aligned}$$

where PD_t^{US} represents the daily U.S. IS or PT, N_t^{US} and N_t^{CAN} are the daily number of trades in the U.S. and Canada, S_t^{US} and S_t^{CAN} are the daily average percentage spreads in both markets, $Time$ is a simple linear trend, and D_t is the announcement day dummy which takes on a value of 1 during an announcement day, or 0 during non-announcement day. We estimate the coefficients using firm

Table 3.5: Regression on daily price discovery

This table reports the estimates of Equation (3.11). The dependent variable is the Ratio IS (PT) which is the daily log ratio of U.S. share of IS (PT) relative to Canada. Time denotes a linear time trend, Ratio Trade and Ratio Spread denote the log ratio of U.S. trades relative to Canada, and the log ratio of percentage spread in the U.S. relative to Canada, respectively. All Announcements denotes a dummy variable for days with macroeconomic news releases. US Announcements and CAN Announcements each represents a dummy variable for U.S. and Canadian macroeconomic news, respectively. Figures in parentheses are heteroscedasticity-consistent t-statistics controlled using clustered standard error. *** denotes significance at 1% level.

	Panel A: Ratio IS		Panel B: Ratio PT	
	(1)	(2)	(1)	(2)
Constant	-1.30***	-1.30***	-1.19***	-1.19***
	(-3.19)	(-3.19)	(-3.31)	(-3.31)
Time	0.00084***	0.00084***	0.00083***	0.00083***
	(9.02)	(9.02)	(10.9)	(10.9)
Ratio Trade	0.75***	0.75***	0.33***	0.33***
	(5.4)	(5.4)	(3.16)	(3.16)
Ratio Spread	-1.10***	-1.10***	-1.03***	-1.03***
	(-3.07)	(-3.07)	(-3.1)	(-3.1)
All Announcements	0.036***		0.031***	
	(4.82)		(4.84)	
US Announcements		0.036***		0.031***
		(4.42)		(4.65)
CAN Announcements		0.035***		0.032***
		(4.35)		(4.03)
R sq(Adj)	0.491	0.491	0.447	0.447

fixed effects estimator with clustered standard errors.

Table 3.5 illustrates the linkage between microstructure variables and the price discovery estimates. For both the IS and PT, the announcement day dummy variable strongly explains the increase in price discovery. Even after separating the Canadian and U.S. announcements as shown in the second column of each panel, the result still holds strongly. This suggests that the U.S. market becomes more informative not only during days with Canadian macroeconomic news announcements, but also during days with U.S. news announcements. There also appears to be a strong time trend effect as captured by the *Time* variable. *Ratio Trade* is positive and highly significant, implying that an increase in relative number of trades in the U.S. increases the U.S. portion of price discovery. This is consistent with Engle and Lange (2001) who find that a large price adjustment is normally driven by trades. *Ratio Spread* is negative and also highly significant which suggests price premium in the U.S. (represented by the increase in relative spread in the U.S.) lowers the U.S. portion of price discovery. This is in line with Fleming et al. (1996) who indicate that informed traders will transact in the market with the lowest transaction costs in order to maximise profits generated from trading on their information. The $R^2(adj)$ from Equation (3.11) range from 49.1% for the IS model to 44.7% for the PT model. We conclude that macroeconomic news announcements and standard liquidity measures strongly capture the daily fluctuations in price discovery between Canada and the U.S.

3.5.2 Intraday Price Discovery

We also test the impact of announcements using smaller event windows, particularly on periods surrounding news releases. Several studies show that prices adjust within minutes of the announcement (see Fleming and Remolona, 1999; Nowak et al., 2011; Scholtus et al., 2014). Such an immediate and short-lived effect would not be picked up in a daily estimation. We therefore investigate the news effect using a 20-minute time window (10 minutes pre and post) surrounding a specific announcement. We select this window to enable us to capture the impact of news which occurs earlier than the officially scheduled time.[8] This may cause prices and therefore price discovery measures to adjust before the announcements and then continue to affect the news interpretation.

We focus on U.S. announcements (10 in total) which occur after the stock market opens at 9:30 AM in both markets. There are no Canadian announcements after

[8]Scholtus et al. (2014) point out that although, on average, macroeconomic news arrivals are reasonably punctual, substantial differences can be found across the different announcements.

Table 3.6: Absolute change in price discovery surrounding news releases (20-minute window)

This table provides the change in IS and PT for 38 Canadian cross-listed stocks during announcement days. The IS and PT are computed on 20 minutes surrounding the announcement times; 10 minutes prior and 10 minutes after. The figures reported are the absolute percentage differences in 20 minutes IS and PT during announcement and non-announcement days $\frac{|(IS(PT)_{Announcement} - IS(PT)_{Non-Announcement})|}{IS(PT)_{Non-Announcement}}$. The figures under "Total" denote the number of firms (out of 38 firms) showing significant shift in Price Discovery during announcement times at 5% significance level obtained using the bootstrap procedure. Figures in parentheses are the t-statistics. *** denotes significance at 1% level.

January 2004 - January 2011		Panel A: Information Share (IS)			Panel B: Component Share (PT)		
Price Discovery	**Time**	**Diff**	**t-stat**	**Total**	**Diff**	**t-stat**	**Total**
All Announcements		4.9%***	(6.34)	35.7	3.6%***	(8.15)	34.8
Chicago PMI	9:45	4.3%***	(6.38)	35	3.6%***	(7.36)	36
US New Home Sales	10:00	4.0%***	(6.35)	36	3.1%***	(7.9)	37
US Factory Orders	10:00	3.4%***	(7.72)	35	2.5%***	(8.14)	36
US Business Inventories	10:00	4.0%***	(7.47)	35	3.0%***	(8.64)	35
US Construction Spending	10:00	5.2%***	(6.46)	37	3.3%***	(5.4)	34
US Consumer Confidence Index	10:00	4.7%***	(8.14)	36	3.1%***	(8.1)	36
US Leading Indicators Index	10:00	3.5%***	(9.7)	36	2.6%***	(8.78)	33
US Government Budget	14:00	4.6%***	(9.99)	36	3.4%***	(8.47)	32
Federal Funds Rate	14:15	11.8%***	(9.68)	37	7.3%***	(10.65)	35
US Consumer Credit	15:00	4.1%***	(6.76)	34	3.6%***	(7.84)	34

the opening time. We first construct a price series by selecting the 20-minute data (1200 observations) surrounding the news release on a particular announcement day. Based on this series, the VECM model is estimated on a daily basis and the IS and PT computed.

Table 3.6 presents the absolute difference in price discovery during non-announcement and various announcement days. Panel A and B in Table 3.5 present the IS and PT over the different announcement days, respectively. On average, macroeconomic news announcements cause a 4.9% shift in IS and a 3.6% shift in PT. These numbers, as expected, are larger than those of the daily coefficients. Looking at the number of firms, the IS (PT) measure reports 35.7 (34.8) firms with significant shifts in price discovery. For the individual announcements, we find significant shifts in the IS and PT during all ten announcements. Fed Funds Rate announcement in particular,

Table 3.7: Change in price discovery surrounding news releases (20-minute window)

This table provides the change in U.S. IS and PT for 38 Canadian cross-listed stocks during announcement days. The IS and PT are computed on 20 minutes surrounding the announcement times; 10 minutes prior and 10 minutes after. The figures reported are the percentage differences in 20 minutes IS and PT during announcement and non-announcement days $\frac{(IS(PT)_{Announcement}-IS(PT)_{Non-Announcement})}{IS(PT)_{Non-Announcement}}$. The figures under "-"("+") denote the number of firms (out of 38 firms) showing a decrease (increase) in U.S. Price Discovery during announcement times at 5% significance level obtained using the bootstrap procedure. Figures in parentheses are the t-statistics. *, **, and *** denotes significance at 10%, 5%, and 1% level, respectively.

		Panel A: Information Share (IS)				Panel B: Component Share (PT)			
US Price Discovery	**Time**	**Diff**	**t-stat**	**-**	**+**	**Diff**	**t-stat**	**-**	**+**
All Announcements		2.4%**	(2.18)	11.9	23.8	1.4%**	(2.2)	13.5	21.3
Chicago PMI	9:45	3.5%***	(4.45)	5	30	2.1%***	(3.05)	10	26
US New Home Sales	10:00	2.7%***	(3.37)	8	28	1.8%***	(3.22)	7	30
US Factory Orders	10:00	0.4%	(0.61)	15	20	-0.1%	(-0.17)	18	18
US Business Inventories	10:00	-0.4%	(-0.46)	21	14	-0.3%	(-0.42)	20	15
US Construction Spending	10:00	2.3%**	(2.11)	12	25	1.5%*	(1.89)	13	21
US Consumer Confidence Index	10:00	2.1%**	(2.35)	14	22	0.8%	(1.26)	18	18
US Leading Indicators Index	10:00	1.1%*	(1.75)	12	24	0.6%	(1.22)	17	16
US Government Budget	14:00	-1.0%	(-1.17)	22	14	-0.5%	(-0.68)	17	15
Federal Funds Rate	14:15	11.6%***	(9.12)	1	36	6.3%***	(6.78)	5	30
US Consumer Credit	15:00	1.8%**	(2.14)	9	25	1.2%*	(1.73)	10	24

leads to a very large shift in both IS and PT.

As for the directional impact of announcements, the results are reported in Table 3.7. For the information share, Panel A shows that, on average, the announcements lead to a 2.4% increase in IS. For 7 out of 10 announcements, the information share shifts to the U.S. The magnitudes of the figures are higher than the figures for daily estimation as reported in Table 3.3. For example, Chicago PMI reports an increase in IS by 3.5% at the intraday level as compared to 2.0% at the daily level. New Home Sales announcement leads to an increase in IS by 2.7% as opposed to 2.0%, while Construction Spending leads to an increase in IS by 2.3% as opposed to -3.4%. These results suggest that the smaller event window allow us to pick up stronger price formation process as well as more precise reaction which may not be captured accurately in daily estimation. Another interesting finding is that U.S. IS increases by 11.6% during Fed Funds Rate announcements. This indicates a strong reaction

Table 3.8: Regression on intraday price discovery

This table reports the estimates of Equation (3.11). The dependent variable is the Ratio IS (PT) which is the daily log ratio of U.S. share of IS (PT) relative to Canada. The IS and PT are computed on 20 minutes surrounding the announcement times. Time denotes a linear time trend, Ratio Trade and Ratio Spread denote the log ratio of U.S. trades relative to Canada, and the log ratio of percentage spread in the U.S. relative to Canada, respectively. All Announcements denotes a dummy variable for days with macroeconomic news which are released after 9:30AM. Figures in parentheses are heteroscedasticity-consistent t-statistics controlled using clustered standard error. *, and *** denotes significance at 10% and 1% level, respectively.

	Panel A: Ratio IS	Panel B: Ratio PT
Constant	-2.04***	-1.71***
	(-16.37)	(-16)
Time	0.0037***	0.0037***
	(10.23)	(11.75)
Ratio Trade	0.32***	0.076***
	(7.92)	(2.42)
Ratio Spread	-1.66***	-1.57***
	(-30.33)	(-31.23)
All Announcements	0.079*	0.054*
	(1.83)	(1.77)
R sq(Adj)	0.273	0.272

from market players in the U.S. towards interest rates releases. As for the PT, the average increase is 1.4%, with only 5 out of 10 announcements showing a significant increase. Fed Funds Rate show a consistent and significant increase of 6.3%.

We re-estimate Equation (3.11) at the intraday level on a 20-minute window and report the results in Table 3.8. Similar to our previous finding, Announcement time dummy is positive and significant at 10% level for both the IS and PT models. This suggests that the impact of macroeconomic news announcements is not only observable at daily, but also intraday level. This result further confirms our previous findings that the U.S. market becomes more informative during the release of macroeconomic news announcements. Time trend and liquidity shocks contribute significantly to the level of IS and PT during announcement times. An increase in relative trade in the U.S. increases the IS and PT while an increase in relative spread in the U.S. decreases them. The R^2(adj) range from 27.3% for the IS model to 27.2% for the PT model. Overall, we can conclude that price discovery shifts to the U.S. during macroeconomic news announcements, and our findings are robust to model and time specifications.

3.6 Conclusion

In this chapter, we examine the impact of macroeconomic news announcements on the price discovery of Canadian stocks listed in Canada and in the U.S. Using a sample of 38 Canadian stocks listed on the TSX that are also listed in the U.S. market with the NYSE as primary listing, we measure price discovery over the period January 2004 to January 2011. We assess the contribution of macroeconomic news by comparing the level of price discovery during days with and without announcements. We also assess when the news originates either from Canada or the U.S.

Our analyses yield several important findings. First, we observe that price discovery shifts for most of the firms in our sample during news announcement days. Second, both Canadian and U.S. macroeconomic news announcements lead to price discovery shifts towards the U.S. as represented by significant increases in U.S. IS and PT. Third, the impact of news announcements remains strong even after controlling for time trends and liquidity shocks. These findings are further supported by intraday analyses of price discovery on periods surrounding news releases. On the whole, we find that the U.S. market sees an increase in price discovery relative to the Canadian market during announcement times, thus implying the difference in information processing capability between the two markets, particularly with regard to the processing of market-wide information.

Our results have several important implications. First, for financial markets, our findings suggest a decline in the importance of the Canadian market during macroeconomic news announcements time. The U.S. market seems to be better at processing information from macroeconomic news. Second, the fact that Canadian announcements lead to the same price discovery shift to the U.S. as the U.S. announcements indicates that Canadian market participants actually put less emphasis on domestic macroeconomic news releases than U.S. market participants. Finally, the significant increase in the trading ratio and the decrease in the spread ratio of the U.S. markets relative to the Canadian markets suggest that the U.S. markets, as the larger and the more liquid exchange of the two, is the preferred destination for traders who seek liquidity and cheaper trading options.

Chapter 4

The Dynamics of Price Discovery

4.1 Introduction

One central function of financial markets is price discovery, which is often interpreted as the process by which prices impound new information (Madhavan, 2000). Price discovery is important because it determines not only how prices are formed in a market, but also how well a market gathers, interprets, and incorporates information into prices. When an asset lists in multiple markets, price discovery plays an even more important role as information can be incorporated into prices in any of these markets. In such a case, the market which incorporates new information into prices faster has better information processing capacity than other markets, and leads in terms of price discovery. Thus, in a multi-market context, price discovery reflects one form of competitiveness of a market relative to others, and may indicate in which market investors prefer to trade.

Given the importance of price discovery in a multi-market setting, it is crucial for exchanges and market regulators to understand which market contributes more to price discovery, and how such a market can improve its competitiveness. To this end, there have been several studies which show that price discovery predominantly occurs in the home market because it is the market where most information about the company is generated (see e.g. Lieberman et al.,1999; Hupperets and Menkveld, 2002; Grammig et al., 2005). Underlying such an argument is some degree of market segmentation where investors cannot easily exploit information in any other market but their own. Those studies, therefore, assume that price discovery does not change over time with the home market being the leader in terms of price discovery.

Contrary to the above studies, price discovery may shift from one market to another over time due to many factors.[1] For instance, investors have the tendency to trade in the cheaper and more liquid market. Such liquidity-motivated trading may cause information clustering in a market, which may lead to a shift in price discovery (Admati and Pfleiderer, 1988). Furthermore, the automation of trading activity helps investors scan public information faster and trade on this information. Such speed and intensity of trading activity may lead to changes in price discovery between markets (Abergel et al., 2012). This evidence indicates that the information processing capacity of a market may not be constant over time.

Currently, a clear understanding of how price discovery between markets changes over time and what drives such dynamics, is lacking. For example, it is yet to be explored whether price discovery is persistent over time, whether the dynamics of price discovery is attributable to changes in market liquidity, and whether algorithmic trading (AT) activities affect the dynamics of price discovery.[2] To address these issues, studying price discovery over a longer time period is necessary. Existing studies tend to examine price discovery at one point in time over a certain period, which typically is relatively short.[3] As such, these studies lean towards explaining cross-sectional differences in price discovery and determinants of those differences, rather than the dynamics of price discovery over time. The importance of studying

[1]In Chapter 3, we show, for example, that price discovery shifts from Canada to the U.S. with the arrival of macroeconomic news.

[2]In this study, we do not distinguish between algorithmic and high-frequency traders. As such, we use the terms "algorithmic trading" and "high-frequency trading" interchangeably. The explanation can be found in Section 4.3 where we define our AT proxy.

[3]For instance, Pascual et al. (2006) study Spanish firms cross-listed on the NYSE in the year 2000. Eun and Sabherwal (2003) study Canadian firms cross-listed on the NYSE from February to July 1998, while Chen and Choi (2012) use data from January 1998 to December 2000.

price discovery over longer periods is further emphasized by the changing financial market landscape as a result of, for example, regulatory changes. One such change is the adoption of regulation National Market Services (Reg. NMS) in the U.S.

In this chapter, we assess the dynamics of price discovery of Canadian stocks traded in Canada and the U.S. Our work contributes to the literature in several ways. First, by measuring Hasbrouck (1995) information share (IS) and Gonzalo and Granger (1995) permanent-transitory (PT) decomposition daily over time, we explore trends and persistence in price discovery, issues that have not yet been explored in a multi-market context. This also allows us to examine whether the adoption of Reg NMS in the U.S. affected the dynamics of price discovery. Second, we assess how measures of price discovery, liquidity, and AT activity interact with each other over longer periods. Our analyses shed light on what drives price discovery between markets (i.e. whether changes in relative liquidity and AT activity affect the contribution to price discovery of a market), as well as the importance of price discovery for a market (i.e. whether an improvement in price discovery affects liquidity and AT activity).[4] These findings are valuable for exchanges as they indicate what areas exchanges would need to focus on to improve price discovery. Third, from an empirical perspective, we model the interactions between price discovery measures, liquidity, and AT activity using a vector autoregression (VAR). We estimate both a reduced-form and a structural VAR that uses the identification through heteroskedasticity approach developed by Rigobon (2003) and recently implemented by Chaboud et al. (2014). In contrast to the reduced-form Granger causality tests, which measure predictive relationships, the structural VAR estimation allows for identification of the contemporaneous interactions among the variables, while at the same time, taking

[4] The analysis of the impact of AT activity on price discovery is especially relevant given that AT activity proliferated in the U.S. and Canada at different times, hence price discovery between the two markets may have changed over time. In the U.S., high-frequency trading (HFT), a subset of AT, became especially popular in 2007 and 2008 (Rogow, 2009). By 2009, 26 HFTs participate in 68.5% of the dollar volume traded on average (Brogaard, 2010). Gibbs (2007) explains that U.S. players will continue to dominate the market because while Canadian traders ramp up their algorithmic capabilities, they tend to partner with U.S. broker-dealers to leverage their offerings.

into account the possible endogeneity among them.[5]

Applying our model to Canadian stocks listed on the Toronto Stock Exchange (TSX) and cross-listed on the New York Stock Exchange (NYSE) over the period January 2004 to January 2011, we document several important findings. First, we observe that over time, the U.S. market is gaining in terms of price discovery. Second, we find that several measures of liquidity are related to price discovery. Improvements in liquidity (an increase in trading volume and a decrease in effective spread) increase an exchange's contribution to price discovery. This impact is incorporated instantaneously as well as with a protracted lag. Conversely, we find that an increase in price discovery leads to improved liquidity. Third, we find that relative algorithmic trading activity is negatively related to price discovery. This finding is in line with the literature on negative externalities of high-frequency trading. Particularly, as arbitrageurs use computer algorithms to trade aggressively and compete for latency arbitrage opportunity that exists in the market, they cause a crowding-out effect. Consequently, high-frequency trading by these arbitrageurs pushes away informed investors, who are disadvantaged in terms of speed. Finally, we find that the dynamics of price discovery persist even after we account for the adoption of Reg. NMS in the U.S. Overall, our findings highlight the importance of liquidity for exchanges in order to improve price discovery, as well as the importance of price discovery to attract more investors. AT activity by arbitrageurs should be of interest to exchange officials as the crowding out effect may push investors away to trade in another market.

The rest of this chapter is structured as follows. Section 4.2 discusses the studies on the determinants of price discovery and how our work differs to existing studies. In

[5] The idenfitication through heteroskedasticity approach was recently applied in several finance studies. For example, Chaboud et al. (2014) use the approach to identify the contemporaneous causal impact of AT on triangular arbitrage opportunities. Ehrmann et al. (2011) use the same approach to assess international transmission of shocks between money, bond, equity and foreign exchange markets. Andersen et al. (2007) use similar model to assess contemporaneous spillover effects among U.S., German and British stock, bond and foreign exchange markets during U.S. macroeconomic news announcements.

Section 4.3, we discuss the data and descriptive statistics, as well as our measures of liquidity and AT activity. We explain our measures for price discovery as well as the formal measures for assessing dynamics in price discovery in Section 4.4. In Section 4.5, we report our findings. Section 4.6 concludes.

4.2 Literature Review

A market's contribution to price discovery may change over time for various reasons. In this section, we first discuss factors that may contribute to the change in price discovery over time. We then show how these factors can be modeled to assess the dynamics of price discovery in a dual-market scenario.

There has been a growing literature examining price discovery of cross-listed stocks. The majority of it focuses on the determinants of price discovery, with liquidity playing an important role. As discussed in Admati and Pfleiderer (1988), one of the motives for trade in financial markets is liquidity. Given that investors have discretion over where and when to trade, they have the tendency to trade in a cheaper and more liquid market, i.e. when the market is "thick" and their trading has little effect on prices. Such market may attract more traders, leading to information clustering and a shift in price discovery.

One type of liquidity, which is important for price discovery, is trading volume. We often observe that large trades have persistent price impacts, with trade prices lower after large sales and higher after large purchases. One possible explanation is that increased volume reflects a greater likelihood that demand for a stock comes from informed traders (Stickel and Verrechia, 1994). Consequently, investors interpret high volume as an indication that the demand underlying a price change is informative, and therefore should get incorporated into prices. Consistent with this view, Hasbrouck (1995) finds a positive and statistically significant relation between the relative trading volume of a sample of 30 Dow stocks and the NYSE's contribution to price discovery. He explains that markets differ in their ability to process information such as that coming from trades. A market which has an informative trading process can shed light on the interpretation of public information, and therefore, leads in terms of price discovery. Similarly, Pascual et al. (2006) find that a market's relative contribution to the price discovery process is related to its trading activity. Using Spanish stocks that are cross-listed on the NYSE, they find that the Spanish Stock Exchange leads in terms of price discovery due to its large trading activity relative to the NYSE as the satellite market.

Another important determinant of price discovery is the relative bid-ask spread. A market with narrower spreads creates incentives for traders to transact. As a result, trading may be concentrated in that market relative to in other markets. This may affect a market's contribution to price discovery. Eun and Sabherwal (2003) suggest that the lower spread on U.S. exchanges relative to the TSX represents a competitive threat faced by the TSX liquidity providers from their U.S. counterpart. The TSX liquidity providers who face more competition from the U.S. liquidity providers are likely to be more responsive to U.S. prices. The importance of spread on price discovery is also documented in Harris et al. (2002) who compare the bid-ask spread and a measure of price discovery for the years 1988, 1992, and 1995 for 30 Dow stocks. They find that the NYSE's contribution to price discovery relative to the regional exchanges increases when its spreads relative to the regional markets decline. In addition, Chen and Choi (2012) assess differential private information for Canadian stocks traded in Canada and the U.S. They document that the TSX has more informed trades and a larger information share which they attribute to the small but positive premiums in New York.

In addition to liquidity, algorithmic trading (AT) activity has also been linked to price discovery. However, the results are mixed. Academic work using earlier data documents a positive relation between AT and price discovery. For example, Hendershott et al. (2011) assess the impact of quote automation in the NYSE from December 2002 through July 2003. Using proxy to measure the share of AT in the market, they find that for large stocks in particular, AT enhances the informativeness of quotes by more quickly resetting their quotes after news arrivals. Riordan and Storkenmaier (2012) use Deutsche Boerse data from February to June 2007 to study the effect of a latency reduction on price discovery through the introduction of Xetra 8.0 trading platform upgrade. They find that the contribution of quotes to price discovery doubles to 90% post upgrade, indicating that prices are more efficient. Hasbrouck and Saar (2013) use NASDAQ TotalView-ITCH data in the last quarter of 2007 and find that high-frequency trading improves liquidity and price efficiency.

A more recent group of studies suggest that an increase in AT may lead to a decline in price discovery. Stein (2009) explains that recent technological advancements allow traders to detect and exploit price discrepancies between securities in a fraction of a millisecond. These developments have led to the stock market being dominated by sophisticated professionals using extensive quantitative financial models. As a consequence, aggressive investment strategies by these traders have led to a crowding out effect that pushes prices away from their fundamental values, i.e. prices becoming less informative. Gai et al. (2014) explain that since U.S. stock markets observe price, display, and time priority, it is the relative speed but not the absolute speed that matters. This induces economic incentive not only to invest in speed but also to slow down other traders, which is in line with the "quote stuffing" argument of Biais and Wooley (2011) and Foucault et al. (2013) that HFT submits a profuse number of orders to generate market congestion on purpose. In this respect, Egginton et al. (2014) show that by submitting large numbers of orders that are canceled very quickly, a high-frequency trader may create exploitable latency arbitrage opportunities. Kozhan and Tham (2012) show that as computers enter the same trade at the same time to exploit an arbitrage opportunity, high-frequency trading by arbitrageurs causes a crowding out effect. Therefore, in contrast to the common notion that competition improves price efficiency, they find that competition among arbitrageurs limits efficiency because competing arbitrageurs inflict negative congestion externalities to financial markets.[6]

While there are currently no studies that have looked at how AT activity affects price discovery of cross-listed stocks, there are a few studies which have looked at how liquidity affects price discovery. However, these studies are predominantly cross-sectional studies or look at time-variation only on an annual basis. For example, Harris et al. (2002) study price discovery using a sample of 30 Dow stocks for the years 1988, 1992, and 1995. They calculate differences in price discovery from one year to the next, and relate these differences to changes in the relative spreads between the NYSE and the U.S. regional exchanges. Their findings suggest that higher NYSE spreads reduce the NYSE contribution to price discovery. Frijns et al. (2010) measure price discovery annually for four Australian stocks cross-listed in New Zealand and five New Zealand stocks cross-listed in Australia from 2002 to 2007. Using a total of 54 observations, they regress Hasbrouck (1995) information share on several variables such as the log number of trades in each market, the percentage bid-ask spread in each market, and the log of the market capitalization. They indicate that the growth in the importance of the Australian market is positively related to the growth in the size of the firm and negatively related to the size of the percentage spread in the Australian market. Similarly, Frijns et al. (2015) measure price discovery annually from 1996 to 2011 for Canadian stocks which are cross-listed on the NYSE, NASDAQ, and AMEX. Their study examines, in particular, the issue of endogeneity between price discovery and measures of liquidity and market quality.

Our work extends the above studies by focusing on the dynamics of price discovery.

[6] Biais et al. (2015) find that the improvement in trading speed can either increase or decrease social wefare. In line with this argument, Pagnotta and Philippon (2012) explain that the impact of latency on social welfare depends on the initial level of speed. Particularly, allowing venues to compete on speed improves welfare if the default speed is relatively low, but decreases welfare once the default speed reaches a certain threshold.

Specifically, we assess, at daily frequency, how measures of price discovery, trading volume, bid-ask spread, and AT activity of the U.S. relative to the Canadian markets interact with each other over longer periods. We acknowledge that these variables may be determined simultaneously. For instance, improvements in liquidity and AT activity may lead to a higher contribution to price discovery, while at the same time, higher price discovery may lead to improvements in liquidity and AT activity. To accommodate such relationships, we employ a structural VAR that models the interaction between the variables. We follow Chaboud et al. (2014) and account for possible contemporaneous interactions among the VAR variables using the identification through heteroskedasticity approach developed by Rigobon (2003). The variables and methodologies will be discussed in the following sections.

4.3 Data and Descriptive Statistics

Our sample consists of Canadian stocks that are traded on the TSX and NYSE from January 2004 through January 2011. The end of the sample is chosen to avoid confounding effects from the adoption of the consolidated tape in Canada (see Clark, 2011). Data are collected from the Thomson Reuters Tick History (TRTH) database maintained by Securities Industry Research Centre of Asia-Pacific (SIRCA). These Canadian stocks are traded in both markets throughout the sample period, had no stock splits, and have data available from TRTH. In total, there are 38 stocks which meet these criteria.[7]

We collect intraday data on trade price, trade volume, and the bid and ask quotes at a second and at a millisecond frequency. We use the data at a one-second frequency

[7] We also conduct analysis using a more stringent screening by imposing a minimum message count following the approach of Hasbrouck and Saar (2013). A firm is excluded from the sample if more than 10% of the 10-minute intervals have fewer than 250 messages (trade and quote). This screening reduces the number of stocks in the sample to 28. As the results are very similar to those discussed in Section 4.5 and presented in Tables 4.4 - 4.8, we do not report them, but they are available upon request.

to compute price discovery measures and construct liquidity measures[8] and use the data sampled at a millisecond frequency to construct the AT proxy. We omit the first and last five minutes of the trading day to avoid capturing any effects from the open and close of the market. For the U.S. market, we use the national best bid and offer (NBBO) quotes and for the Canadian market, we use quotes posted at the TSX. Following Grammig et al. (2005), we use midpoints of quotes as these are less affected by bid-ask bounce that is normally observed in transaction prices. We also obtain the intraday Canadian - U.S. Dollar exchange rate quotes from TRTH and use the midpoint to convert prices into U.S. dollar. This is to facilitate the specification of the error-term and ensure the comparability of prices between the two markets, similar to Eun and Sabherwal (2003) and Chen and Choi (2012).

4.3.1 Liquidity Measures and Algorithmic Trading Proxy

As measures of liquidity, we use the trading volume and the effective spread. To make inferences about the relations between price discovery and measures of liquidity from both markets, we employ the trading volume and effective spread of the U.S. market relative to the Canadian market (see also, Eun and Sabherwal, 2003). Relative trading volume represents the stock's trading activity and is defined as:

$$Ratio\_Vol_j = \frac{Vol_j^{US}}{Vol_j^{US} + Vol_j^{CAN}}, \tag{4.1}$$

where Vol_j^{US} and Vol_j^{CAN} are the average U.S. and Canadian trading volume on day j, respectively. The second liquidity measure is the relative effective spread, which measures trading costs. Effective spreads are more meaningful for the NYSE than quoted spreads because specialists and floor brokers are sometimes willing to trade

[8] Hasbrouck (1995, 2003) indicates that more powerful tests of market efficiency can be carried out by sampling at very high frequencies to reduce the contemporaneous correlation in the reduced form residuals between markets that is created by time aggregation. Hasbrouck (2003) uses a sampling frequency of 1 second, which produces a low contemporaneous residual correlation and a narrow range of information shares. Similarly, Hendershott and Jones (2005) also sample at 1 second and find low residual correlations in their price discovery study.

at prices within the quoted bid and ask prices. The effective spread is measured as:

$$Espread_j = \frac{1}{x} \sum_{t=1}^{T} 2D_t(p_t - m_t)/m_t, \tag{4.2}$$

where D_t is a trade indicator variable at time t. We assign +1 for buyer-initiated trades and -1 for seller-initiated trades. We follow the standard trade signing approach of Lee and Ready (1991) and use contemporaneous quotes to sign trades, following Bessembinder (2003). p_t and m_t are the trade price and quote midpoint prevailing at time t, respectively. When aggregating over a trading day j, we average the effective spreads over x trades. Subsequently, the relative effective spread is computed as:

$$Ratio\_Espread_j = \frac{Espread_j^{US}}{Espread_j^{US} + Espread_j^{CAN}}. \tag{4.3}$$

As a proxy for AT, we follow Hendershott et al. (2011) and calculate the negative trading volume in USD100 divided by the raw message traffic number,

$$AT_j^i = \frac{-(Dollar\_Vol_j^i)/100}{Total\_messages_j^i}, \tag{4.4}$$

where AT_j^i is the AT activity for market i on day j, $Dollar\_Vol$ is the total dollar trading volume, and $Total\_messages$ is the total number of observations in the order book, which includes all trade executions, order submissions and order cancellations. This ratio represents the negative dollar volume associated with each trade or quote update. An increase in this measure reflects an increase in algorithmic trading activity.[9] Hendershott et al. (2011) explain that there may be an increase in trading volume over the same interval, and without normalization, a raw message

[9] Since we do not have data sets that identify actual high-frequency activity, we rely on proxies for identifying AT. Our AT proxy is used in studies such as Hendershott et al. (2011), and Boehmer et al. (2014). As an alternative AT proxy, we also use quote-to-trade ratio (see Hagstromer and Norden, 2013; Skjeltorp et al., 2014). This proxy also reflects AT activity as strategies used by algorithmic traders have contributed to a huge increase in the amount of order traffic relative to trade executions. Nevertheless, we find similar findings.

traffic measure may just capture the increase in trading rather than the change in the nature of trading. However, it is important to note that since this AT proxy draws inferences from total message traffics, it makes little distinction between HFT and slower traders with automated trading systems. Since AT is negative, relative AT activity is measured as

$$Ratio\_AT_j = \frac{AT_j^{CAN}}{AT_j^{US} + AT_j^{CAN}}. \tag{4.5}$$

Table 4.1 provides a summary of the liquidity measures and AT proxy for the 38 cross-listed stocks in our sample. We report the symbols for the stocks as listed on the U.S. market. The next few columns report the average trading volume, effective spread, number of messages, and AT activity in both markets, as well as their values in the U.S. relative to Canada.

On average, daily trading volume is higher in the U.S. with 1,463,000 shares traded compared with 1,368,000 shares in Canada. This results in a relative trading volume of 52% for the U.S. market, suggesting that trading activity is slightly higher in the U.S. relative to Canada. In terms of effective spread, the U.S. market has a lower spread, with 8.5 bps compared with 10.5 bps in Canada. Relative effective spread for the U.S. market is 45%, indicating that, on average, trading costs in the U.S. are lower than in Canada. The number of messages per 10-minute period is similar in both markets. In the U.S., there are 1,159 messages every 10 minutes and 1,107 messages in Canada, leading to a ratio of 51% for the U.S. market. Algorithmic trading activity, on average, is higher (less negative) in the U.S. compared with Canada with a value of -10.7 and -17.5, respectively. This leads to an AT ratio of 62% for the U.S. relative to Canada.

Figure 4.1 plots the 20-day moving average of trading volume, effective spread, and AT activity of the U.S., Canada and their relative values. Panel A shows that relative trading volume, $Ratio\_Vol$, has an upward trend. The increase is notable

Table 4.1: Summary statistics (by firm)

This table provides a summary statistics of the 38 stocks in our sample. It reports the company names, symbols, and market capitalization. It also reports the average daily trading volume, the average daily effective spread, the average number of messages per 10-minute periods, and the average daily algorithmic trading activity in both markets. Also reported are the ratios of the variables in terms of the U.S. market relative to the Canadian market.

			Trading Volume ('000)			Effective Spread (bps)			Number of Messages (10min)			Algorithmic Trading Activity		
No.	Company	Symbol	US	CAN	RATIO	US	CAN	RATIO	US	CAN	RATIO	US	CAN	RATIO
1	Barrick Gold	ABX	7,061	2,758	72%	4.0	5.7	41%	3,889	3,372	54%	-22.6	-13.8	38%
2	Agnico-Eagle Mines Limited	AEM	2,228	734	75%	5.8	8.8	40%	1,760	1,585	53%	-14.7	-5.8	28%
3	Agrium Inc.	AGU	1,929	806	71%	5.7	8.7	39%	1,806	1,681	52%	-13.4	-7.2	35%
4	BCE Inc.	BCE	634	3,124	17%	5.1	5.9	46%	772	932	45%	-6.1	-29.2	83%
5	Bank of Montreal	BMO	325	1,617	17%	5.6	5.1	52%	879	828	51%	-3.6	-40.8	92%
6	Bank of Nova Scotia	BNS	281	2,073	12%	6.9	5.2	57%	796	896	47%	-3.1	-43.5	93%
7	Brookfield Office	BPO	1,593	364	81%	7.6	11.6	40%	911	881	51%	-8.5	-2.3	21%
8	Cameco Corp.	CCJ	1,975	1,191	62%	5.9	7.9	43%	1,450	1,475	50%	-17.9	-14.9	45%
9	Celestica Inc.	CLS	1,181	851	58%	12.7	16.0	44%	460	438	49%	-7.6	-5.1	40%
10	Canadian Imperial Bank Communication	CM	234	1,295	15%	5.9	5.2	53%	725	703	51%	-3.8	-46.1	92%
11	Canadian National Railway Company	CNI	1,047	999	51%	3.7	5.4	41%	1,128	1,090	51%	-15.2	-16.6	52%
12	Canadian Natural Resources Ltd.	CNQ	1,958	1,830	52%	4.6	6.1	43%	1,864	1,733	52%	-17.4	-24.2	58%
13	COTT Corp.	COT	484	286	63%	24.9	34.0	42%	208	222	52%	-6.2	-2.9	32%
14	Canadian Pacific	CP	498	624	44%	5.4	7.3	43%	723	726	50%	-9.7	-14.1	59%
15	Encana Corp.	ECA	2,791	2,341	54%	3.6	5.1	42%	2,186	1,988	52%	-22.6	-27.3	55%
16	Enbridge Inc.	ENB	227	664	25%	6.8	7.4	48%	489	474	51%	-3.8	-15.7	81%
17	Enerplus Corp.	ERF	585	311	65%	7.8	10.7	42%	438	471	48%	-16.6	-7.2	30%
18	Goldcorp Inc.	GG	6,489	2,775	70%	5.1	7.1	42%	3,715	3,371	52%	-18.6	-12.2	40%
19	CGI Group	GIB	123	968	11%	17.3	17.0	50%	238	223	48%	-1.2	-9.0	88%
20	Gildan Activewear Inc.	GIL	497	345	59%	8.8	11.9	42%	449	504	47%	-6.7	-6.2	48%
21	Kingsway Financial Services Inc.	KFS	45	172	21%	36.8	35.1	51%	88	76	46%	-0.9	-5.5	86%
22	Kinross Gold Corp.	KGC	4,436	3,566	55%	10.0	11.8	46%	2,430	2,167	53%	-9.0	-11.4	56%
23	Manulife Financial Corp.	MFC	1,360	3,193	30%	5.0	6.1	45%	1,331	1,448	48%	-11.7	-28.4	71%
24	MI Developments Inc.	MIM	104	32	77%	15.2	23.5	39%	94	122	56%	-5.9	-1.1	16%
25	Nexen Inc.	NXY	1,540	1,646	48%	6.5	8.0	45%	1,506	1,562	49%	-9.2	-19.0	67%
26	Precision Drilling Trust	PDS	945	738	56%	10.3	13.0	44%	508	476	48%	-12.5	-10.1	45%
27	Pengrowth Energy Corp.	PGH	966	466	67%	10.8	15.5	41%	330	340	51%	-15.9	-13.9	47%
28	Potash Corporation of Saskatchewan Inc.	POT	4,334	758	85%	4.1	5.9	41%	3,164	2,691	54%	-37.6	-10.3	22%
29	Ritchie Brothers Auctioneers	RBA	227	54	81%	10.7	21.6	33%	217	271	56%	-7.5	-1.9	20%
30	Rogers Communication Inc.	RCI	328	1,435	19%	5.3	8.4	39%	607	573	51%	-13.7	-25.4	65%
31	Royal Bank of Canada	RY	585	2,517	19%	4.7	4.8	49%	1,103	1,204	48%	-5.3	-46.5	90%
32	Shaw Communications Inc.	SJR	176	771	19%	9.0	11.3	44%	339	350	51%	-3.2	-10.0	76%
33	Sun Life Financial	SLF	335	1,240	21%	6.3	7.2	47%	624	662	49%	-4.9	-23.0	82%
34	Suncor Energy Incorporated	SU	4,389	2,672	62%	4.1	5.5	43%	3,074	2,937	51%	-26.5	-21.2	44%
35	TransAlta Corp.	TAC	36	646	5%	13.2	11.0	55%	267	219	45%	-0.7	-16.2	96%
36	Toronto-Dominion Bank	TD	677	1,928	26%	4.5	4.7	49%	1,207	1,158	51%	-6.4	-39.7	86%
37	Talisman Energy Inc.	TLM	2,705	2,990	47%	6.5	8.2	44%	1,784	1,664	52%	-11.0	-17.4	61%
38	TransCanada Corp.	TRP	249	1,210	17%	6.0	6.3	49%	483	558	46%	-4.2	-20.8	83%
	Mean		1,463	1,368	52%	8.5	10.5	45%	1,159	1,107	51%	-10.7	-17.5	62%

from 2004 to 2008 prior to the Global Financial Crisis when U.S. trading volume peaked. The trend steadied between 2009 and 2010, but declined in early 2011.

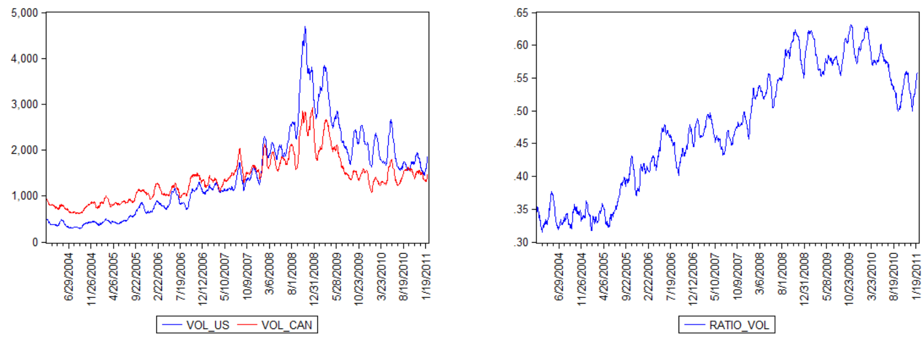
Panel B plots the relative effective spread, $Ratio\_Espread$ over the years. Throughout the entire sample period, the relative effective spread is lower than 0.50, suggesting that trading costs in the U.S. are lower than in Canada during our sample period. Between 2005 to early 2008, the relative spread was declining due to lower costs of trading in Canada. The spreads in both markets spiked in the middle of 2008 due to the financial crisis. From 2009 onwards, the relative spread increased due to further lowering of trading costs in Canada.

Panel C plots AT activity of the U.S. relative to Canada. The plot for the $Ratio\_AT$ shows that the trend has been downward sloping over the years. This can be attributed to the Canadian market increasing their algorithmic trading activity over the recent years, especially after the emergence of alternative trading systems in mid-2007 to compete with the TSX (Clark, 2011). Where the U.S. used to report higher AT activity than Canada (ratio of greater than 0.5) before 2008, it has declined to the point that AT activity in Canada is higher than in the U.S. from 2009 onwards.

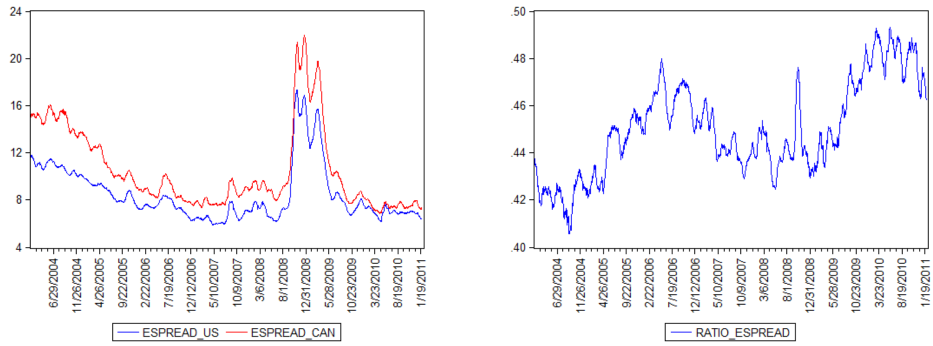
Figure 4.1: Liquidity and AT activity of the US relative to Canada

This figure shows time series plots of the U.S. relative daily trading volume, U.S. relative daily effective spread, and U.S. AT activity. The figures are the 20-day moving averages computed from the mean *Ratio_Vol*, *Ratio_Espread*, and *Ratio_AT* for the 38 firms in the sample, respectively. The x-axis represent the sample period from January 2004 to January 2011, while the y-axis represents the value of the levels for each respective variable.

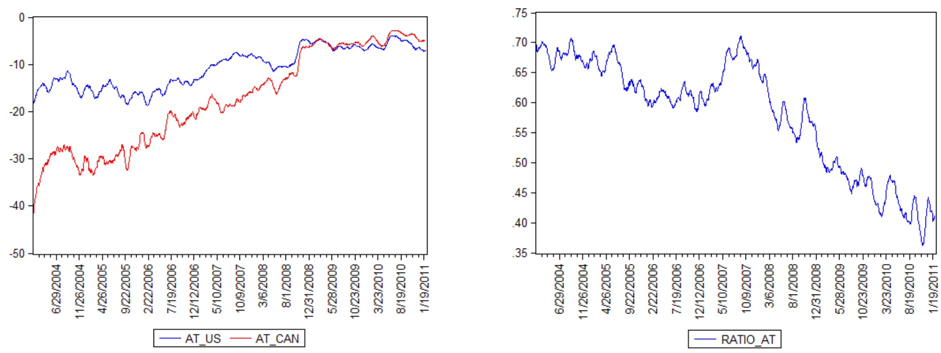
Panel A: Trading Volume



Panel B: Effective Spread



Panel C: Algorithmic Trading Activity



4.4 Methodology

4.4.1 Measuring Price Discovery

The study of price discovery relies on the assumption that when a security is cross-listed in multiple markets, prices in these markets share a common trend, i.e., prices are cointegrated. Cointegration implies that prices can deviate from each other in the short-run due to frictions, but are bound together in the long-run. In our dual-market case, such a relationship can be presented by two $I(1)$ price series, y_t^{US} and y_t^{CAN} being cointegrated with a cointegrating vector, $\beta' = \begin{pmatrix} 1 & -1 \end{pmatrix}$. The Engle-Granger Representation Theorem suggests that a cointegrated system can be expressed as an error-correction model. Hence, the stationary process, $\beta' y_t = y_t^{US} - y_t^{CAN}$, can be applied as an error-correction term for the following VECM,

$$\Delta y_t = c + \alpha\beta' y_{t-1} + \sum_{n=1}^{N} \Gamma_n \Delta y_{t-1} + \epsilon_t. \tag{4.6}$$

where Δy_t is the (2×1) vector of log returns, c is a vector of constants, α is a (2×1) vector that measures the speed of adjustment to the error-correction term (i.e. $\alpha = \begin{pmatrix} \alpha^{US} \\ \alpha^{CAN} \end{pmatrix}$), Γ_n are (2×2) matrices of AR coefficients, and ϵ_t is a (2×1) vector of innovations. The VECM has two parts: the first part, $\beta' y_{t-1}$ represents the long-run equilibrium between the price series. The second part, $\sum_{n=1}^{N} \Gamma_n \Delta y_{t-1}$ represents the short-term dynamics induced by market imperfections.

We use the above VECM to compute the price discovery measures between two markets. Our price discovery measures are the Gonzalo and Granger (1995) permanent–transitory (PT) decomposition, and the Hasbrouck (1995) information share (IS). Both are directly related and both measures are derived from the VECM.

The PT measure is concerned with permanent shocks that result in a disequilibrium as markets process news at different speeds. It measures each market's contribution to the common factor, where the contribution is defined to be a function of the speed of adjustment coefficients, α. Hence, the PT can be computed using the following equation,

$$PT^{US} = \frac{\alpha^{CAN}}{(\alpha^{CAN} + |\alpha^{US}|)}, \tag{4.7}$$

where α^{US} is negative, and α^{CAN} is positive given our definition of $\beta' = \begin{pmatrix} 1 & -1 \end{pmatrix}$. This ratio provides an indication of the degree of dominance of one market over the other market. A higher value of this ratio reflects a greater feedback or contribution from the US. Therefore, a PT^{US} of zero would imply that the NYSE does not contribute to the price discovery of the stocks, whereas a PT^{US} greater than zero would imply feedback from the NYSE to the TSX. PT^{CAN} can be computed as $1 - PT^{US}$.

The IS measures the proportion of variance contributed by one market with respect to the variance of the innovations in the common efficient price. To assess this, note that we can rewrite Equation (4.6) as a vector moving average (Wold representation):

$$\Delta y_t = \Psi(L)e_t, \tag{4.8}$$

where $\Psi(L)$ is a matrix polynomial in the lag operator ($\Psi(L) = 1+\psi_1 L+\psi_2 L^2+\cdots$). Following the Beveridge and Nelson (1981) decomposition, which states that every (matrix) polynomial has permanent and transitory structure, we can write Equation (4.8) in its integrated form as:

$$y_t = \Psi(1)\textstyle\sum_{s=1}^{t} e_s + \Psi^*(L)e_t. \tag{4.9}$$

where $\Psi(1)$ is the sum of all moving average coefficients, and measures the long-run impact of an innovation to the level of prices. Since prices are cointegrated, $\beta' y_t$ is a stationary process, which implies that $\beta'\Psi(1) = 0$, i.e. the long-run impact is the same for all prices. If we denote $\psi = \begin{pmatrix} \psi^{US} & \psi^{CAN} \end{pmatrix}$ as the common row vector in $\Psi(1)$, Equation (4.9) becomes:

$$y_t = \iota\psi \textstyle\sum_{s=1}^{t} e_s + \Psi^*(L)e_t. \tag{4.10}$$

The increment ψe_t in Equation (4.10) is the component of price change that is permanently impounded into the price and is due to new information. Hasbrouck (1995) decomposes the variance of the common factor innovations, i.e., $var(\psi e_t) = \psi\Omega\psi'$. The information share of a market is defined as the proportion of variance in the common factor that is attributable to innovations in that market. Since Hasbrouck (1995) uses the Cholesky factorization of $\Omega = MM'$ to handle contemporaneous correlation, where M is a lower triangular matrix, the information share of market i is defined as:

$$S_i = \frac{([\psi M]_i)^2}{(\psi\Omega\psi')}. \tag{4.11}$$

The Cholesky decomposition of Ω orthogonalizes the innovation terms and assigns all common variance to one market. To account for multiple markets, Hasbrouck (1995) suggests that different orderings of the innovation terms be used so that upper and lower information share bounds can be computed. Specifically, we reverse the order of the $\Psi(1)$ as well as M and recompute Equation (4.11). The midpoint of these bounds is the IS value.

4.4.2 Modelling Price Discovery Dynamics

Section 4.2 indicates that factors such as trading volume, bid-ask spread, and algorithmic trading activity may be related to price discovery. If such relations exist, the ratio of those variables in one market relative to another, may determine the dynamics of price discovery between the two markets. To examine such dynamics, we use a VAR to model the interactions between price discovery measures, trading volume, bid-ask spread, and AT activity. We estimate both a reduced-form of the VAR and a structural VAR that uses the identification through heteroskedasticiy approach developed by Rigobon (2003). Doing so, we are able to assess lagged and contemporaneous interactions among the VAR variables.

In this section, we start by describing the framework to estimate a structural VAR. Given that price discovery measures, trading volume, bid-ask spread, and AT activity may have contemporaneous effects on each other, and assuming these variables exhibit persistence, the dynamics of price discovery can be expressed in the following structural VAR:

$$A\Delta Y_t = c + \sum_{k=1}^{K} \Pi_k \Delta Y_{t-k} + \varepsilon_t. \tag{4.12}$$

We model in first differences to eliminate unit roots that each variable may exhibit. As such, we define ΔY_t as a (4×1) vector of changes in variables, i.e. $\Delta Y_t = (\Delta IS_t, \Delta Ratio\_Vol_t, \Delta Ratio\_Espread_t, \Delta Ratio\_AT_t)'$, Π_k is a (4×4) matrix of coefficients for the autoregressive terms with lag k, and ε_t is a vector of error terms. We are particularly interested in matrix A, which is a (4×4) matrix capturing the structural parameters. Matrix A is normalized such that all diagonal elements are equal to 1, and its off-diagonal elements capture the contemporaneous interactions between the variables, i.e.,

$$A = \begin{pmatrix} 1 & a_{12} & a_{13} & a_{14} \\ a_{21} & 1 & a_{23} & a_{24} \\ a_{31} & a_{32} & 1 & a_{34} \\ a_{41} & a_{42} & a_{43} & 1 \end{pmatrix}.$$

The off-diagonal elements indicate the interactions among the variables. For instance, a_{12}, a_{13}, a_{14} represent the contemporaneous impact of $\Delta Ratio\_Vol$, $\Delta Ratio\_Espread$

and $\Delta Ratio\_AT$ on ΔIS, while a_{21}, a_{31}, a_{41} represent the contemporaneous impact of ΔIS on $\Delta Ratio\_Vol$, $\Delta Ratio\_Espread$ and $\Delta Ratio\_AT$. Since the degree of contemporaneous relations among the VAR variables are not equal, matrix A is not symmetrical. Consequently, the parameters in matrix A cannot be obtained using OLS. To overcome this issue, we estimate Equation (4.12) using the identification through heteroskedasticity methodology. This approach starts with transforming Equation (4.12) into its reduced-form below:

$$\begin{aligned} \Delta Y_t &= A^{-1}c + A^{-1}\sum_{k=1}^{K} \Pi_k \cdot \Delta Y_{t-k} + A^{-1}\varepsilon_t \\ \Delta Y_t &= \tilde{c} + \sum_{k=1}^{K} \tilde{\Pi}_k \cdot \Delta Y_{t-k} + \tilde{\varepsilon}_t, \end{aligned} \tag{4.13}$$

where the residuals $\tilde{\varepsilon}_t$ from the reduced-form VAR are related to the residuals ε_t from the structural VAR through matrix A. Here, matrix $\tilde{\Pi}_k$ allows us to test for Granger causality among the VAR variables. At the same time, Equation (4.13) serves as the basis for the heteroskedasticity identification scheme, because it can be estimated by OLS. Hence, we can obtain $\tilde{\varepsilon}_t$ and use it to identify different variance regimes. To do so, we split $\tilde{\varepsilon}_t$ into different subsamples, such that the covariance matrices under these subsamples are not proportional to each other.[10] Once different heteroskedastic regimes have been identified, we can increase the number of available moment conditions and use them to estimate matrix A. The variance of the residuals of the structural equations will differ across all the different regimes, but matrix A needs to be the same across these regimes.

In our empirical setting, we obtain the parameters in matrix A through the following procedures. First, we estimate the reduced-form of Equation (4.13) using OLS. The lag specification is determined by the Schwartz Information Criterion (SIC), which

[10] Rigobon (2003) suggests that at least two distinct variance regimes for the error terms are required in order for the identification scheme to work.

in our case suggests a lag-length of 5 days to remove any serial correlation. From this step, we obtain the reduced-form residuals, which contain only the contemporaneous effects.

Second, from the reduced-form residuals, we define the heteroskedastic regimes. We do so by computing rolling window variances of 20 observations each, following Ehrmann et al. (2011). A regime is identified if one variance of a variable exceeds the average variance of that variable over the sample period plus one standard deviation, while at the same time the variances of the other three variables do not exceed their average variances plus one standard deviation. Using this approach, we identify 6 regimes in total: 1 regime to represent a tranquil state where all the four variables do not exhibit elevated conditional volatility; 4 regimes where only one variable exhibits elevated conditional volatility while the other three are stable; and 1 regime where at least 2 variables exhibit elevated conditional volatility.

Third, once the regimes are identified, we can estimate the variance-covariance matrices, Ω_s, of the reduced-form residuals in variance regime s ($s = 1, 2, ..., 6$). Given that $\Omega_{\varepsilon,s}$ are the variance-covariance matrices of the structural VAR that we are interested in, and assuming the following moment conditions hold,

$$A\Omega_s A' = \Omega_{\varepsilon,s}, \tag{4.14}$$

the parameters in A and $\Omega_{\varepsilon,s}$ can then be estimated using GMM by minimizing the following function:

$$\min g'g \text{ with } g = A\Omega_s A' - \Omega_{\varepsilon,s}. \tag{4.15}$$

Identification is achieved as long as the covariance matrices constitute a system of equations that is linearly independent. This is assured by the fact that the average variance of one of the observed variables is elevated, while the others are relatively stable.

4.5 Empirical Findings

In this section, we begin by showing how price discovery measures for Canadian cross-listed stocks vary over time. We then present the Granger causality results from the reduced-form VAR and the results from the structural VAR as formal approaches to assess the dynamics of price discovery. Finally, we examine whether the adoption of the Reg NMS affected the dynamics of price discovery between the U.S. and Canadian markets.

4.5.1 Price Discovery Over Time

To obtain price discovery estimates over time, the IS and PT are estimated daily for each firm.[11] The daily estimation eliminates the overnight price jumps which typically generate excessive noise. Throughout this chapter, our price discovery estimates are based on the U.S. portion of IS and PT. The VECM of Equation (4.6) is estimated by applying OLS with optimal lag length suggested by the Schwartz Information Criterion.

Table 4.2 reports the descriptive statistics of the PT and IS. Panel A reports the statistics for the levels. During the entire sample, the average (median) IS for the U.S. market is 52.2% (55.4%), while for PT, it is 59.0% (60.8%). These figures indicate that the U.S. contribution to price discovery tends to be higher than the Canadian contribution. We observe a wide range in price discovery measures, from 18.5% to 80.8%, and from 29.0% to 84.7% at the 5^{th} and 95^{th} percentile for IS and PT, respectively. Both measures are negatively skewed, but do not display excess kurtosis. The autocorrelation (AC) for IS and PT are 0.674 and 0.667 for the first

[11] Prior to estimating the IS and PT, we conduct the usual procedures of unit root and cointegration tests. First, we perform non-stationarity tests using the Augmented-Dickey Fuller test using SIC to select optimal lag length. For all stocks, we cannot reject the presence of a unit root. Subsequently, we conduct Johansen's (1988) test for cointegration. In all tests, we reject the null of no cointegration in favour of the alternative of one cointegrating vector. Since the price series in our sample satisfy both conditions, we conclude that each pair of our sample stocks is cointegrated.

Table 4.2: Descriptive statistics of the price discovery measures

This table reports the descriptive statistics for the price discovery measures. IS and PT are estimated daily from January 2004 to January 2011. The figures reported are the averages for all 38 Canadian cross-listed stocks in the sample. Panel A reports statistics for the levels, and Panel B reports statistics for the first differences. ADF is the t-statistics for the Augmented Dickey-Fuller test. *** denotes significance at the 1% level.

	IS	PT
Panel A: Summary Statistics for levels		
Mean	0.522	0.590
5th	0.185	0.290
Median	0.554	0.608
95th	0.808	0.847
Std. Dev.	0.208	0.179
Skewness	-0.345	-0.347
Kurtosis	2.525	2.732
AC	0.672	0.667
ADF	-2.147	-2.169
Panel B: Summary Statistics for 1st difference		
Mean	0.00004	0.00008
5th	-0.21854	-0.19921
Median	0.00043	0.00002
95th	0.21655	0.19747
Std. Dev.	0.137	0.125
Skewness	0.008	-0.014
Kurtosis	5.636	5.326
AC	-0.450	-0.448
ADF	-13.619***	-13.422***

lags, and decrease with increasing lags, hence indicating autoregressive processes. The Augmented Dickey Fuller (ADF) test statistics are insignificant, suggesting that unit roots are present in the IS and PT series.

Panel B reports summary statistics for the first differences. The mean values of the first differences are close to zero, although there is quite some variation on a daily basis as can be seen from the range of the 5^{th} and 95^{th} percentile and the standard deviation. The series have skewness values close to zero with excess kurtosis, suggesting that observations occur predominantly around the mean. We do not observe the first differences to be serially correlated as the AC quickly drops to zero after one lag. Furthermore, the ADF test statistics are highly significant. Thus, we confirm that the first difference series for IS and PT are stationary.

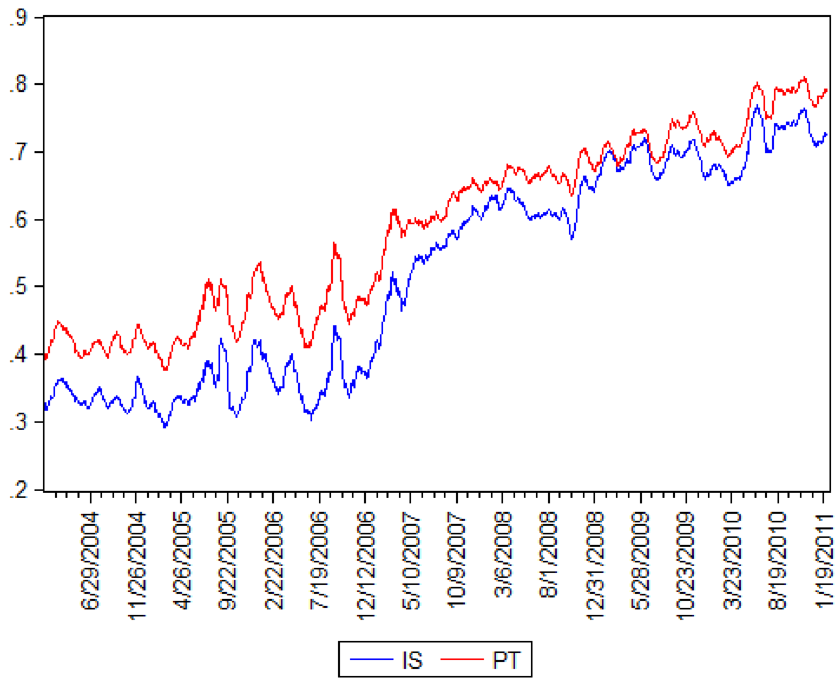
In Figure 4.2, we plot IS and PT from January 2004 to January 2011, based on 20-day moving average for the 38 stocks in our sample. The IS and PT track each other closely with the PT being consistently higher than the IS. According to both measures, price discovery for the U.S. is lower than 50% prior to 2007. This is consistent with earlier studies which show that the home market for the Canadian-U.S. cross-listed stocks dominate in terms of price discovery.[12] We observe that the sharp increase in price discovery is around the year 2007. From 2007 onwards, the U.S. market seems to gain dominance with IS and PT greater than 50%. The IS and PT reach around 80% in 2010. One possible explanation for the increase in the U.S.'s contribution to price discovery is the implementation of the Reg NMS which started in 2006 and was finalised in October 2007, an explanation we examine in Section 4.5.4.

Apart from the slight decrease in IS and PT in late 2008, the increasing trend in price discovery measures does not seem to be substantially affected by the Global Financial Crisis. Overall, Figure 4.2 illustrates that price discovery as measured by IS and PT exhibits persistence over time. Once price discovery is gained by a particular market, it tends to stay. The next section analyzes what drives this dynamics in price discovery.

[12] See for example, Eun and Sabherwal (2003) Chen and Choi (2012).

Figure 4.2: Price discovery measures (US relative)

This figure shows time series plots of the IS and PT over the sample period January 2004 to January 2011. The figures are the 20-day moving averages computed from the mean IS and PT for the 38 firms in the sample.



4.5.2 Reduced-Form VAR Results

In this section, we investigate what drives changes in price discovery over time, i.e. how measures of price discovery, liquidity, and AT activity interact with each other. To gain preliminary insight about the relation between these measures, we test for correlation among them. Table 4.3 presents the correlation matrix among the VAR variables. Correlation between ΔIS and ΔPT is 0.906, which supports a strong linkage between the two price discovery measures. We observe that $\Delta Ratio\_Vol$ is positively correlated with ΔIS and ΔPT, which is consistent with the literature. Both $\Delta Ratio\_Espread$ and $\Delta Ratio\_AT$ are negatively correlated with ΔIS and

Table 4.3: Correlation matrix between VAR variables

This table presents the correlation matrix for the series ΔIS, ΔPT, $\Delta Ratio\_Vol$, $\Delta Ratio\_Espread$, and $\Delta Ratio\_AT$. ΔIS and ΔPT are the first differences in the price discovery measures IS and PT, respectively. $\Delta Ratio\_Vol$ is the first difference in the U.S. trading volume relative to Canada. $\Delta Ratio\_Espread$ is the first difference in the U.S. effective spread relative to Canada. $\Delta Ratio\_AT$ is the first difference of the U.S. AT activity relative to Canada.

	ΔIS	ΔPT	$\Delta Ratio\_Vol$	$\Delta Ratio\_Espread$	$\Delta Ratio\_AT$
ΔIS	1				
ΔPT	0.906	1			
$\Delta Ratio\_Vol$	0.175	0.130	1		
$\Delta Ratio\_Espread$	-0.121	-0.138	-0.103	1	
$\Delta Ratio\_AT$	-0.221	-0.183	-0.702	0.212	1

ΔPT. Furthermore, $\Delta Ratio\_AT$ is also negatively correlated with $\Delta Ratio\_Vol$ and positively correlated with $\Delta Ratio\_Espread$.

To assess the strength and statistical significance of these relations, we start by estimating the reduced-form VAR of Equation (4.13) for 38 firms. The sums of the 5-day lagged coefficients are collected and reported in Table 4.4, and the p-values from the Granger causality tests are reported in parentheses.

Panel A and B of Table 4.4 report the results of the VAR for the IS and PT, respectively. The second column in each panel presents the factors which affect the changes in price discovery measures. We observe that ΔIS (ΔPT) is positively related to the lagged values of $\Delta Ratio\_Vol$ with a coefficient of 0.166 (0.140). A positive change in relative trading volume between the U.S. and Canada over the previous five days leads to a positive change in IS (PT) in the following day. This is in line with the argument of Stickel and Verrechia (1994) that high volume indicates that the demand underlying a price change is informative, and therefore should be incorporated into prices.

We also observe that ΔIS (ΔPT) is negatively related to the lagged values of

Table 4.4: VAR estimation results

This table presents the sum of the lag coefficients of the VAR in Equation (13). The column variable is the dependent variable while the row variable is the explanatory variable. Panel A reports the coefficients from the IS VAR model. Panel B reports the coefficients from the PT VAR model. Figures in parentheses are the p-values from the Granger Causality Test. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: IS reduced-form VAR model				
	Dependent Variable			
	ΔIS	$\Delta Ratio\_Vol$	$\Delta Ratio\_Espread$	$\Delta Ratio\_AT$
$\sum \Delta IS_{t-k}$	-2.155***	**0.028*** **	**-0.001** **	**-0.025***
	[0.000]	**[0.000]**	**[0.017]**	**[0.078]**
$\sum \Delta Ratio\_Vol_{t-k}$	**0.166*** **	-1.876***	-0.015	**-0.089*** **
	[0.000]	[0.000]	[0.214]	**[0.000]**
$\sum \Delta Ratio\_Espread_{t-k}$	**-0.144** **	**-0.053*** **	-2.033***	**0.029** **
	[0.024]	**[0.006]**	[0.000]	**[0.020]**
$\sum \Delta Ratio\_AT_{t-k}$	**-0.057** **	**-0.074*** **	-0.006	-1.830***
	[0.025]	**[0.000]**	[0.436]	[0.000]
Adj. R-squared	0.36	0.30	0.34	0.28

Panel B: PT reduced-form VAR model				
	Dependent Variable			
	ΔPT	$\Delta Ratio\_Vol$	$\Delta Ratio\_Espread$	$\Delta Ratio\_AT$
$\sum \Delta PT_{t-k}$	-2.091***	**0.051*** **	**-0.0003***	**-0.049*** **
	[0.000]	**[0.000]**	**[0.090]**	**[0.000]**
$\sum \Delta Ratio\_Vol_{t-k}$	**0.140*** **	-1.885***	-0.014	**-0.093*** **
	[0.000]	[0.000]	[0.250]	**[0.000]**
$\sum \Delta Ratio\_Espread_{t-k}$	**-0.172*** **	**-0.034** **	-2.036***	**0.030** **
	[0.006]	**[0.012]**	[0.000]	**[0.018]**
$\sum \Delta Ratio\_AT_{t-k}$	**-0.007*** **	**-0.079*** **	-0.002	-1.842***
	[0.003]	**[0.000]**	[0.305]	[0.000]
Adj. R-squared	0.35	0.30	0.34	0.28

$\Delta Ratio\_Espread$ with a coefficient of -0.144 (-0.172). A decrease in relative effective spread over the past five days leads to a positive change in IS (PT) on the following day. This indicates that as trading costs decrease, price discovery tends to increase, indicating intermarket competition between liquidity providers. This is consistent with the cross-sectional findings of Eun and Sabherwal (2003) who suggest that a lower spread in one market represents a competitive threat faced by liquidity providers in another market. In this case, Canadian liquidity providers become more responsive to U.S. prices.

The impact of $\Delta Ratio\_AT$ on ΔIS (ΔPT) is negative and significant with a coefficient of -0.057 (-0.007). This implies an increase of AT activity in the U.S. relative to Canada leads to a lower contribution of the U.S. market to price discovery. We interpret this finding as higher algorithmic trading activity in a market causing a crowding out effect as arbitrageurs use high-frequency trading algorithms to trade aggressively and compete with each other for arbitrage opportunity that exists in the market. This leads to less trading by informed investors who are disadvantaged in terms of speed. Furthermore, Abergel et al. (2012) explain that high-frequency traders often use their speed advantage to free-ride on trade-related information (e.g. order flow, prices, volume, duration between trades) acquired by informed investors. This may reduce investors' incentives to acquire information in the first place, leading to lower price discovery.

The third column in each panel reports the factors which affect the changes in relative trading volume. We observe that lagged values of ΔIS (ΔPT) have an impact on $\Delta Ratio\_Vol$ with a coefficient of 0.028 (0.051). This suggests that improvements in price discovery lead to an increase in relative trading volume. The coefficients of $\Delta Ratio\_Espread$ on $\Delta Ratio\_Vol$ are negative and significant at -0.053 (-0.034) which suggest that as trading becomes cheaper (relative effective spread decreases), trading volume increases. Furthermore, we find negative coefficients of $\Delta Ratio\_AT$ on $\Delta Ratio\_Vol$ at -0.074 (-0.079). As relative AT activity increases, relative trading volume decreases. This finding again indicates that algorithmic traders push away other traders in the market who are disadvantaged in terms of speed.

The fourth column shows that there is a spillover from lagged values of ΔIS (ΔPT) to $\Delta Ratio\_Espread$ with a magnitude of -0.001 (-0.0003). The Granger causality tests show statistically significant results, suggesting that trading costs reduce as a market's contribution to price discovery increases.

The fifth column shows the factors affecting changes in relative AT activity. We observe that the impact of ΔIS (ΔPT) on $\Delta Ratio\_AT$ is negative and significant with a coefficient of -0.025 (-0.049). This suggests that algorithmic trading activities increase as a markets' contribution to price discovery decreases. We conjecture the increase in AT is due to an increase in high-frequency trading through latency arbitrage strategies. Arbitrageurs trade more actively as markets become less efficient in processing and incorporating information into their prices. This finding is in line with Kozhan and Tham (2012), Gai et al. (2014), and Egginton et al. (2014). The negative coefficients of $\Delta Ratio\_Vol$ and positive coefficients of $\Delta Ratio\_Espread$ on ΔIS (ΔPT), respectively, further suggest that inefficiencies in the market attract algorithmic traders who use speed to benefit from these inefficiencies.

Overall, these results suggest that relative increases in liquidity (i.e. higher relative trading volume and lower effective spread) lead to a greater contribution of a market to price discovery. Conversely, an improvement in price discovery leads to greater liquidity. Moreover, an increase in algorithmic trading activity of a market relative to another market leads to lower price discovery, while the inverse is also true.

4.5.3 Structural VAR Results

In addition to lagged effects, we also assess the contemporaneous causal relations between variables using the identification through heteroskedasticity approach (Rigobon, 2003). The structural VAR of Equation (4.12) is estimated using GMM for each of the 38 firms separately. The coefficients are then averaged while the standard errors are computed cross-sectionally.

Panel A and B of Table 4.5 report the results for the contemporaneous relation between the variables in the structural VAR model. The second column reports the impact of liquidity and AT activity on price discovery. We observe a significant

Table 4.5: Contemporaneous relation between variables

This table presents the coefficients for the contemporaneous interactions between the VAR variables. Note that the coefficients in this table have the opposite signs to the coefficients of matrix A because matrix A is on the left-hand side of Equation (12). When taken to the right-hand side the effects become positive. Subsequently, the column variable is the dependent variable while the row variable is the explanatory variable. Panel A reports the results from the IS VAR model. Panel B reports the results from the PT VAR model. Figures in parentheses are the p-values. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: IS structural VAR model				
	Dependent Variable			
	ΔIS	$\Delta Ratio\_Vol$	$\Delta Ratio\_Espread$	$\Delta Ratio\_AT$
ΔIS_t	1	0.011	-0.008	**-0.043***
		[0.185]	[0.112]	**[0.000]**
$\Delta Ratio\_Vol_t$	**0.080***	1	0.005	**-0.352***
	[0.003]		[0.610]	**[0.000]**
$\Delta Ratio\_Espread_t$	**-0.337***	**-0.073***	1	**0.269***
	[0.000]	**[0.086]**		**[0.000]**
$\Delta Ratio\_AT_t$	**-0.084****	**-0.489***	**0.033****	1
	[0.012]	**[0.000]**	**[0.022]**	

Panel B: PT structural VAR model				
	Dependent Variable			
	ΔPT	$\Delta Ratio\_Vol$	$\Delta Ratio\_Espread$	$\Delta Ratio\_AT$
ΔPT_t	1	0.006	**-0.018****	**-0.021***
		[0.440]	**[0.011]**	**[0.063]**
$\Delta Ratio\_Vol_t$	0.014	1	0.015	**-0.335***
	[0.487]		[0.115]	**[0.000]**
$\Delta Ratio\_Espread_t$	**-0.241***	-0.041	1	**0.391***
	[0.001]	[0.288]		**[0.000]**
$\Delta Ratio\_AT_t$	**-0.153***	**-0.515***	**0.030****	1
	[0.000]	**[0.000]**	**[0.024]**	

and positive causal effect of $\Delta Ratio\_Vol$ on ΔIS with a coefficient of 0.080. There is a strong negative contemporaneous effect of $\Delta Ratio\_Espread$ on ΔIS (ΔPT) with a coefficient of -0.337 (-0.241). The last row of each Panel indicates a negative contemporaneous interaction of $\Delta Ratio\_AT$ on ΔIS (ΔPT) at -0.084 (-0.153). The fact that these relations are observed in both structural and reduced-form VAR models suggests that liquidity and AT activity affect price discovery instantaneously as well as with some lags.

The third column reports the coefficients for the determinants of $\Delta Ratio\_Vol$. We observe a significant negative relation between $\Delta Ratio\_Espread$ and $\Delta Ratio\_Vol$, and between $\Delta Ratio\_AT$ and $\Delta Ratio\_Vol$. However, we do not observe a significant contemporaneous causal effect of ΔIS (ΔPT) on $\Delta Ratio\_Vol$. This finding suggests that price discovery tends to affect trading volume with lags. Furthermore, the contemporaneous impact of $\Delta Ratio\_AT$ on $\Delta Ratio\_Vol$ is highly significant at -0.489 (-0.515), indicating that the impact of AT on relative trading volume is more prevalent contemporaneously, i.e. as algorithmic traders enter the market, trading activity by non-AT traders decreases.

In the fourth column, we observe that ΔPT negatively affects $\Delta Ratio\_Espread$ with a coefficient of -0.018, suggesting that an increase in PT leads to a decrease in relative spread. We also observe that $\Delta Ratio\_AT$ significantly affects $\Delta Ratio\_Espread$, which we did not observe in Table 4.4. We interpret this as AT pushes away other traders in the market who are relatively disadvantaged in terms of speed, hence causing spread to increase.

Finally, in the last column, we observe similar significant relations as previously observed in Table 4.4. However, the coefficients of $\Delta Ratio\_Vol$ on $\Delta Ratio\_AT$ and of $\Delta Ratio\_Espread$ on $\Delta Ratio\_AT$ are greater in magnitude at -0.352 (-0.335) and 0.269 (0.391) for the IS (PT) model, respectively. These results suggest that AT activity reacts strongly to changes in liquidity within the same day. Specifically, when the spread is wide and there are only few traders in the market, algorithmic traders enter the market and react to these inefficiencies very quickly.

Overall, Table 4.5 shows that there exists not only lagged, but also contemporaneous relations between relative liquidity, AT activity, and price discovery. Furthermore, our findings emphasize the importance of speed by algorithmic traders, and how other traders in the market react to them.

4.5.4 Price Discovery Dynamics Pre- and Post-Regulation NMS

As a further test, we assess the impact of regulatory changes in the U.S. market. Reg NMS was prompted by the Securities and Exchange Commission's belief that market fragmentation reduces liquidity and that the new regulation would help create a more integrated market.[13] Hendershott and Jones (2005) suggest that an increase in market fragmentation leads to slower price discovery. Hence, regulatory changes to create a more integrated market should improve price discovery. Furthermore, Barclay et al. (2008) find that the consolidation of orders is important for producing efficient prices, especially during times of high liquidity demand. On the contrary, Chung and Chuwonganant (2012) examine the liquidity of the U.S. stock markets one month before and after the adoption of Reg NMS and find that liquidity was reduced in the form of increased quoted and effective spreads, as well as decreased quoted dollar depth. These evidences indicate that there may be an impact of Reg NMS on the dynamics of price discovery.

In this section, we first show how price discovery, liquidity, and AT activity changed after the Reg NMS. We then examine whether the adoption of the Reg NMS affects the dynamics of price discovery for cross-listed stocks. We split our data into two sub-periods based on the completion date of the Reg NMS on 8 October 2007. The first sub-period is from 2 January 2004 to 5 October 2007 as the pre-NMS period. The second sub-period is from 8 October 2007 to 31 January 2011 as the post-NMS period.

Table 4.6 reports the percentage change in price discovery, liquidity, and AT measures between pre- and post-NMS periods. We observe that trading volume in the

[13] The regulation was intended to improve fairness in price execution, and to improve the displaying of quotes and access to market data. One of the most influential components of the Reg. NMS is the Order Protection Rule (OPR) which requires that marketplaces enforce policies to ensure consistent price quotation and prevent trading through a better priced order on another market.

Table 4.6: Changes in variables surrounding the Regulation NMS

This table provides the change in price discovery, liquidity, and algorithmic trading activity measures for 38 Canadian cross-listed stocks. The figures reported are the percentage differences before and after the adoption of Regulation NMS on 8 October 2007. Figures in parentheses are the t-statistics. **, and *** denote significance at the 5%, and 1% levels, respectively.

	Diff	t-stat
Vol^{US}	279%***	(7.52)
Vol^{CAN}	84%***	(4.51)
$Ratio\_Vol$	78%***	(5.00)
$Espread^{US}$	-4%	(-0.31)
$Espread^{CAN}$	-10%	(-0.89)
$Ratio\_Espread$	3%**	(2.02)
AT^{US}	40%***	(7.21)
AT^{CAN}	69%***	(33.53)
$Ratio\_AT$	-19%***	(-8.68)
IS	97%***	(8.50)
PT	53%***	(10.75)

U.S. increased significantly by 279% compared with Canada where it only increased by 53%. This indicates a much larger increase in liquidity in the U.S. compared to Canada after Reg NMS. Consequently, relative trading volume increased by 78%. Effective spreads, on the other hand, did not change significantly in either markets. Contrary to Chung and Chuwonganant (2012), we do not observe a decline in spreads after the adoption of Reg NMS, but rather an improvement in trading volume. As for AT activity, the U.S. market experienced a significant increase by 40%. In Canada, the increase in AT activity is more substantial at 69%. These findings are in line with Panel C of Figure 1, which shows that the increase in AT activity is much higher in Canada than in the U.S.

We find that both IS and PT increased significantly by 97% and 53%, respectively, suggesting that the U.S. contribution to price discovery has increased significantly after the Reg NMS. These findings are in line with Hendershott and Jones (2005) and Barclay et al. (2008) who advocate that a new regulation to create a more integrated market would lead to greater price discovery. Based on the statistics in Table 4.6, it is evident that price discovery has increased significantly after the Reg NMS.

We test the impact of Reg NMS on price discovery dynamics by examining the relations between liquidity, AT activity and price discovery measures during the two sub-periods. Table 4.7 shows the result of the VAR analysis of Equation (4.13) for the two sub-periods. For brevity, we only report the results from IS VAR model.[14] Overall, we do not observe any significant differences from those reported in Table 4.5. As shown in Panel A and B of Table 4.7, changes in relative trading volume positively affect the changes in IS as shown by the highly significant p-values from the Granger causality tests. We also observe that changes in relative effective spread and relative AT activity are negatively related to changes in IS. In the opposite direction, we observe that changes in IS lead to positive changes in relative trading volume as shown by the first row of the third column in each Panel. The impact on changes in relative effective spread remains small and significant for the first sub-period, but insignificant for the second sub-period. The negative coefficients for the changes in relative AT activity are also negative, despite being significant only for the second sub-period. Based on these observations, we conclude that the drivers of price discovery have not changed significantly after the adoption of the Reg NMS.

Table 4.8 shows the contemporaneous relations of the VAR variables in Equation (4.12) during the two sub-periods. Similar to the results in Table 4.6, we observe uni-directional relation between liquidity and price discovery measure. Specifically, changes in relative trading volume contemporaneously and positively affect the changes in IS, while changes in relative effective spread contemporaneously and negatively affect the changes in IS. The bi-directional negative relation between AT

[14]The PT VAR model yields similar results and are available upon request.

Table 4.7: Sub-periods VAR estimation results

This table presents the sum of the lag coefficients of the IS VAR in Equation (13) at two sub-periods surrounding Reg NMS: before and after 8 October 2007. The column variable is the dependent variable while the row variable is the explanatory variable. Panel A reports the coefficients from the IS VAR model with the pre-NMS sample. Panel B reports the coefficients from the IS VAR model with the post-NMS sample. Figures in parentheses are the p-values from the Granger Causality Test. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: IS reduced-form VAR model (pre Reg NMS)				
	Dependent Variable			
	ΔIS	$\Delta Ratio\_Vol$	$\Delta Ratio\_Espread$	$\Delta Ratio\_AT$
$\sum \Delta IS_{t-k}$	-2.202***	**0.012****	**-0.003****	-0.024
	[0.000]	**[0.018]**	**[0.041]**	[0.409]
$\sum \Delta Ratio\_Vol_{t-k}$	**0.160*****	-1.881***	-0.024	**-0.107*****
	[0.003]	[0.000]	[0.342]	**[0.000]**
$\sum \Delta Ratio\_Espread_{t-k}$	**-0.095***	**-0.091****	-2.096***	**0.002****
	[0.071]	**[0.018]**	[0.000]	**[0.021]**
$\sum \Delta Ratio\_AT_{t-k}$	**-0.088****	**-0.100*****	0.007	-1.902***
	[0.035]	**[0.000]**	[0.819]	[0.000]
Adj. R-squared	0.37	0.31	0.34	0.29

Panel B: IS reduced-form VAR model (post Reg NMS)				
	Dependent Variable			
	ΔIS	$\Delta Ratio\_Vol$	$\Delta Ratio\_Espread$	$\Delta Ratio\_AT$
$\sum \Delta IS_{t-k}$	-2.025***	**0.069*****	0.0035	**-0.039*****
	[0.000]	**[0.000]**	[0.276]	**[0.003]**
$\sum \Delta Ratio\_Vol_{t-k}$	**0.157*****	-1.886***	0.006	**-0.076****
	[0.000]	[0.000]	[0.982]	**[0.037]**
$\sum \Delta Ratio\_Espread_{t-k}$	**-0.237*****	**-0.329*****	-1.913***	0.143
	[0.001]	**[0.000]**	[0.000]	[0.145]
$\sum \Delta Ratio\_AT_{t-k}$	**-0.026*****	**-0.065*****	**-0.010***	-1.750***
	[0.005]	**[0.000]**	**[0.092]**	[0.000]
Adj. R-squared	0.34	0.30	0.32	0.27

activity and price discovery measures still persists. Overall, the results presented in Table 4.8 are similar to those reported in Table 4.6.

Both Table 4.7 and 4.8 show that the relations between price discovery and liquidity and AT measures persist even after taking into account the regulatory changes in the U.S. financial markets. We still observe a positive relation of relative trading volume on price discovery, as well as negative relation of relative effective spread and AT activity on price discovery.

4.6 Conclusion

In this chapter, we study price discovery dynamics for a sample of Canadian cross-listed stocks in the U.S. from January 2004 to January 2011. We compute daily measures of price discovery and assess the causal relations between price discovery, liquidity, and algorithmic trading activity. To accommodate both lagged and contemporaneous relations among the variables, we follow the approach of Chaboud et al. (2014) by estimating a reduced-form VAR, as well as a structural VAR using the identification through heteroskedasticity approach developed by Rigobon (2003).

We show that price discovery of the U.S. market relative to Canada exhibits an upward trend, suggesting that over time, the U.S. market is becoming more dominant in terms of the price formation process of Canadian cross-listed stocks. Assessing the dynamics involved, we find that liquidity is related to price discovery. Improvements in relative liquidity (an increase in trading volume and a decrease in effective spread in one market relative to another) increase an the market's contribution to price discovery. This impact is felt instantaneously as well as with a protracted lag. Conversely, we find that an increase in price discovery leads to better liquidity. We also find that relative algorithmic trading activity is negatively related to price discovery. This finding is consistent with the literature on negative externalities of high-frequency trading. Particularly, as arbitrageurs use computer algorithms to

Table 4.8: Sub-periods contemporaneous relation results

This table presents the coefficients for the contemporaneous interactions between the IS VAR variables at two sub-periods surrounding Reg NMS: before and after 8 October 2007. Note that the coefficients in this table have the opposite signs to the coefficients of matrix A because matrix A is on the left-hand side of Equation (12). When taken to the right-hand side the effects become positive. Subsequently, the column variable is the dependent variable while the row variable is the explanatory variable. Panel A reports the results from the IS VAR model with the pre-NMS sample . Panel B reports the results from the IS VAR model with the post-NMS sample. Figures in parentheses are the p-values. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: IS structural VAR model (pre Reg NMS)				
	Dependent Variable			
	ΔIS	$\Delta Ratio\_Vol$	$\Delta Ratio\_Espread$	$\Delta Ratio\_AT$
ΔIS_t	1	-0.002	-0.006	**-0.032****
		[0.832]	[0.335]	**[0.016]**
$\Delta Ratio\_Vol_t$	**0.123***	1	**0.067****	**-0.392*****
	[0.084]		**[0.010]**	**[0.000]**
$\Delta Ratio\_Espread_t$	**-0.327*****	0.012	1	**0.278*****
	[0.002]	[0.772]		**[0.000]**
$\Delta Ratio\_AT_t$	**-0.175****	**-0.590*****	**0.155*****	1
	[0.016]	**[0.000]**	**[0.000]**	

Panel B: IS structural VAR model (post Reg NMS)				
	Dependent Variable			
	ΔIS	$\Delta Ratio\_Vol$	$\Delta Ratio\_Espread$	$\Delta Ratio\_AT$
ΔIS_t	1	0.023	**-0.014***	**-0.032***
		[0.309]	**[0.078]**	**[0.060]**
$\Delta Ratio\_Vol_t$	**0.087****	1	-0.015	**-0.359*****
	[0.020]		[0.100]	**[0.000]**
$\Delta Ratio\_Espread_t$	**-0.150****	-0.054	1	**0.230*****
	[0.037]	[0.349]		**[0.001]**
$\Delta Ratio\_AT_t$	**-0.057***	**-0.430*****	-0.006	1
	[0.090]	**[0.000]**	[0.657]	

trade aggressively and compete for latency arbitrage opportunity that exists in the market, they cause a crowding-out effect. Consequently, high-frequency trading by these arbitrageurs pushes away informed investors, who are disadvantaged in terms of speed. We further observe that while the U.S. market's contribution to price discovery increased after the adoption of the Regulation NMS, the dynamics of price discovery persist.

Overall, our findings highlight the importance of liquidity for exchanges in order to improve price discovery, as well as the importance of price discovery to attract more investors. AT activity by arbitrageurs should be of interest to exchange officials as the crowding out effect may push investors away to trade in another market.

Chapter 5

Quote Dynamics of Cross-Listed Stocks

5.1 Introduction

A substantial amount of market microstructure research focuses on the process of how information is incorporated into security prices. When information enters a market, investors and liquidity providers update their expectations about the value of a security, resulting in a price change. Such information can be inferred from trades (see e.g. Bagehot, 1971; Copeland and Galai, 1983; and Glosten and Milgrom, 1985), and from quotes (see e.g. Jang and Venkatesh, 1991; Huang and Stoll, 1994). Trades are informative because of the presence of informed investors who buy when they have good news, and sell when they have bad news. Quotes are informative because they reflect the information acquired by liquidity providers. For example, the difference between bid and ask prices (the spread) reflects a balancing of losses to the informed with gains from the uninformed traders. Both trades and quotes reflect information signals from various market participants. The relations between these information signals and prices have become the basis of many microstructure theories as discussed in O'Hara (1995).

Numerous studies have documented how information from quotes and trades affects stock prices in a single market. How this information affects prices across markets, however, has not been examined. As such, the understanding of how prices are determined and the mechanisms underlying security trades in multiple markets is limited. Despite the lack of evidence, we can expect that prices of cross-listed stocks in any given market be determined by information being revealed in any of the markets where the stock is traded in. Prices in various markets are linked because, despite the difference in trading venue, these stocks share a common efficient price. Intermarket arbitrage keeps prices in different markets from drifting too far apart and hence prices are cointegrated (see e.g. Lieberman et al., 1999; Baillie et al., 2002; and Pascual et al., 2006).

In this paper, we aim to improve our understanding of the price formation process for stocks with foreign listings. We do so by assessing the mechanism of how information is incorporated into prices. As shown in Kavajecz and Odders-White (2001), Engle and Patton (2004), and Escribano and Pascual (2005), there is additional information gained from analyzing the dynamics of ask and bid prices jointly rather than averaging them through the quote midpoint. The reason is that information causes asymmetric revisions of market quotes, i.e. bid and ask prices do not respond symmetrically to buyer- and seller-initiated trades. Hence, we conjecture that the dynamics of bid and ask prices will provide insights into the price formation process in multiple markets. Understanding how bid and ask prices are determined and the mechanism underlying such a process is crucial for exchanges and regulators in order to adjust and introduce new trading rules, keeping markets competitive. This is important, given the growth in foreign listings and the increased intermarket competition between exchanges in recent years.[1]

We develop a general model to study quote dynamics of stocks traded in dual markets. This model builds on the framework of cointegrated quotes which assumes that quotes of the same stocks in various markets are driven by the same information. A similar framework was implemented in Engle and Patton (2004) and Escribano

[1] See for example Pagano et al. (2002), Halling et al. (2008) and Fernandes and Ferreira (2008) for evidences of cross-listings.

and Pascual (2006). The model incorporates various variables which according to market microstructure theories should affect prices. We use the bid-ask spread (Demsetz, 1968; Jang and Venkatesh, 1991) and depth difference (Huang and Stoll, 1994) to represent quote-related information. We also use the direction of trade (Glosten and Milgrom, 1985; Jang and Venkatesh, 1991), trading volume (Easley and O'Hara, 1987; Barclay and Warner, 1993), trade duration (Easley and O'Hara, 1992) and trade order flow (Kyle, 1985) to represent trade-related information.

Our work contributes to the literature in several ways. First, we provide a tool, which can be used to study the mechanism of how information affects prices in two different markets, and to assess the degree of information spillover between them. Second, the model allows us to assess the relevance of existing microstructure theories in explaining price dynamics in a dual-market setting. Third, we demonstrate how our model can be transformed to an implied vector autoregression (VAR) for the bid-ask spreads in the two markets, the change in price midpoint and the difference in midquotes across markets.[2] Our implied model allows us to study how information affects these variables, which are fundamental for cross-listed stocks. For instance, spreads measure the degree of friction in each of the markets, the midpoint of quotes of the two markets represents the implied efficient price of the cross-listed stock, and the cross-market difference in midquotes represents the relative premium of trading in one market over another.

Applying our model to Canadian stocks which are cross-listed in the U.S., we document several important findings. First, we observe that quote changes in one market lead to quote changes in another market, indicating that prices in both markets are linked directly to each other. Second, quote-related information such as bid-ask spread and the difference in bid and ask depths directly affect prices in

[2] A similar structure has been proposed by Engle and Patton (2004). In their study, the VECM model is transformed into an implied VAR for the bid-ask spread and the change in quote midpoint. Our multi-market quote revision model extends their analysis by constructing the bid-ask spreads in each of the markets, the change in midpoint of prices of the two markets, and the cross-market difference in midquotes.

both markets, indicating some degree of intermarket competition between liquidity providers. Third, we observe that while prices adjust primarily to trades in their respective market, they are also affected by trades from the other market. We therefore conjecture that there is a small degree of information spillover between the two markets. Finally, we find that information plays a greater role in the U.S than in Canada, leading to a greater impact of U.S. trades on the midpoint returns (implied efficient price) and on the difference in midquotes (price premium).[3]

The remainder of this chapter is structured as follows. In Section 5.2, we review the literature. In Section 5.3, we present the model for the quote dynamics. In Section 5.4, we describe the data. In Section 5.5, we analyze the empirical results of the quote model as well as the design and findings of the implied model. Finally, Section 5.6 concludes.

5.2 Literature Review

Market microstructure studies show that information can be inferred from various sources, such as quotes and trades. Throughout this chapter, we refer to this information as quote- and trade-related information. As such, we start this section with a discussion on how quote- and trade-related information affects prices. We discuss studies which assess the role of information on bid and ask prices in a single market. We then explain why it is important to study the dynamics of quotes in multiple markets.

Studies have shown that quote-related information such as the bid-ask spread affects prices. Demsetz (1968) calls the spread the cost of immediacy. Investors who want to buy immediately need to pay the ask price, while those who want to sell immediately need to agree with the bid price. As such, the spread represents a profit to liquidity

[3]This is in line with the findings in Chapter 3 where we observe price discovery shifts from Canada to the U.S. during macroeconomic news announcements.

providers. It is informative because competition between liquidity providers will determine the change in spread. Jang and Venkatesh (1991) show that the bid-ask spread affects bid and ask prices through error-correcting behavior - a large spread at the previous quote leads to a rise in the bid price and a fall in the ask price at the following quote, to restore the spread to its long-run equilibrium value.

Information can also be inferred from the difference in quoted depth. Depth represents the extent to which an asset is able to absorb buy and sell orders without the price dramatically moving in either direction. Huang and Stoll (1994) suggest that the difference between the depth at the ask and the bid conveys important information. High depth at the ask relative to bid indicates an excess number of sellers relative to buyers, signalling that the stock is overpriced (signalling effect). A higher depth at the ask relative to bid also means less trade volume is required before a downward movement than an upward movement, making a downward movement in prices more likely, leading to lower bid and ask prices (barrier effect).

Market microstructure theory further suggests that stock prices are affected by trade-related information. The importance of trades was originally explained in Bagehot (1971). A market comprises both informed and uninformed traders. Trades by the informed would result in liquidity providers losing on average to these traders. Glosten and Milgrom (1985) explain that the direction of trade is informative because in a competitive market, informed agents' trades will reflect their information, either selling if they have received bad news or buying if they have received good news. Jang and Venkatesh (1991) show how a liquidity provider revises his quotes following a transaction. For instance, following a transaction at the bid price, both the bid and the ask prices will be revised downward. This is because a trade at the bid price indicates that some informed traders know that the true value of the asset is lower. Knowing that, the liquidity provider will subsequently lower his bid and ask prices.

Apart from the direction of trade, information can also be gleaned from other trade-related features. First is trade size. Easley and O'Hara (1987) explain that trade size induces an adverse selection problem, because given the same price, the informed traders always prefers to trade larger quantities to maximize their expected profits. Since uninformed traders do not share this size bias, a rational liquidity provider will interpret large orders as a signal that an information event has occurred and adjust prices accordingly by increasing his bid and ask prices. Barclay and Warner (1993) and Chakravarty (2001), however, suggest that informed traders may prefer to trade in a size that is not too large and not too small in order to disguise their private information (stealth trading). In such a case, medium-sized trade should provide the strongest signal of private information and stock prices should react to those trades the most. Another trade-related feature is trade duration. Easley and O'Hara (1992) and Dufour and Engle (2000) show that since trades provide signals of the direction of any new information, the lack of trade provides a signal of no new information (event uncertainty). Hence the absence of trade could provide information to market participants. Finally, signed order flow leads to changes in prices. Kyle (1985) proposes that because liquidity providers cannot distinguish the individual quantities traded by the insider or liquidity (noise) traders separately, nor do they have any other kind of special information, they set prices based on the observations of the current and past aggregate quantities traded by the insider and noise traders combined, known as the order flow.

The literature above discusses the theories and empirical evidence on how information affects quotes in a single-market. As discussed in Escribano and Pascual (2006), quotes do not respond identically to information, i.e. bid and ask prices do not respond symmetrically to buyer- and seller-initiated trades. Hence, there is additional information gained from analyzing the dynamics of ask and bid prices jointly rather than averaging them through the quote midpoint. Consequently, empirical studies on bid and ask dynamics have improved our understanding of the price formation process. For example, Kavajecz and Odders-White (2001) model bid and ask prices, and bid and ask depths simultaneously to examine how NYSE liquidity providers update their prices and quoted depths. They find that changes in the best prices and the depths of the limit order book have a significant impact on each other. Engle and Patton (2004) specify an error-correction model for the log difference of the bid and the ask price with the spread acting as the error-correction term, and include various trade-related information as regressors. They show that the dynamics of the bid-ask spread is heavily influenced by the differential response of bids and asks to buys and sells; a buy has a greater impact on the ask price than on the bid price, while a sell has a greater impact on the bid price than on the ask price.

The existing literature to date has only focused on examining quote dynamics in a single-market context. The question how information affects quotes in multiple markets has not been examined. Furthermore, the relevance of microstructure theories in a multiple-market context is still untested. In order to improve the understanding of price formation process for stocks with foreign listings, we start by analyzing the dynamics of quotes in dual markets. We propose that bid and ask prices from two markets be modelled jointly. Such specification allows us to examine how prices in each market respond to information entering any of the two markets. This model will be discussed in the next section.

5.3 Dual-Market Quote Dynamics

In this section, we present the model for dual-market quote dynamics. We build on the framework of cointegrated quotes as applied in Engle and Patton (2004) and Escribano and Pascual (2006). These studies employ an error-correction model between bid and ask prices, of which quotes are cointegrated with the bid-ask spread being the error-correction term. The VECM is widely used to analyze asymmetries in the short-run impacts of trades on the bid or ask price, and it is more dynamic since it controls for serial dependencies of the variables. One appealing feature of the VECM is that it allows the cointegrating relationship to be known a priori, and therefore sets a very general parameterization of the model. Furthermore, it is flexible enough to accommodate a multi-market extension.

Empirically, we extend a VECM into a dual-market setting and represent bid and ask prices from two markets in simultaneous equations. We follow the specification of Engle and Patton (2004) and model the quote revisions as a function of quote and trade-related information, which reflects the mechanism of how information is aggregated and disseminated into quotes. We specify the model in terms of log-differences, of which the log levels of the bid and ask prices in each market are cointegrated of order one.

$$\begin{bmatrix} \Delta\log(ASK_t^A) \\ \Delta\log(BID_t^A) \\ \Delta\log(ASK_t^B) \\ \Delta\log(BID_t^B) \end{bmatrix} = c + \sum_{j=1}^{10} A_{(j)} \cdot \begin{bmatrix} \Delta\log(ASK_{t-j}^A) \\ \Delta\log(BID_{t-j}^A) \\ \Delta\log(ASK_{t-j}^B) \\ \Delta\log(BID_{t-j}^B) \end{bmatrix} + B \cdot \begin{bmatrix} SPREAD_{t-1}^A \\ SPREAD_{t-1}^B \end{bmatrix} + \Gamma_1 \cdot \begin{bmatrix} DEPTH\_DIFF_{t-1}^A \\ DEPTH\_DIFF_{t-1}^B \end{bmatrix}$$
$$+ \sum_{k=1}^{3} \Gamma_2^{(k)} \cdot \begin{bmatrix} BUY_{\tau(t)-k}^A \cdot 1 \\ BUY_{\tau(t)-k}^A \cdot V_{\tau(t)-k}^{A,med} \\ BUY_{\tau(t)-k}^A \cdot D_{\tau(t)-k}^A \\ BUY_{\tau(t)-k}^B \cdot 1 \\ BUY_{\tau(t)-k}^B \cdot V_{\tau(t)-k}^{B,med} \\ BUY_{\tau(t)-k}^B \cdot D_{\tau(t)-k}^B \end{bmatrix} + \sum_{k=1}^{3} \Gamma_3^{(k)} \cdot \begin{bmatrix} SELL_{\tau(t)-k}^A \cdot 1 \\ SELL_{\tau(t)-k}^A \cdot V_{\tau(t)-k}^{A,med} \\ SELL_{\tau(t)-k}^A \cdot D_{\tau(t)-k}^A \\ SELL_{\tau(t)-k}^B \cdot 1 \\ SELL_{\tau(t)-k}^B \cdot V_{\tau(t)-k}^{B,med} \\ SELL_{\tau(t)-k}^B \cdot D_{\tau(t)-k}^B \end{bmatrix}$$
$$+ \Gamma_4 \cdot \begin{bmatrix} \sum_{k=1}^{l(t)} BUY_{\tau(t)-k}^A \\ \sum_{k=1}^{l(t)} SELL_{\tau(t)-k}^A \\ \sum_{k=1}^{l(t)} BUY_{\tau(t)-k}^B \\ \sum_{k=1}^{l(t)} SELL_{\tau(t)-k}^B \end{bmatrix} + \sum_{d=1}^{7} \Gamma_5^{(d)} \cdot \left[DIURN_t^d \right] + \varepsilon_t. \tag{5.1}$$

where c is a (4×1) vector of constants, $A_{(j)}$ are (4×4) matrices of AR coefficients at lag j, B is a (4×2) matrix of spreads coefficients, Γ_1 is a (4×2) matrix of depth difference coefficients, $\Gamma_2^{(k)}$ and $\Gamma_3^{(k)}$ are (4×6) matrices of trade-related variables at the kth most recent trade at the buy and sell side, respectively, Γ_4 is a (4×4) matrix of total trade coefficients, $\Gamma_5^{(d)}$ are (4×1) vectors of diurnalilty (intraday seasonality) coefficients at time of the day d, and ε_t is a $(4{\times}1)$ vector of innovations.

The model is defined in quote time which means a new observation is recorded each time there is a change in quotes. The subscript t, denotes the t^{th} observation in the chronological sequence of quotes, while trades are indexed according to the quote they precede: $\tau(t)-k$ indexes the k^{th} most recent trade to quote observation t. The function $l(t)$ counts the number of trades occuring between quote $t-1$ and quote t. Microstructure data such as the changes in quotes often show evidence of negative serial correlation (Stoll, 2000). To control for this serial correlation, we employ ten lags of the dependent variables, and include information on the three most recent trades as exogenous regressors in our model.

Table 5.1 lists and describes the variables used in this study. We use $SPREAD$ and $DEPTH\_DIFF$ to represent quote-related information potentially affecting quote revisions. The log spreads are also the error-correction terms because the log levels of the bid and ask prices are cointegrated. We include BUY and $SELL$ to represent trades at both sides of the market. We follow the standard trade signing approach of Lee and Ready (1991) and use contemporaneous quotes to sign trades, following Bessembinder (2003). If the trade price was higher than the mid-quote, the trade is considered a buy, while if the trade price is lower than the mid-quote, the trade is considered a sell. A trade that occurs exactly at the mid-quote is considered indeterminate and given a value of zero. With regard to trade size, we include a volume indicator, V^{med} which takes a value one if the trade volume was between 1,000 and 10,000 shares and zero otherwise. We do not employ an indicator for big volume trades since they are extremely rare for our sample stocks (refer to Table 5.2 on the summary statistics). To capture the impact of trading intensity, we include trade duration variable, D, which is calculated as the difference in seconds between two consecutive trades. The signed order flow variables $\sum_{k=1}^{l(t)} BUY_{\tau(t)-k}$ and $\sum_{k=1}^{l(t)} SELL_{\tau(t)-k}$ count the number of buys or sells between the current and

Table 5.1: List and Descriptions of Variables

This table lists and describes the variables used in our study.

Variable	Description
Quote Variables	
$\Delta log(ASK_t^i)$	The log difference in ask price in market i between quote t and quote $t-1$.
$\Delta log(BID_t^i)$	The log difference in bid price in market i between quote t and quote $t-1$.
$SPREAD_t^i$	The log spread in market i: $log(ASK_t^i) - log(BID_t^i)$.
$DEPTH\_DIFF_t^i$	The log difference between the depth at the ask and bid prices in market i at quote t.
$\Delta log(MQ_t)$	The log difference in average midquote from all markets, between quote t and quote $t-1$.
$log(MQ_t^{A-B})$	The difference in log midquotes between market A and market B, at quote t.
Trade-Related Variables	
$l(t)$	The number of trades between quote t and quote $t-1$.
$\tau(t)-k$	Denotes the kth most recent trade at quote t.
$BUY_{\tau(t)-k}^i$	Buy indicator in market i: returns 1 if $l(t) \geq k$ and the kth most recent trade at quote t was identified as a buy, else returns 0.
$SELL_{\tau(t)-k}^i$	Sell indicator in market i: returns 1 if $l(t) \geq k$ and the kth most recent trade at quote t was identified as a sell, else returns 0
$V_{\tau(t)-k}^{i,med}$	Medium volume trade indicator in market i: returns 1 if the kth most recent trade at quote t had volume between 1,000 and 10,000 shares, else returns 0.
$D_{\tau(t)-k}^i$	The duration in market i of the kth most recent trade at quote t. (in seconds)
Deterministic Variables	
$DIURN_t^d$	Diurnal adjustment variable: the value of the dth diurnal indicator variable at quote t.
Market Innovations	
ε_t	The vector of market innovation at quote t.

the previous quotes, and represent order flow in the market. Finally, to capture any deterministic component of intra-day dynamics, we follow the commonly used approach by including time-of-the-day dummies, $DIURN$ into the model.[4]

5.4 Data

Our sample consists of 64 cross-listed stocks and spans eleven months from February 1, 2011 to December 31, 2011.[5] This sample constitutes all Canadian stocks listed on both the Toronto Stock Exchange and the New York Stock Exchange, which are readily tradeable in both markets over the sample period, and are available in the database. We use tick level data from TRTH (Thomson Reuters Tick History) database maintained by Securities Industry Research Centre of Asia-Pacific (SIRCA). Specifically, we obtain the time stamp (to the nearest microsecond) of bid and ask prices, bid and ask depths, trade prices, and trade volumes for the stocks in each market over 225 trading days. For each of these variables, we use data from the consolidated tape to ensure that our analysis captures the quote dynamics in the two markets accurately. In addition, we also obtain CAD/USD quotes from TRTH, and use the midpoint to convert the Canadian quotes and trade prices into U.S. Dollar to facilitate the specification of the error-term and ensure the comparability of prices between the two markets.[6]

Table 5.2 presents the stocks in our sample and the summary statistics of the data over the sample period. The average number of daily trades ranges from 44 trades (STN) to 25,616 trades (SLW) with an average of 5,934 trades in the U.S. Average daily trades in the U.S. are higher than the average daily trades in Canada of 4,284 trades which ranges from 55 trades (NOA) to 14,496 trades (SU). In terms of trading

[4] For example, see Dufour and Engle (2000), Engle and Patton (2004).

[5] The starting date is chosen following the Order Protection Rule which was introduced on Feb 1, 2011 in Canada.

[6] We use the standing exchange rate midpoint prior to any Canadian quotes to convert the quotes into U.S. dollar.

Table 5.2: Summary statistics

This table reports the summary statistics for trades in the U.S. and Canada for 64 stocks in the sample. The figures are computed over 225 trading days from February 1, 2011 to December 31, 2011. The first two columns report the ticker symbols in the U.S. and the company names. N denotes the average daily number of trades, Volume denotes the average daily trading volume, Sml, Med, and Big are trade indicators which count the number of trades with a volume of less than 1,000 shares, between 1,000 and 10,000 shares, and over 10,000 shares, respectively. %Spread denotes the percentage difference between log ask and log bid prices. Duration is the average time taken between two consecutive trades, measured in seconds.

		US							CAN						
Symbol	Company Name	N	Volume	Sml	Med	Big	%Spread	Duration	N	Volume	Sml	Med	Big	%Spread	Duration
AAV	Advantage Oil and Gas Ltd.	1,214	302	1,159	55	0	0.193%	22.8	1,444	717	1,308	131	5	0.161%	19.1
ABX	Barrick Gold	22,695	299	21,807	881	7	0.022%	1.1	10,782	295	10,440	338	3	0.024%	2.4
AEM	Agnico-Eagle Mines Limited	7,326	211	7,211	114	1	0.054%	3.7	2,844	198	2,816	28	1	0.051%	9.4
AG	First Majestic Silver Corp.	3,712	308	3,569	143	0	0.128%	9.1	3,210	297	3,107	102	1	0.102%	8.7
AGU	Agrium Inc.	6,040	188	5,987	53	0	0.060%	4.4	2,848	198	2,827	21	1	0.051%	9.2
AT	Atlantic Power Corp.	1,125	271	1,086	39	0	0.115%	29.8	697	261	674	23	0	0.089%	48.6
AUY	Yamana Gold Inc.	16,297	539	14,366	1914	17	0.067%	1.7	6,636	715	5,694	930	12	0.071%	3.9
BAM	Brookfield Asset Management Inc.	3,872	217	3,810	61	1	0.048%	7.0	3,259	268	3,208	49	2	0.041%	7.9
BCE	BCE Inc.	2,457	211	2,421	37	0	0.039%	10.7	5,688	341	5,454	231	4	0.027%	4.4
BMO	Bank of Montreal	3,434	211	3,389	44	1	0.028%	8.3	6,901	257	6,748	151	3	0.020%	3.7
BNS	Bank of Nova Scotia	2,081	178	2,067	14	0	0.042%	14.6	8,254	286	8,046	204	4	0.022%	3.1
BPO	Brookfield Office	6,136	320	5,854	278	4	0.058%	4.4	2,125	386	2,025	97	2	0.059%	12.8
BTE	Baytex Energy Corp.	1,140	177	1,131	8	0	0.100%	25.6	1,435	215	1,418	15	1	0.077%	19.9
CAE	CAE Inc.	69	231	68	1	0	0.217%	443.0	1,403	493	1,341	59	3	0.092%	18.4
CCJ	Cameco Corp.	9,326	264	9,025	299	2	0.049%	3.1	5,760	283	5,609	148	3	0.045%	4.8
CLS	Celestica Inc.	2,598	254	2,514	83	0	0.121%	11.4	1,485	662	1,389	93	3	0.110%	19.3
CM	Canadian Imperial Bank Communication	1,159	155	1,154	5	0	0.055%	25.3	4,602	227	4,532	68	2	0.027%	5.6
CNI	Canadian National Railway Company	4,043	164	4,023	20	0	0.043%	6.6	3,695	191	3,667	27	1	0.032%	6.9
CNQ	Canadian Natural Resources Ltd.	12,500	232	12,263	235	2	0.031%	2.1	10,364	311	9,975	384	4	0.029%	2.5
COT	COTT Corp.	1,684	296	1,625	57	2	0.159%	17.9	364	461	355	8	0	0.159%	99.7
CP	Canadian Pacific	3,943	167	3,916	26	1	0.047%	8.4	2,783	197	2,759	22	1	0.039%	10.1
CVE	Cenevous Energy Inc.	5,440	210	5,366	73	1	0.047%	4.8	6,923	269	6,777	142	4	0.036%	3.7
ECA	Encana Corp.	13,298	294	12,761	534	3	0.038%	2.0	7,923	375	7,496	422	5	0.038%	3.2
EGO	Eldorado Gold Corp.	10,466	331	9,874	590	2	0.057%	2.4	6,271	479	5,766	499	6	0.057%	4.1
ENB	Enbridge Inc.	2,161	181	2,140	21	0	0.049%	13.7	4,682	275	4,603	76	3	0.032%	6.0
EQU	Equal Energy Ltd.	215	338	203	12	0	0.591%	160.8	96	461	89	7	0	0.687%	392.3
ERF	Enerplus Corp.	2,932	240	2,872	60	0	0.065%	9.5	2,165	203	2,142	22	0	0.051%	12.6
EXK	Endeavour Silver Corp.	6,257	392	5,836	418	3	0.115%	4.4	1,686	334	1,606	79	0	0.123%	19.4
GG	Goldcorp Inc.	19,357	270	18,796	554	6	0.024%	1.3	9,989	269	9,713	274	2	0.025%	2.5
GIB	CGI Group	901	190	893	8	0	0.086%	30.1	1,959	438	1,899	55	5	0.057%	14.5
GIL	Gildan Activewear Inc.	2,250	183	2,227	22	0	0.073%	13.0	1,914	244	1,887	25	2	0.059%	15.4
HBM	Hudbay Minerals Inc.	97	219	95	2	0	0.237%	356.5	1,776	442	1,686	86	3	0.096%	15.0
IAG	IAMGOLD Corp.	8,440	261	8,180	260	1	0.052%	3.1	5,193	347	4,986	204	4	0.052%	5.1
KGC	Kinross Gold Corp.	15,860	460	14,249	1602	9	0.060%	1.6	8,551	787	7,184	1,347	19	0.062%	2.9
MFC	Manulife Financial Corp.	8,411	346	7,901	508	2	0.063%	3.2	8,555	868	6,921	1,609	25	0.067%	3.0
MGA	Magna International Inc.	4,778	189	4,735	43	1	0.060%	5.8	3,200	214	3,162	37	2	0.050%	8.4
MIM	MI Developments Inc.	470	254	463	7	1	0.175%	81.8	113	954	110	2	1	0.236%	456.4
NDZ	Nordion Inc.	562	225	552	9	0	0.185%	53.7	153	373	150	2	0	0.222%	229.3

Table 5.2 – continued from previous page

		US							CAN						
Symbol	**Company Name**	**N**	**Volume**	**Sml**	**Med**	**Big**	**%Spread**	**Duration**	**N**	**Volume**	**Sml**	**Med**	**Big**	**%Spread**	**Duration**
NOA	North American Energy Partners Inc.	831	241	810	21	1	0.371%	49.3	55	226	54	1	0	0.754%	725.0
NXY	Nexen Inc.	10,352	290	9,930	418	3	0.049%	2.5	5,560	388	5,259	298	3	0.049%	4.7
PDS	Precision Drilling Trust	5,778	301	5,531	246	2	0.085%	4.8	3,720	599	3,428	285	7	0.085%	7.6
PGH	Pengrowth Energy Corp.	2,832	353	2,659	171	1	0.093%	9.1	2,086	496	1,904	179	3	0.086%	12.3
POT	Potash Corporation of Saskatchewan Inc.	23,180	277	22,474	700	6	0.029%	1.1	7,836	237	7,685	150	1	0.028%	3.5
PWE	Penn West Petroleum Ltd.	6,558	272	6,335	222	1	0.050%	4.0	4,156	342	3,986	167	3	0.048%	6.2
RBA	Ritchie Brothers Auctioneers	1,619	213	1,599	19	1	0.102%	18.3	288	192	285	2	0	0.137%	115.0
RCI	Rogers Communication Inc.	1,701	180	1,689	12	0	0.051%	16.0	4,767	324	4,613	149	5	0.032%	5.3
RY	Royal Bank of Canada	3,003	218	2,954	49	0	0.036%	9.9	11,497	338	11,055	435	7	0.020%	2.2
SA	Seabridge Gold Inc.	1,097	199	1,082	14	0	0.241%	25.4	84	165	83	0	0	0.343%	388.2
SJR	Shaw Communications Inc.	634	174	630	5	0	0.075%	48.5	2,891	347	2,800	89	3	0.050%	8.6
SLF	Sun Life Financial	2,362	212	2,321	41	0	0.057%	12.0	5,633	352	5,435	193	4	0.039%	4.6
SLW	Silver Wheaton Corp.	25,616	324	24,384	1223	9	0.032%	1.1	6,518	296	6,319	197	2	0.037%	4.0
STN	Stantec Inc.	44	150	44	0	0	0.407%	770.0	271	486	266	4	1	0.201%	106.3
SU	Suncor Energy Incorporated	21,600	295	20,794	802	4	0.028%	1.2	14,496	425	13,425	1,064	8	0.029%	1.8
SVM	Silvercorp Metals Inc.	8,566	395	7,886	675	6	0.106%	3.4	2,879	423	2,613	264	1	0.108%	9.8
TAC	TransAlta Corp.	143	209	141	2	0	0.115%	208.8	2,086	313	2,015	71	1	0.050%	12.2
TC	Thompson Creek Metals Company Inc.	5,934	346	5,569	363	2	0.110%	4.5	2,142	475	1,964	176	3	0.110%	12.6
TCK	Teck Resources Ltd.	13,436	229	13,207	228	2	0.035%	2.0	9,196	289	8,909	284	3	0.033%	2.9
TD	Toronto-Dominion Bank	2,943	182	2,919	23	0	0.040%	9.4	7,385	236	7,263	119	2	0.021%	3.5
THI	Tim Hortons Inc.	1,041	155	1,038	3	0	0.067%	27.0	1,707	224	1,694	13	1	0.051%	14.8
TLM	Talisman Energy Inc.	10,969	325	10,397	569	3	0.052%	2.4	7,568	522	6,845	714	9	0.056%	3.4
TRI	Thomson Reuters Corp.	3,638	202	3,589	49	0	0.043%	7.7	3,768	331	3,675	89	3	0.033%	6.7
TRP	TransCanada Corp.	2,348	194	2,323	25	0	0.044%	12.7	5,740	317	5,597	138	5	0.027%	4.6
TU	Telus Corp	481	150	479	2	0	0.093%	66.3	2,134	231	2,113	20	2	0.039%	11.9
VRX	Valeant Pharmaceuticals International Inc.	8,300	238	8,138	157	5	0.054%	3.5	2,008	195	1,987	20	1	0.063%	14.2
	Mean	5,934	252	5,695	236	2	0.096%	42.7	4,284	365	4,076	205	3	0.091%	47.0

volume, average transaction size is lower in the U.S. than in Canada. The majority of transactions fall in the small trade category (volume of less than 1,000 shares). A small portion of trades falls in the medium category, while big trades are extremely rare. Average daily percentage spread is higher in the U.S., 0.096% compared to 0.091% in Canada, and 41 out of 64 stocks report higher percentage spread in the U.S. than in Canada. Spread is negatively correlated with trades. For example, EQU and STN trade at the highest spread in the U.S. Similarly, EQU and NOA have the highest spread in Canada. These stocks are some of the least frequently traded stocks in their respective markets. Finally, if we look at trade duration, STN and CAE in the U.S. and NOA and MIM in Canada are the least frequently traded stocks and have the highest average trade durations of 770, 443, 725 and 456 seconds, respectively. Apart from these stocks, most transactions occur within 60 seconds of each other with many of them trade within less than 10 seconds.

For our analyses, we first discard any transactions and quotes that occur outside trading hours between 9.35AM to 16.00PM.[7] Second, high-frequency data contains a high ratio of number of quotes in a period to the number of trades. Since a large proportion of these quotes are adjustments to the quote depths at a particular price, and not changes in actual quote prices, we only keep a new quote observation whenever one (or both) quotes change. Third, we sometimes observe trades executed at different prices but at the same time stamp. In such cases, we treat them as one trade. We assign the appropriate price of the trade using value weighted average price and as for the volume, we sum the total volume of the trades. Finally, we combine the U.S. and Canadian datasets by first compiling a series of quote time using the time stamps from both markets. Once the series is constructed, we connect

[7]We omit the first five minutes of the trading day to ensure synchronicity of the data in both markets, since sometimes trading in one of the markets starts later than 9:30AM. This also allows us to avoid contamination of prices by overnight news arrival.

the data from each market according to the time stamps.[8] If there is no data for any one market at a particular time stamp, we assign a value of zero.[9]

5.5 Empirical Results

5.5.1 Quote Dynamics Model

In this section, we present the results for our quote model. We estimate Equation (5.1) for each of the 64 stocks daily. This totals to 14,400 separate estimations. The average $R^2(adj)$ statistics for the U.S. bid and ask equations is 0.253 while for the Canadian bid and ask equations is 0.208. We report the results in the form of the mean coefficients for each stock throughout the entire sample period, along with a percentage count of the number of times the coefficient is significantly positive and negative at the 5% level. We use White's (1980) robust standard errors in our estimations to correct for possible heteroskedasticity.

We observe substantial evidence of increased bid and ask spreads at the beginning of the trading day in both markets, as can be seen from Table 5.3. From 9.30AM to 10AM especially, the diurnal variables show significant positive coefficients on the ask prices and significant negative coefficients on the bid prices in both markets. The coefficients of the diurnal variables decrease gradually over the subsequent time of the day. This implies that the beginning of trading day displays a significant deterministic component, consistent with the literature; for example, Hasbrouck (1999) and Dufour and Engle (2000).

[8] We acknowledge that there can be differences in how Thomson Reuters record time between the U.S. and Canada. Therefore, the time stamps from TRTH may differ from the actual time recorded by the exchanges. However, since there is no actual exchange time recorded for quotes, we do not know which market is first to record quotes.

[9] Since our quote model is in first differences, adding zeros to the series will only mean that there is no change in quotes at that particular time stamp.

Table 5.3: Diurnality Coefficients of The Quote Model

This table reports the coefficients for the first lag of the diurnality variables (coefficients $\Gamma_5^{(d)}$ in Equation 5.1). "Sig + / -" denote the percentage count of number of times the variable was significantly positive and negative at the 5% level, respectively, out of a total of 14,400 observations.

	ΔASK^{US}	ΔBID^{US}	ΔASK^{CAN}	ΔBID^{CAN}
$DIURN_{9.30AM}$	0.004	-0.005	0.002	-0.002
Sig + / - (in %)	49/1	1/51	25/2	2/28
$DIURN_{10AM}$	0.002	-0.002	0.001	-0.001
Sig + / - (in %)	34/2	2/36	17/3	3/18
$DIURN_{11AM}$	0.001	-0.001	0.000	0.000
Sig + / - (in %)	26/3	3/26	13/3	3/13
$DIURN_{12PM}$	0.001	-0.001	0.000	0.000
Sig + / - (in %)	19/3	3/20	9/4	3/11
$DIURN_{1PM}$	0.001	-0.001	0.000	0.000
Sig + / - (in %)	17/3	3/17	9/4	4/9
$DIURN_{2PM}$	0.000	-0.001	0.000	0.000
Sig + / - (in %)	13/3	3/14	7/4	4/8
$DIURN_{3PM}$	0.000	0.000	-0.001	0.000
Sig + / - (in %)	7/3	3/6	5/4	4/4

Lags of Dependent Variables And Quote-Related Information

We report the coefficients for the first lag of the dependent variables in Panel A of Table 5.4.[10] We observe strong negative serial correlation between the dependent variables and their first lag in the home market. We attribute this to quote revisions due to inventory effects as documented in the literature such as Stoll (2000) and Engle and Patton (2004).[11] Across markets, we observe reactions to changes in the lagged quotes. The coefficient for the lagged ask price in one market is significantly positive on the ask dependent variable of the other market, and significantly negative on the bid dependent variable. An increase in the ask price in one market leads to an increase in the ask price and a decrease in the bid price of the other market in the following period. The opposite is true for the lagged bid price. This indicates direct interactions between prices in the two markets.

[10] For brevity, we only report the first lag. Full results are available upon request.

[11] Liquidity suppliers adjust quotes to induce inventory equilibrating trades. For example, when a sale takes place, the bid price tends to fall to discourage additional sales.

Table 5.4: Coefficients of the first lagged dependent variables on the quote model

This table reports the mean of the estimated coefficients for the first lag of the dependent variables (coefficients $A_{(l)}$, B, Γ_l in Equation 5.1). "Sig + / -" denote the percentage count of number of times the variable was significantly positive and negative at the 5% level, respectively, out of a total of 14,400 observations.

Panel A: Lagged Dependent Variables

	ΔASK^{US}	ΔBID^{US}	ΔASK^{CAN}	ΔBID^{CAN}
ΔASK^{US}_{t-1}	**-0.279**	**0.258**	**0.073**	**-0.078**
Sig + / - (in %)	**0 / 88**	**87 / 0**	**65 / 0**	**0 / 67**
ΔBID^{US}_{t-1}	**0.262**	**-0.274**	**-0.076**	**0.075**
Sig + / - (in %)	**88 / 0**	**0 / 88**	**0 / 66**	**66 / 0**
ΔASK^{CAN}_{t-1}	**0.174**	**-0.183**	**-0.294**	**0.321**
Sig + / - (in %)	**90 / 0**	**0 / 91**	**0 / 83**	**86 / 0**
ΔBID^{CAN}_{t-1}	**-0.177**	**0.180**	**0.324**	**-0.289**
Sig + / - (in %)	**0 / 90**	**91 / 0**	**87 / 0**	**0 / 83**

Panel B: Bid-Ask Spread

	ΔASK^{US}	ΔBID^{US}	ΔASK^{CAN}	ΔBID^{CAN}
$SPREAD^{US}_{t-1}$	**-0.176**	**0.184**	**-0.084**	**0.087**
Sig + / - (in %)	**0 / 90**	**91 / 0**	**0 / 66**	**67 / 0**
$SPREAD^{CAN}_{t-1}$	**-0.198**	**0.205**	**-0.113**	**0.116**
Sig + / - (in %)	**0 / 90**	**91 / 0**	**0 / 62**	**64 / 0**

Panel C: Depth Difference

	ΔASK^{US}	ΔBID^{US}	ΔASK^{CAN}	ΔBID^{CAN}
$DEPTH\_DIFF^{US}_{t-1}$	**-0.663**	**-0.662**	0.000	-0.002
Sig + / - (in %)	**0 / 91**	**0 / 91**	5 / 7	6 / 7
$DEPTH\_DIFF^{CAN}_{t-1}$	0.001	0.000	**-0.338**	**-0.347**
Sig + / - (in %)	9 / 8	8 / 10	**0 / 83**	**0 / 84**

With regard to spreads, studies such as Jang and Venkatesh (1991) and Easley and O'Hara (1992) document that a large spread leads to a fall in the ask price and a rise in the bid price at the following quote, to restore the spread to its long-run equilibrium value. Similarly, we expect that a wide spread in one market will narrow the spread in the other market to ensure the competitiveness of prices in the two markets. This will be reflected in a decrease in ask price and an increase in bid price.

The empirical results in Panel B of Table 5.4 show the impact of the lagged spread on quotes in both markets. A wide spread in the home market leads to a decrease in the ask price and an increase in the bid price of the same market, moving the spread toward its equilibrium value. We find that the coefficient of the U.S. spread on the changes in U.S. ask (bid) is significant and consistent with the hypothesized sign in 90% (91%) of the time. The coefficient of the Canadian spread on the changes in Canadian ask (bid) is significant and consistent with the hypothesized sign in 62% (64%) of the time. Bid and ask prices react to changes in spreads, indicating error-correcting behavior of the spread. We attribute this to competition between liquidity providers. This finding also suggests that new orders tend to be placed within the quotes when the spread is large. Therefore, changes in spread is not permanent but temporary. This is consistent with the arguments of Jang and Venkatesh (1991) and Easley and O'Hara (1992), as well as the findings of Engle and Patton (2004).

We also observe that spreads affect quotes across markets. For instance, an increase in spreads in the U.S. leads not only to a decrease in the ask price and an increase in the bid price in the U.S., but also in Canada. Similarly, an increase in spreads in Canada leads to a decrease in the ask price and an increase in the bid price in both Canada and the U.S. These findings indicate some degree of intermarket competition between liquidity providers to ensure the comparability of prices between the two markets. In addition, the magnitude of the Canadian spread coefficients are higher on the U.S. quotes than the U.S. spread coefficients on the Canadian quotes. This finding can be attributed to the fact that percentage spread, on average, is higher in the U.S. than in Canada as shown in the summary statistics in Table 5.2, of which 41 out of 64 stocks report higher percentage spreads in the U.S. than in Canada. Consistent with Jang and Venkatesh (1991) and Escribano and Pascual (2006), the responses of the bid and ask prices are greater when the bid-ask spread is wide than when the spread is narrow.

Next, we investigate the impact of depth on quotes. Huang and Stoll (1994) suggest that the difference between the depth at the ask and at the bid is informative. The signalling effect suggests that high depth at the ask relative to the bid indicates excess number of sellers relative to buyers, indicating that the stock is overpriced. The barrier effect suggests that excess depth means less volume is required before a downward movement than an upward movement. Either of these effects lead to less buyers and more sellers, thus lowering the ask price and increasing the bid price.

Panel C of Table 5.4 reports the coefficients of the lagged depth difference on the bid and ask prices. We observe that an increase in depth difference in the U.S. leads to a strong decrease in the home market bid and ask prices. The coefficients for $DEPTH\_DIFF_{t-1}^{US}$ are negative in 91% of the time for both U.S. ask and bid quotes, respectively. The same applies to the depth difference in Canada, of which the coefficients are negative in 83% (84%) of the time for the ask and bid quotes, respectively. This is strong evidence for the signalling and barrier effects which leads to lower bid and ask prices.

The cross-market impact of depth difference is insignificant and almost negligible. Traders do not seem to pick up information conveyed in depth difference from across market. This indicates an absence of information spillover across market. In this respect, we conclude that the signalling and barrier effects as shown in Huang and Stoll (1994) only affect quotes of the same market.

The Importance of Trade-Related Information

Another important concept in market microstructure is that trades convey information and affect the fundamental value of a stock. Trade-related features such as direction, size, duration, and order flow are known to be informative and may cause revisions in market quotes.

Panel A of Table 5.5 reports the coefficients of the trade direction variables on the bid and ask prices. Our findings on the impact of trade on home market quotes are

Table 5.5: Coefficients of the trade-related variables on the quote model

This table reports the average of the estimated coefficients for the first lag of the trade-related variables (coefficients $\Gamma_2^{(l)}$, $\Gamma_3^{(l)}$, and Γ_4 in Equation 5.1). "Sig + / -" denote the percentage count of number of times the variable was significantly positive and negative at the 5% level, respectively, out of a total of 14,400 observations.

Panel A: Trade Direction

	ΔASK^{US}	ΔBID^{US}	ΔASK^{CAN}	ΔBID^{CAN}
BUY_{t-1}^{US}	**0.147**	**0.104**	**-0.003**	**0.002**
Sig + / - (in %)	**71 / 1**	**51 / 1**	**0 / 19**	**18 / 0**
$SELL_{t-1}^{US}$	**-0.104**	**-0.152**	**-0.002**	**0.003**
Sig + / - (in %)	**1 / 51**	**1 / 71**	**0 / 18**	**20 / 0**
BUY_{t-1}^{CAN}	**-0.004**	**0.003**	**0.092**	**0.076**
Sig + / - (in %)	**0 / 18**	**16 / 0**	**42 / 1**	**32 / 2**
$SELL_{t-1}^{CAN}$	**-0.002**	**0.004**	**-0.091**	**-0.107**
Sig + / - (in %)	**0 / 16**	**17 / 0**	**2 / 30**	**1 / 41**

Panel B: Trade Volume

	ΔASK^{US}	ΔBID^{US}	ΔASK^{CAN}	ΔBID^{CAN}
$BUYVMED_{t-1}^{US}$	**0.026**	**0.036**	0.000	-0.001
Sig + / - (in %)	**11 / 7**	**12 / 5**	3 / 2	2 / 2
$SELLVMED_{t-1}^{US}$	**-0.033**	**-0.026**	0.000	0.000
Sig + / - (in %)	**6 / 12**	**7 / 11**	3 / 1	1 / 3
$BUYVMED_{t-1}^{CAN}$	0.001	-0.002	**0.081**	**0.082**
Sig + / - (in %)	4 / 3	3 / 4	**16 / 4**	**17 / 4**
$SELLVMED_{t-1}^{CAN}$	0.001	0.000	**-0.087**	**-0.087**
Sig + / - (in %)	4 / 3	3 / 4	**4 / 16**	**4 / 16**

Panel C: Trade Duration

	ΔASK^{US}	ΔBID^{US}	ΔASK^{CAN}	ΔBID^{CAN}
$BUYVDURATION_{t-1}^{US}$	**0.002**	**0.002**	**0.000**	**-0.000**
Sig + / - (in %)	**13 / 4**	**20 / 2**	**16 / 0**	**0 / 16**
$SELLVDURATION_{t-1}^{US}$	**-0.002**	**-0.002**	**0.000**	**-0.000**
Sig + / - (in %)	**2 / 21**	**4 / 13**	**16 / 0**	**1 / 16**
$BUYVDURATION_{t-1}^{CAN}$	**0.000**	**-0.000**	**0.000**	**0.001**
Sig + / - (in %)	**16 / 1**	**1 / 16**	**7 / 7**	**11 / 4**
$SELLVDURATION_{t-1}^{CAN}$	**0.000**	**-0.000**	**-0.001**	**-0.001**
Sig + / - (in %)	**15 / 1**	**1 / 16**	**4 / 11**	**7 / 7**

Panel D: Total Trade

	ΔASK^{US}	ΔBID^{US}	ΔASK^{CAN}	ΔBID^{CAN}
$TOTALBUY^{US}$	**0.261**	**0.312**	-0.003	0.000
Sig + / - (in %)	**66 / 1**	**74 / 0**	1 / 7	4 / 2
$TOTALSELL^{US}$	**-0.393**	**-0.270**	0.001	0.004
Sig + / - (in %)	**0 / 75**	**1 / 68**	2 / 4	7 / 1
$TOTALBUY^{CAN}$	-0.001	-0.001	**0.410**	**0.409**
Sig + / - (in %)	2 / 9	7 / 5	**66 / 1**	**68 / 1**
$TOTALSELL^{CAN}$	0.003	0.006	**-0.479**	**-0.508**
Sig + / - (in %)	4 / 7	10 / 2	**0 / 70**	**1 / 68**

consistent with the proposition of Glosten and Milgrom (1985) and Huang and Stoll (1994), a buyer-initiated trade raises both the bid and the ask prices, while the seller-initiated trade lowers the quotes. Bid and ask prices do not respond symmetrically to trade-related information. Buyer-initiated trades are more important to the ask price, while seller-initiated trades are more important to the bid price, in either market.[12]

When we consider the cross-market impacts of trades, we observe that liquidity providers across markets react by reducing their spreads. For instance, a buyer-initiated trade in the U.S. leads to a decrease in the ask price and an increase in the bid price in Canada by 19% and 18% of the time, respectively. Despite the small coefficients, these findings suggest that liquidity providers adjust their prices based on trades from across markets to some extent. Hence, there seems to be some degree of information spillover coming from trades between the two markets.

Our empirical results reported in Panel B of Table 5.5 indicate that medium-sized trades matter only to a small extent.[13] The coefficients $BUYVMED$ and $SELLVMED$ are significant in 11% for the ask and bid price in the U.S., and 16% for the ask and bid price in Canada despite their relatively large magnitudes. These coefficients have the priori expected signs: where a $BUYVMED$ variables all have positive signs on the bid and ask prices while $SELLVMED$ all have negative signs. Across market, however, we do not observe significant impacts of trading volume on quotes.

Panel C in Table 5.5 reports the coefficients on the interaction between bid and ask prices and trade duration. We find that the coefficients are small but significant, both on home market quotes, as well as across market. A buy transaction in the U.S

[12] The results for the other lags are consistent with these findings, albeit lower significance. They are available upon request.

[13] We also conducted the analysis by adding the small size trades alongside the medium size trades. We did not observe significance for the small size trade variables, nor did we find significantly different results for the medium size trades.

leads to an increase in the ask and bid prices 13% and 20% of the time, respectively. This finding suggests that trades that occur after a long period of inactivity is informative and affect prices. This is consistent with Easley and O'Hara (1992) and Dufour and Engle (2000) who explain that the absence of trade could provide information to market participants. Across markets, we find that trades occuring after a long period of inactivity leads to a wider spread. For example, an increase in $BUYVDURATION_{t-1}^{US}$ leads to an increase in the ask price and a decrease in the bid price in Canada 16% of the time. We interpret this finding as inactivity in one market implies that trades are taking place in the other market. In such a case, liquidity providers in the other market have the incentive to increase their spreads.

Panel D on Table 5.5 reports our empirical findings on the importance of order flow on quotes. We find that order flow is highly significant in explaining quote dynamics. We observe that $TOTALBUY$ strongly increases both ask and bid prices in their respective markets, while $TOTALSELL$ strongly decreases them. This suggests that liquidity providers set quotes based on the observations of the current and past aggregate quantities traded in the market, consistent with Kyle (1985). We further observe negligible impacts of order flow on quotes across market.

Overall, Table 5.5 shows that while trades tend to be more significant in their respective market, prices are also affected by trades from another market. We therefore conclude that prices in each market are primarily determined by information generated in the same market, and to a small extent, by information generated in the foreign market.

5.5.2 Implied Model for Spreads, Midpoint Returns, and Price Premium

The linkages between quote revisions and quote- and trade-related information are assessed using the model in Equation (1). Based on the quote model, we can derive an implied VAR for various market microstructure variables. In this study, we assess the bid-ask spreads in the two markets, the midpoint returns and the difference in midquotes across markets. The impacts of information on spreads are of particular interest because spreads measure the amount of friction in each of the markets. The impact of information on midpoint returns is also important as the midpoint represents the implied efficient price of the cross-listed stock. This allows us to test whether the fundamental value of the stock varies from buyer- and seller-initiatied trades, as well as quote-related information. Finally, the difference in midquotes across markets represents the relative premium of prices in one market over the other.

The implied VAR is derived by rotating Equation (5.1). The derivation of this model can be found in Appendix (A.1). We transform the quote model into a model for the log spread in each market, $SPREAD_t^A$ and $SPREAD_t^B$, the log difference in the midquotes from both markets, $\Delta\log(MQ_t)$, and the cross-market difference in log midquotes, $\log(MQ_t^{A-B})$ as specified below:

$$
\begin{bmatrix} SPREAD_t^A \\ SPREAD_t^B \\ \Delta\log(MQ_t) \\ \log(MQ_t^{A-B}) \end{bmatrix} = \widetilde{c} + \sum_{j=1}^{10} \widetilde{A}_{(j)} \cdot \left(T_1 \cdot \begin{bmatrix} SPREAD_{t-j}^A \\ SPREAD_{t-j}^B \\ \Delta\log(MQ_{t-j}) \\ \log(MQ_{t-j}^{A-B}) \end{bmatrix} - T_2 \cdot \begin{bmatrix} SPREAD_{t-(j+1)}^A \\ SPREAD_{t-(j+1)}^B \\ \Delta\log(MQ_{t-(j+1)}) \\ \log(MQ_{t-(j+1)}^{A-B}) \end{bmatrix} \right)
$$
$$
+ \left(K + \widetilde{B} \cdot T_3\right) \cdot \begin{bmatrix} SPREAD_{t-1}^A \\ SPREAD_{t-1}^B \\ \Delta\log(MQ_{t-1}) \\ \log(MQ_{t-1}^{A-B}) \end{bmatrix} + \widetilde{\Gamma}_1 \cdot \begin{bmatrix} DEPTH\_DIFF_{t-1}^A \\ DEPTH\_DIFF_{t-1}^B \end{bmatrix}
$$
$$
+ \sum_{k=1}^{3} \widetilde{\Gamma}_2^{(k)} \cdot \begin{bmatrix} BUY_{\tau(t)-k}^A \cdot 1 \\ BUY_{\tau(t)-k}^A \cdot V_{\tau(t)-k}^{A,med} \\ BUY_{\tau(t)-k}^A \cdot D_{\tau(t)-k}^A \\ BUY_{\tau(t)-k}^B \cdot 1 \\ BUY_{\tau(t)-k}^B \cdot V_{\tau(t)-k}^{B,med} \\ BUY_{\tau(t)-k}^B \cdot D_{\tau(t)-k}^B \end{bmatrix} + \sum_{k=1}^{3} \widetilde{\Gamma}_3^{(k)} \cdot \begin{bmatrix} SELL_{\tau(t)-k}^A \cdot 1 \\ SELL_{\tau(t)-k}^A \cdot V_{\tau(t)-k}^{A,med} \\ SELL_{\tau(t)-k}^A \cdot D_{\tau(t)-k}^A \\ SELL_{\tau(t)-k}^B \cdot 1 \\ SELL_{\tau(t)-k}^B \cdot V_{\tau(t)-k}^{B,med} \\ SELL_{\tau(t)-k}^B \cdot D_{\tau(t)-k}^B \end{bmatrix}
$$
$$
+ \widetilde{\Gamma}_4 \cdot \begin{bmatrix} \sum_{k=1}^{l(t)} BUY_{\tau(t)-k}^A \\ \sum_{k=1}^{l(t)} SELL_{\tau(t)-k}^A \\ \sum_{k=1}^{l(t)} BUY_{\tau(t)-k}^B \\ \sum_{k=1}^{l(t)} SELL_{\tau(t)-k}^B \end{bmatrix} + \sum_{d=1}^{7} \widetilde{\Gamma}_5^{(d)} \cdot \left[DIURN_t^d\right] + \widetilde{\varepsilon}_t, \tag{5.2}
$$

where T_1, T_2, and T_3 are rotation matrices specified in the same appendix.

The coefficients for our implied model are obtained through linear combination of the parameters estimated in Equation (5.1), while the standard errors are obtained by applying the same rotation steps to the residuals and variance-covariance matrix of the same equation. We report the results in the form of mean coefficient for each stock throughout the entire sample period, along with a percentage count of the number of times the coefficient was significantly positive and negative at 5% level. We use White (1980) corrected standard errors in our estimations to correct for possible heteroskedasticity. Consistent with the findings in Table 5.3, we find that spreads in both markets are higher at the beginning of the day compared to other periods. We find no evidence of an increase in average spreads towards the end of the day.

Lags of Dependent Variables And Quote-Related Information

In Table 5.6. we report the results for the implied VAR model. Panel A reports the coefficients for the lagged dependent variables and Panel B reports the coefficients for the depth difference. The first column of each panel lists the explanatory variables and their statistical significance, while the first row of each panel lists the dependent variables. We discuss the results of each panel one row at a time.

Table 5.6: Coefficients of the first lagged dependent and liquidity variables on the implied model

This table reports the mean of the estimated coefficients for the first lag of the dependent variables. "Sig + / -" denote the percentage count of number of times the variable was significantly positive and negative at the 5% level, respectively, out of a total of 14,400 observations.

Panel A: Lagged Dependent Variables

	$SPREAD^{US}$	$SPREAD^{CAN}$	$\Delta MIDPOINT$	$PREMIUM$
$\Delta MIDPOINT_{t-1}$	0.001	-0.002	**0.094**	**-0.063**
Sig + / - (in %)	0 / 0	0 / 0	**55 / 3**	**1 / 20**
$PREMIUM_{t-1}$	0.000	0.000	**0.038**	**0.759**
Sig + / - (in %)	1 / 1	1 / 1	**68 / 6**	**100 / 0**
$SPREAD^{US}_{t-1}$	**0.233**	**-0.066**	0.001	0.001
Sig + / - (in %)	**61 / 6**	**2 / 43**	12 / 10	9 / 8
$SPREAD^{CAN}_{t-1}$	**-0.192**	**0.352**	0.001	0.000
Sig + / - (in %)	**0 / 88**	**81 / 0**	12 / 12	9 / 9

Panel B: Depth Difference

	$SPREAD^{US}$	$SPREAD^{CAN}$	$\Delta MIDPOINT$	$PREMIUM$
$DEPTH\_DIFF^{US}_{t-1}$	-0.003	0.006	**-0.470**	**-0.342**
Sig + / - (in %)	3 / 3	2 / 2	**0 / 99**	**4 / 70**
$DEPTH\_DIFF^{CAN}_{t-1}$	0.000	0.007	**-0.175**	**0.250**
Sig + / - (in %)	7 / 5	1 / 1	**0 / 93**	**79 / 1**

In Panel A of Table 5.6, we first assess the impacts of lagged midpoint returns on the dependent variables. A change in midpoint return does not seem to affect spreads in either market. Midpoint returns (the implied efficient price), however, are observed to be persistent. Past returns in midpoint predict subsequent midpoint returns, indicating positive correlation in prices. Huang and Stoll (1994) explain that the ability to predict returns on the basis of microstructure variables is not necessarily inconsistent with an efficient market. Institutional constraints such as the difficulty to continuously adjust limit orders to information contained in prices may explain such predictive power.[14] The impact of midpoint returns on the price premium is negative. This finding suggests that positive returns in price lead to a greater increase in Canadian prices relative to the U.S. prices, leading to a decrease in the price premium.

Second, we examine the impact of price premium on the dependent variables. We do not observe the impact of price premium on spreads to be significant in either market. The price premium, however, has a positive and significant impact on the midpoint returns. An increase in premium suggests that the midquote in the U.S. increases more than the midquote in Canada, leading to an increase in midpoint returns. The price premium also appears to be persistent with highly positive and significant coefficients. This finding suggests that positive premiums in the U.S. tends to be positively and serially correlated.

The third and fourth rows of Panel A report the coefficients of the bid-ask spreads on the dependent variables. The spreads appear to be persistent in each market. The coefficients for $SPREAD_{t-1}^{US}$ and $SPREAD_{t-1}^{CAN}$ are positive and significant 61% and 81% of the time, respectively. The lagged spreads also seem to affect the spreads across market in the subsequent period. In particular, the coefficients for $SPREAD_{t-1}$ are negative for the spread dependent variables of the other market. Since spreads mean-revert, intermarket competition implies that an increase in spread in one market leads to a decline in spreads in another market. We do not observe a clear pattern on the impact of spreads on the midpoint returns and the price premium since the coefficients seem to be equally significant in both directions.

Panel B of Table 5.6 reports the coefficients of the lagged depth difference on the

[14] Positive short-run autocorrelation may occur as a result of prices being less than fully informationally efficient. Once prices reflect all public and private information, returns no longer display autocorrelation.

implied model. We do not observe any impact of the depth difference on spreads. However, the coefficients for $DEPTH\_DIFF_{t-1}$ on the midpoint returns are negative and significant. This can be interpreted as large depth difference in either market indicating oversupply of assets traded, thus suggesting that the stock is overpriced, leading to less buying and more selling by investors. Since a change in depth difference lowers quotes of the home market, the impacts on the price premium are significantly negative and significantly posistive for $DEPTH\_DIFF^{US}_{t-1}$ and $DEPTH\_DIFF^{CAN}_{t-1}$, respectively. In terms of magnitude, the impacts on midpoint returns and price premium are greater (in absolute terms) for the U.S. compared to Canadian depth difference, indicating asymmetric reactions by investors in the two markets.

The Importance of Trade-Related Information

Finally, we examine the importance of trade-related information on the implied variables of spreads, midpoint returns, and price premium. Panel A in Table 5.7 shows that trade direction has very little impact on spreads. We observe positive coefficients of buyer and seller-initiated trades on the U.S. bid-ask spread which are significant 19% of the time. While the asymmetric impacts of buys and sells on the bid and ask prices are apparent as shown in Panel A of Table 5.5, it is not easily detectable in a model for the spread. Similar relations between trades and spread are observed in Canada, in which the coefficients are positive, but not statistically significant. We do not observe a noticable impact of trades on spreads across market.

In terms of the implied efficient price, both purchases in the U.S. and Canada lead to an increase in midpoint returns, whereas sells from either market lead to a decrease. Glosten and Milgrom (1985) explain that the presence of informed agents in the market means that trade increases the uncertainty about the true price of a stock. Hence, bid and ask prices increase following a trade, leading to a rise in midpoint. As for the price premium, purchases in the U.S. lead to an increase in price premium,

Table 5.7: Coefficients of the trade-related variables on the implied model

This table reports the mean of the estimated coefficients for the first lag of the trade-related variables (coefficients $\widetilde{\Gamma}_2^{(l)}$, $\widetilde{\Gamma}_3^{(l)}$, and $\widetilde{\Gamma}_4$ in Equation 5.2). "Sig + / -" denote the percentage count of number of times the variable was significantly positive and negative at the 5% level, respectively, out of a total of 14,400 observations.

Panel A: Trade Direction

	$SPREAD^{US}$	$SPREAD^{CAN}$	$\Delta MIDPOINT$	$PREMIUM$
BUY_{t-1}^{US}	**0.041**	-0.013	**0.065**	**0.118**
Sig + / - (in %)	**19 / 3**	0 / 8	**74 / 1**	**73 / 1**
$SELL_{t-1}^{US}$	**0.044**	-0.013	**-0.063**	**-0.121**
Sig + / - (in %)	**19 / 3**	0 / 8	**1 / 74**	**1 / 74**
BUY_{t-1}^{CAN}	-0.007	0.015	**0.043**	**-0.070**
Sig + / - (in %)	2 / 13	2 / 1	**49 / 2**	**2 / 46**
$SELL_{t-1}^{CAN}$	-0.004	0.014	**-0.038**	**0.074**
Sig + / - (in %)	2 / 12	2 / 1	**2 / 48**	**44 / 2**

Panel B: Trade Volume

	$SPREAD^{US}$	$SPREAD^{CAN}$	$\Delta MIDPOINT$	$PREMIUM$
$BUYVMED_{t-1}^{US}$	-0.013	0.003	**0.016**	**0.035**
Sig + / - (in %)	2 / 3	1 / 1	**19 / 9**	**18 / 9**
$SELLVMED_{t-1}^{US}$	-0.011	0.004	**-0.015**	**-0.032**
Sig + / - (in %)	2 / 3	1 / 1	**10 / 19**	**10 / 18**
$BUYVMED_{t-1}^{CAN}$	0.002	0.002	**0.037**	**-0.069**
Sig + / - (in %)	5 / 5	1 / 2	**26 / 6**	**6 / 24**
$SELLVMED_{t-1}^{CAN}$	0.003	-0.001	**-0.039**	**0.079**
Sig + / - (in %)	5 / 5	1 / 1	**6 / 25**	**24 / 6**

Panel C: Trade Duration

	$SPREAD^{US}$	$SPREAD^{CAN}$	$\Delta MIDPOINT$	$PREMIUM$
$BUYVDURATION_{t-1}^{US}$	0.000	0.000	**0.001**	**0.002**
Sig + / - (in %)	1 / 3	9 / 0	**23 / 5**	**25 / 5**
$SELLVDURATION_{t-1}^{US}$	0.000	0.000	**-0.001**	**-0.002**
Sig + / - (in %)	1 / 3	8 / 0	**4 / 25**	**4 / 26**
$BUYVDURATION_{t-1}^{CAN}$	0.000	-0.001	**0.000**	**-0.001**
Sig + / - (in %)	8 / 4	0 / 1	**14 / 10**	**10 / 13**
$SELLVDURATION_{t-1}^{CAN}$	0.000	0.000	**0.000**	**0.001**
Sig + / - (in %)	8 / 4	0 / 1	**10 /15**	**14 / 9**

Panel D: Total Trade

	$SPREAD^{US}$	$SPREAD^{CAN}$	$\Delta MIDPOINT$	$PREMIUM$
$TOTALBUY^{US}$	-0.027	-0.016	**0.154**	**0.244**
Sig + / - (in %)	0 / 3	0 / 3	**83 / 1**	**74 / 1**
$TOTALSELL^{US}$	-0.075	-0.010	**-0.194**	**-0.299**
Sig + / - (in %)	0 / 2	0 / 3	**1 / 84**	**1 / 75**
$TOTALBUY^{CAN}$	-0.008	0.006	**0.184**	**-0.334**
Sig + / - (in %)	3 / 13	0 / 0	**78 / 1**	**1 / 75**
$TOTALSELL^{CAN}$	-0.016	0.044	**-0.204**	**0.392**
Sig + / - (in %)	3 / 13	0 / 0	**1 / 80**	**77 / 1**

while sells in the U.S. lead to a decrease in premium. The opposite is true for trades in Canada. In terms of magnitude, larger coefficients for U.S. trades compared to Canadian trades on midpoint returns and relative premium indicate strong evidence of information asymmetry between the two markets. The implied efficient price appears to be more affected by trading activity occuring in the U.S. rather than the activity occuring in Canada.

Panel B of Table 5.7 shows that medium-size trades do not affect spreads in either market. However, they affect midpoint returns and price premium. For the midpoint, the coefficients $BUYVMED$ ($SELLVMED$) are significant 19% (19%) of time in the U.S., and 26% (25%) in Canada. For the price premium, the coefficients $BUYVMED$ ($SELLVMED$) are significant in 18% (18%) in the U.S., and 24% (24%) in Canada. These findings further confirm that the fundamental value of cross-listed stocks are determined by trading activities in the markets they are traded in.

As for trade duration, Panel C on Table 5.7 shows that trade duration are significant in explaining the change in midpoint returns, and the change in price premium between the U.S. and Canada. Although the coefficients are small, $BUYVDURATION$ and $SELLVDURATION$ from both markets lead to an increase and a decrease in the midpoint returns, respectively. Furthermore, trade duration in the U.S. leads to an increase in the price premium while trade difference in Canada leads to a decrease in the price premium. The inverse is true for trade duration variables in Canada. These findings suggest that trading inactivities are informative and priced, consistent with Easley and O'Hara (1992) and Dufour and Engle (2000).

The impact of order flow is highly apparent, as shown in Panel D of Table 5.7, particularly on the midpoint returns and price premium. The buy-side order flow from both markets strongly increase the midpoint returns while the sell-side order flow strongly lowers it. This is a clear evidence of the importance of order flow on the efficient price revision for cross-listed stocks, which is in line with the study of Kyle (1985). As for the market premium, an increase in $TOTALBUY^{US}$ increases the premium further while $TOTALSELL^{US}$ lowers the premium. The inverse is true for $TOTALBUY^{CAN}$ and $TOTALSELL^{CAN}$.

5.6 Conclusion

In this chapter, we develop a general model to study quote dynamics of stocks traded in dual markets. We jointly model revisions of bid and ask prices for two fully-synchronised markets, and use a variety of quote- and trade-related information to explain dynamics as indicated by various microstructure theories. From an empirical perspective, our work extends the VECM specification of Engle and Patton (2004) into a dual-market setting. Our model can be transformed to an implied VAR for various microstructure fundamentals such as the bid-ask spreads, the efficient price, and the price premium.

Applying our model to Canadian stocks which are cross-listed in the U.S., we document several important findings. First, we observe that quote changes in one market leads to quote changes in another market, showing direct interactions between prices in two markets. Second, quote-related information directly affects prices in both markets, indicating some degree of intermarket competition between liquidity providers. Third, while prices adjust primarily to trades in their respective market, they are also affected by trades from another market, indicating a degree of information spillover between the two markets. Finally, we find that information plays a greater role in the U.S than in Canada, leading to a greater impact of U.S. trades on the midpoint returns (implied efficient price) and on the difference in midquotes (price premium).

The findings above describe the mechanisms of how information gets incorporated into prices for dually-listed stocks. The prominent impact of bid-ask spread on quotes suggests that competition between liquidity providers is an important channel of information in multiple markets. The majority of information coming from trades gets incorporated into prices in their respective market, but there is a small degree of information spillover coming from across market. We also show that the fundamentals of cross-listed stocks such as the change in efficient price and the relative premium are not only driven by quote-related information, but also by trade-related information from any of the two markets. These results suggest that both sources provide investors with valuable information on the fundamental value of cross-listed stocks.

Appendix A.1. Derivation of the Implied Model

Consider the simplified form of the quote model:

$$\Delta Y_t = c + \sum_{j=1}^{10} A_{(j)} \cdot \Delta Y_{t-j} + B \cdot spread_{t-1} + \sum_{\mu=1}^{5} \Gamma_\mu \cdot X_{t-1}^{\mu} + \varepsilon_t, \tag{A1}$$

where $\Delta Y_t = \begin{bmatrix} \Delta\log(ASK_t^A) \\ \Delta\log(BID_t^A) \\ \Delta\log(ASK_t^B) \\ \Delta\log(BID_t^B) \end{bmatrix}$, $spread_{t-1} = \begin{bmatrix} SPREAD_{t-1}^A \\ SPREAD_{t-1}^B \end{bmatrix}$, X_{t-1}^{μ} and Γ_μ represent other variables and their coefficients. We multiply each of the variables in Equation (A1) with a rotation matrix, $T = \begin{bmatrix} 1 & -1 & 0 & 0 \\ 0 & 0 & 1 & -1 \\ 0.25 & 0.25 & 0.25 & 0.25 \\ 0.5 & 0.5 & -0.5 & -0.5 \end{bmatrix}$, such that $\Delta\widetilde{Y}_t = T \cdot \Delta Y_t =$ $\begin{bmatrix} \Delta SPREAD_t^A \\ \Delta SPREAD_t^B \\ \Delta\log(MQ_t) \\ \Delta\log(MQ_t^{A-B}) \end{bmatrix}$, and obtain the following:

$$\Delta\widetilde{Y}_t = \widetilde{c} + \sum_{j=1}^{10} \widetilde{A}_{(j)} \cdot \Delta Y_{t-j} + \widetilde{B} \cdot spread_{t-1} + \sum_{\mu=1}^{5} \widetilde{\Gamma}_\mu \cdot X_{t-1}^{\mu} + \widetilde{\varepsilon}_t. \tag{A2}$$

From Equation (A2), we can further restructure the expression into a more desirable model of the log spread in each market, SPR_t^A and SPR_t^B, the log difference in the mid-quote from both markets, $\Delta\log(MQ_t)$, and the cross-market difference in log mid-quotes, $\log(MQ_t^{A-B})$.

Given $\widetilde{Z}_t = \begin{bmatrix} SPREAD_t^A \\ SPREAD_t^B \\ \Delta\log(MQ_t) \\ \log(MQ_t^{A-B}) \end{bmatrix}$, $T_1 = \begin{bmatrix} 0.5 & 0 & 1 & 0.5 \\ -0.5 & 0 & 1 & 0.5 \\ 0 & 0.5 & 1 & -0.5 \\ 0 & -0.5 & 1 & -0.5 \end{bmatrix}$, $T_2 = \begin{bmatrix} 0.5 & 0 & 0 & 0.5 \\ -0.5 & 0 & 0 & 0.5 \\ 0 & 0.5 & 0 & -0.5 \\ 0 & -0.5 & 0 & -0.5 \end{bmatrix}$,

$T_3 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$, and $K = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$, we can write the following expressions:

$$\Delta\widetilde{Y}_t = \widetilde{Z}_t - (K \cdot \widetilde{Z}_{t-1}) \tag{A3}$$

$$\Delta Y_{t-j} = T_1 \cdot \widetilde{Z}_{t-j} - T_2 \cdot \widetilde{Z}_{t-(j+1)} \tag{A4}$$

$$spread_{t-1} = T_3 \cdot \widetilde{Z}_{t-1} \tag{A5}$$

Using the espressions in Equation (A3) - (A5), we can therefore rewrite Equation (A2) as:

$$\widetilde{Z}_t - \left(K \cdot \widetilde{Z}_{t-1}\right) = \widetilde{c} + \sum_{j=1}^{10} \widetilde{A}_{(j)} \cdot \left(T_1 \cdot \widetilde{Z}_{t-j} - T_2 \cdot \widetilde{Z}_{t-(j+1)}\right) + \widetilde{B} \cdot \left(T_3 \cdot \widetilde{Z}_{t-1}\right) + \sum_{\mu=1}^{5} \widetilde{\Gamma}_\mu \cdot X^\mu_{t-1} + \widetilde{\varepsilon}_t. \tag{A6}$$

Rearranging Equation (A6) we arrive at the final model:

$$\widetilde{Z}_t = \widetilde{c} + \sum_{j=2}^{10} \widetilde{A}_{(j)} \cdot \left(T_1 \cdot \widetilde{Z}_{t-j} - T_2 \cdot \widetilde{Z}_{t-(j+1)}\right) + \left(K + \widetilde{B} \cdot T_3\right) \cdot \widetilde{Z}_{t-1} + \sum_{\mu=1}^{5} \widetilde{\Gamma}_\mu \cdot X^\mu_{t-1} + \widetilde{\varepsilon}_t. \tag{A7a}$$

Writing Equation (A7a) out, we get:

$$\begin{aligned}
\begin{bmatrix} SPREAD_t^A \\ SPREAD_t^B \\ \Delta\log(MQ_t) \\ \log(MQ_t^{A-B}) \end{bmatrix} =& \widetilde{c} + \sum_{j=2}^{10} \widetilde{A}_{(j)} \cdot \left(T_1 \cdot \begin{bmatrix} SPREAD_{t-j}^A \\ SPREAD_{t-j}^B \\ \Delta\log(MQ_{t-j}) \\ \log(MQ_{t-j}^{A-B}) \end{bmatrix} - T_2 \cdot \begin{bmatrix} SPREAD_{t-(j+1)}^A \\ SPREAD_{t-(j+1)}^B \\ \Delta\log(MQ_{t-(j+1)}) \\ \log(MQ_{t-(j+1)}^{A-B}) \end{bmatrix} \right) \\
&+ \left(K \cdot \widetilde{B} \cdot T_3 \right) \cdot \begin{bmatrix} SPREAD_{t-1}^A \\ SPREAD_{t-1}^B \\ \Delta\log(MQ_{t-1}) \\ \log(MQ_{t-1}^{A-B}) \end{bmatrix} + \widetilde{\Gamma}_1 \cdot \begin{bmatrix} DEPTH_DIFF_{t-1}^A \\ DEPTH_DIFF_{t-1}^B \end{bmatrix} \\
&+ \sum_{k=1}^{3} \widetilde{\Gamma}_2^{(k)} \cdot \begin{bmatrix} BUY_{\tau(t)-k}^A \cdot 1 \\ BUY_{\tau(t)-k}^A \cdot V_{\tau(t)-k}^{A,med} \\ BUY_{\tau(t)-k}^A \cdot D_{\tau(t)-k}^A \\ BUY_{\tau(t)-k}^B \cdot 1 \\ BUY_{\tau(t)-k}^B \cdot V_{\tau(t)-k}^{B,med} \\ BUY_{\tau(t)-k}^B \cdot D_{\tau(t)-k}^B \end{bmatrix} + \sum_{k=1}^{3} \widetilde{\Gamma}_3^{(k)} \cdot \begin{bmatrix} SELL_{\tau(t)-k}^A \cdot 1 \\ SELL_{\tau(t)-k}^A \cdot V_{\tau(t)-k}^{A,med} \\ SELL_{\tau(t)-k}^A \cdot D_{\tau(t)-k}^A \\ SELL_{\tau(t)-k}^B \cdot 1 \\ SELL_{\tau(t)-k}^B \cdot V_{\tau(t)-k}^{B,med} \\ SELL_{\tau(t)-k}^B \cdot D_{\tau(t)-k}^B \end{bmatrix} \\
&+ \widetilde{\Gamma}_4 \cdot \begin{bmatrix} \sum_{k=1}^{l(t)} BUY_{\tau(t)-k}^A \\ \sum_{k=1}^{l(t)} SELL_{\tau(t)-k}^A \\ \sum_{k=1}^{l(t)} BUY_{\tau(t)-k}^B \\ \sum_{k=1}^{l(t)} SELL_{\tau(t)-k}^B \end{bmatrix} + \sum_{d=1}^{7} \widetilde{\Gamma}_5^{(d)} \cdot \left[DIURN_t^d \right] + \widetilde{\varepsilon}_t. \qquad \text{(A7b)}
\end{aligned}$$

Chapter 6

Concluding Remarks

This thesis intends to add to the understanding of the price formation process for stocks with foreign listings. Over the past two decades, equity listings in more than one market have benefited companies in terms of gaining access to foreign capital markets. At the same time, foreign listings have intensified intermarket competition among exchanges. These competitions have emphasized the need to understand how prices are determined and the mechanisms underlying security trades in multiple markets. Such understanding is crucial for exchange officials and market regulators in order to adjust or introduce new trading rules, keeping markets competitive. In that respect, the results presented here should be of interest to practitioners, policy-makers, and academics.

Chapter 2 provides an overview of the market microstructure fields that are covered in this thesis, with a focus on how prices are determined in a market. We first discuss the importance of market frictions for prices. We show how frictions lead to costs of trading, how frictions are considered in modelling prices, and how frictions affect a market's contribution to price discovery. Given investors' preference to trade in a market with the least cost of trading, ensuring that frictions and costs of trading are kept to a minimum, should be of consideration to exchange officials and market regulators. The chapter further discusses the importance of information coming from trades. Existing literature suggests that trade-related activities, such as the direction of trade, trading volume, and order flow, are informative and lead to updates in market participants' expectations about the fundamental value of a stock. This evidence leads to a question as to whether such information is relevant for stocks which are listed and traded in multiple markets. Examining such relationships allows us to understand the mechanism by which information is impounded into prices for stocks with multiple listings.

The empirical analysis of this thesis starts in Chapter 3 which examines the impact of information coming from macroeconomic news announcements on price discovery. We show that price discovery, for a sample of Canadian cross-listed stocks, shifts towards the U.S. during the periods when macroeconomic news is released. Previous research has mainly suggested that price discovery tends to occur in the home market, where most of the information regarding the stock is generated. However, the finding that price discovery still shifts to the U.S. even during Canadian macroeconomic news announcements suggests that price discovery is also related to a market's information processing capacity. In this respect, the U.S. market is the more attractive trading venue to investors because it processes market-wide information faster than the Canadian counterpart.

We show that the shift of price discovery to the U.S. market is related to the increase in the trading ratio and the decrease in the spread ratio of the U.S. relative to the Canadian market. These findings suggest that the U.S., as the larger and the more liquid market of the two, is the preferred destination for traders who seek liquidity and cheaper trading options. The TSX may lack the liquidity of the larger U.S. exchanges. One possible explanation is because in the U.S., investors have the options to trade Canadian stocks on the bigger exchange (such as the NYSE), as well as on various regional exchanges (such as the BSE, CSE, BATS). Competition between these exchanges may have kept the U.S. market more liquid and the costs of trading lower. In Canada, on the other hand, investors can only trade in the TSX as the sole exchange that trades senior securities. Despite the emergence of alternative trading venues starting mid-2007, there was no consolidated quotation system nor Order Protection Rule until late-2010 and early 2011, respectively. These factors combined may contribute to the inefficiency of the Canadian market relative to the U.S. market during our sample period. Future research should assess Canada's information processing capacity, particularly after the implementation of the OPR.

In Chapter 4, we investigate the dynamics of price discovery for Canadian cross-listed stocks in the U.S. It is observed that the U.S. contribution to price discovery has increased over the years, especially after the adoption of the Regulation NMS in the U.S. We find that improvements in liquidity contribute to such increase. In particular, an increase in trading volume and a decrease in effective spreads in the U.S. relative to Canada, lead to greater contribution of the U.S. to price discovery. These findings further confirm that investors seem to trade more in a market which is more liquid and has lower cost of trading, hence indicating areas that exchanges should focus on to improve price discovery. In addition, we observe that an increase in price discovery leads to better liquidity, emphasizing the importance of price discovery for a market. Greater price discovery contributes to the competitiveness of a market because it attracts more trades in the long-run. This finding may explain the observed persistence in price discovery; once price discovery is gained by a market, it tends to remain in that market.

We also show that algorithmic trading activity is negatively related to price discovery. This may caused by the crowding out effect as arbitrageurs make use of computers to trade aggresively and compete for arbitrage opportunities in their respective markets. As a consequence, high-frequency trading by these arbitrageurs pushes away informed investors, who are disadvantaged in terms of speed, leading to lower price discovery. Our finding should be of interest to market regulators because it indicates that traders without access to high-frequency trading platform are disadvantaged in capitalising the information that they may have. Subsequently, they may flock to a market with less AT concentration.

In Chapter 5, we propose a model to assess quote dynamics in dual markets. The model can be used to study the mechanism of how information affects prices of cross-listed stocks in two different markets, and to assess the degree of information spillover between them. We show that quote changes in one market leads to quote changes in another market, indicating that prices in the two markets are linked directly to each other. When examining the mechanisms underlying such linkage, we find that the change in spreads directly affects prices in both markets. This finding suggests that there is some degree of intermarket competition between liquidity providers. Knowing that investors are rational and prefer to trade in the cheaper market, liquidity providers determine prices based on the cost of trading that they also observe across market. Our finding implies that markets are not exactly fragmented. Intermarket arbitrage keeps the prices in the different markets from drifting apart.

Furthermore, we show that while prices adjust primarily to trades in their respective market, they are also affected by trades from the other market. This finding indicates that while the majority of information coming from trades is incorporated into prices in their respective market, there is some degree of information spillover coming from the market across. The degree of information spillover seems to be smaller than the degree of intermarket competition, implying that across market, information coming from trades are harder to infer compared to information coming from quotes. Future research should focus on understanding this difference.

Overall, this thesis has covered different aspects of price formation process for stocks with foreign listings. It has examined various information sources which are important for prices of cross-listed stocks. It has assessed the difference in liquidity and information processing capacity of various markets. It has also evaluated the mechanisms underlying the price formation process in multiple markets. The analyses and findings in this thesis highlight areas which exchanges can improve on to make markets more efficient and competitive.

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