Quote Dynamics of Dually-Listed Stocks

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Version: November 2014

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Abstract

This study investigates the quote dynamics of stocks listed and traded in two international fully-synchronized markets. We model how quotes in a dual-market setting react to liquidity shocks and trade-related information. We further develop this model to extract the implied vector autoregression for the spreads, the efficient price, and the relative premium between the two markets. Applying our model to a sample of 64 Canadian stocks listed both in the U.S. and Canada, we observe a strong evidence of the the error-correcting mechanism of spread on the bid and ask quotes, indicating that liquidity in the form of bid-ask spread affects quotes across market. We further find that even though prices in the two markets are cointegrated, trade-related information does not directly affect quotes in another market. Overall, our findings suggest that quotes of dually-listed stocks are directly linked to liquidity, but indirectly linked to trade-related information. Microstructure fundamentals such as changes in the efficient price and the relative premium between markets, however, are driven by liquidity and trade-related information from each of the two markets.

JEL Classification: C32, G15

Keywords: Market Microstructure; Error-correction; Quote Dynamics, Cross-listings

1 Introduction

A central focus of market microstructure research builds on the notion that new information leads to the updates in the market's expectation about the long-run value of a stock. In response to new information, market makers and liquidity providers adjust their positions by updating their bid and ask quotes, leading to movements in stock prices. Such quote behavior in relation to information entering a market has been documented in various studies, most notably Glosten (1987) and O'Hara (1995), and has also been characterized in various econometric models, particularly in Kavajecz and Odders-White (2001), and Engle and Patton (2004).[1] The quote revision process is therefore known to be informative and offers insight into the mechanism in which information is incorporated into prices.

In the case where stocks are listed and traded in two different markets, their quotes should be linked. Because only the trading venue differs, these stocks share the same fundamental value and are therefore affected by the same underlying factors. As discussed in Lieberman et al. (1999), Baillie et al. (2002), and Pascual et al. (2006), prices of cross-listed stocks are cointegrated and share a common efficient price. Hence, the price in any given market is determined by information being gathered and interpreted in one or more of these markets. Consequently, quotes in the two markets are linked and driven by the same information.

Given the growing trend of cross-listings by firms in recent years, it is becoming more important to understand what drives prices in two different markets. Assessing how information affects quotes in multiple markets will shed light on the driving force behind prices of cross-listed stocks, as well as the channels of such processes.[2] This knowledge is not only beneficial for investors and their arbitrage and hedging purposes, but also for exchange officials and policy makers in ensuring the competitiveness of exchanges and the efficiency of markets. What is currently lacking, however, is the understanding of mechanisms underlying the linkages mentioned above. For instance, it is still not well understood whether information affects quotes in both markets directly or whether it is the quotes in one market that drives the movements of quotes in another market. Furthermore,

[1] See also Escribano and Pascual (2006) for a discussion on why modelling quote dynamics is more informative than modelling using the midpoint of quotes.

[2] See for example Pagano et al. (2002), Baker et al. (2002) for this evidence of cross-listings.

existing models are not able to explain cross-market relationship because these models are restricted to studying quote dynamics in a single-market context.

In this paper, we study how information affects the behavior of quotes for cross-listed stocks. We argue that the dynamics of quotes in the two markets are affected by two important sources - liquidity shocks and trade-related information. These two concepts are important cornerstones in market microstructure research (see Demsetz, 1968; Bagehot, 1971; Biais et al., 1995) and represent the channels for quote formation processes within a single market. By assessing the role of microstructure fundamentals in a multi-market context, we contribute to the literature on the following. First, we assess whether liquidity plays a direct role in the quote formation processes in the two markets. Evidence of such linkage will indicate that liquidity affects quotes in more than one market, thus providing evidence on prices of cross-listed stocks being liquidity-driven. Second, we assess whether trade-related activities are incorporated as information signal and thereby, affecting quotes. These findings will indicate whether there is information spillover from trades in one market to another, or whether the two cointegrated markets are still informationally fragmented. Both of these assessments represent the mechanims of how prices in two different markets are linked, and what drives them.

To assess the quote dynamics in the two markets, we build on the framework of cointegrated quotes as commonly applied in the literature (see for example Engle and Patton, 2004; Escribano and Pascual, 2006; and Frijns and Schotman, 2006). Specifically, we model a joint VECM with four equations representing bid and ask quote revisions in two different markets. We allow these quote revisions to be a function of market liquidity such as bid-ask spread and depth difference, and trade-related features such as trade direction, size, duration, and order flow. We assess 64 Canadian stocks listed in Canada and cross-listed in the U.S. from February 1, 2011 to December 31, 2011. These two markets are fully-synchronized, and Canadian stocks traded in the U.S. are listed as ordinary shares. These factors, and the fact that prices in these two markets are cointegrated, imply that the Canadian stocks in the U.S. and Canada are completely fungible.[3] This feature gives a justification for a quote dynamic model which incorporates short-run adjustment mechanisms from the two

[3] Refer to Eun and Sabherwal (2003), Chen and Choi (2012), and Frijns et al. (2014) for cointegration between the U.S. and Canadian markets.

markets.

We find several patterns characterizing the dynamics of market quotes. First, we find strong evidence of error-correcting mechanism of spread on the bid and ask quotes. Competition between market makers in both markets drives spreads in the two markets to be comparable, leading to adjustments in quotes in both markets. Depth difference, on the other hand, only conveys information in the home market, indicating that the only form of liquidity affecting quotes across market is the bid and ask spread. Second, we find that even though prices in the two markets are cointegrated, the markets are still informationally fragmented. Trade-related information affects quotes across market indirectly through the movements it causes on the home market quotes. Third, we find that liquidity and trade-related information play a greater role in the U.S than in Canada. Overall, our results suggest that quote dynamics in two different markets are driven by liquidity, but are still informationally fragmented in terms of trades.

Next, we show how our framework can be transformed into an implied vector autoregression (VAR) for the stock bid-ask spreads in the two markets, midpoint of prices and difference in midquotes across markets.[4] These variables are central in market microstructure studies as they represent fundamental information underlying the cross-listed assets. For instance, the spread represents a key measure of the amount of friction in the market, while the midpoint of quotes of the two markets represents the implied efficient price of the asset. In addition, the cross-market difference in midquotes represents the relative premium of trading in one market over another. Our findings suggest how these fundamentals are driven by buyer-initiated trades, seller-initiated trades, and liquidity shocks from any of the two markets.

The remainder of this paper is structured as follows. In Section 2, we review the literature. In Section 3, we present the model for the quote dynamics. In Section 4, we describe the data. In Section 5, we analyze the empirical results of the quote model as well as the design and findings of the implied model. Finally, Section 6 concludes.

[4] 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 quote midpoint. Our multi-market quote revision model extends their anaylsis by constructing the bid-ask spreads in each of the markets, the midpoint of prices of the two markets, and the cross-market difference in midquotes.

2 Literature Review

A large body of market microstructure research builds on the notion that new information leads to updates in market's expectation about the long-run value of a security. Movements in the bid and ask quotes reflect such changes. We argue in this paper that quote dynamics in markets is affected by two sources - liquidity shocks and trade-related information. As such, we start this section with a discussion on how liquidity affects quotes, and then turn to the impact of trade-related information on quote behavior. We continue by discussing how these variables may also affect quotes in multiple markets.

Market microstructure theory suggests that there is a linkage between liquidity and quote dynamics. Liquidity refers to the degree to which an asset can be bought or sold in the market without affecting that asset's price. One measure of liquidity is the bid-ask spread, which is the difference between the market maker's ask and bid prices. Demsetz (1968) calls this the cost of "immediacy" of exchange in organized markets. Investors who require immediacy to purchase an asset need to pay the market maker's ask price, while those who wish to sell need to agree with the market maker's bid price. Therefore, the spread represents a cost to investors and a profit to market makers. A large spread indicates large profits to be made; leading to competition between market makers that will result in lower spread at the subsequent period. A small spread should do the opposite. Thus, the bid-ask spread is shown to affect bid and ask quotes 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. Jang and Venkatesh (1991) indicate this error-correcting behavior of which spread is more likely to decrease when the spread is greater than some threshold, and more likely to increase when it is below some threshold.

Another measure of liquidity which is typically assessed in the literature is the difference in quoted depth. Depth is the ability of an asset to absorb buy and sell without the price dramatically moving in either direction. Huang and Stoll (1994) suggest that the difference between the depth at the ask and the depth at the bid conveys important information. In line with the adverse-information model in market microstructure, high depth at ask relative to bid indicates an excess number of sellers relative to buyers, signalling that the stock is overpriced (signalling effect). A similar outcome can be explained by the proposition that 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 ask and bid prices (barrier effect).

Market microstructure theory also suggests that stock prices are affected by information that comes from trades. This concept was originally suggested by Bagehot (1971), who explains the importance of information on market prices. In the context of information-based models, a market comprises of both informed and uninformed traders. Trades by informed traders would result the market maker to lose on average to those traders. This implies that trades could reveal information and affect the movements in prices. Glosten and Milgrom (1985) explain 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. Therefore, the direction of trade is informative. As the market maker receives trades, his expectation of the asset's value changes, and this, in turn, causes his prices to change. In addition, Jang and Venkatesh (1991) show how the market maker revises his quotes following a transaction. For instance, following a transaction at the bid price, both the bid and the ask quotes will be revised downward for two reasons. First, based on the inventory cost reason, the market maker wants to discourage further public sales and encourage public purchases in order to square off his inventory. Second, based on adverse selection reason, a trade at the bid price indicates that some informed traders know that the true value of the asset is lower. Knowing that, the market maker will subsequently lower his bid and ask quotes.

Apart from the direction of trade, information can also be gleaned from other trade-related features. The first of them is the information contained in trade size. Easley and O'Hara (1987) explain that trade size induces an adverse selection problem, because at 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 market maker will interpret large orders as a signal that an information event has occurred and adjust prices accordingly by increasing his bid and ask quotes. Barclay and Warner (1993) and Chakravarty (2001), however, suggest that the informed traders may prefer to trade in a size that is not too large and not too small in order to disguise their trades as being informed (stealth trading). In such case, stock price changes should take place on trades of medium-size. The second feature is related to the trade duration. Easley and O'Hara

(1992) 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). If information events are not certain, then the occurence of trade may provide a signal to the market. Similarly, Dufour and Engle (2000) find that the time between trades contains information. Finally, signed order flow leads to changes in bid and ask prices. Kyle (1985) proposes that because market makers 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." As a consequence, bid and ask quotes are driven by order flow innovations.

The above concepts have been used to explain dynamics of quotes, where bid and ask quotes are modeled in simultanous equations as a cointegrated system, and each equation represents the quote revision in either side of the market. Such models are used in assessing the movements in quotes induced by the learning of the market makers and other liquidity suppliers responding to new information. For example, Kavajecz and Odders-White (2001) examine how NYSE specialists update bid prices, ask prices, bid depths, and ask depths in a simultaneous equations model. They find that changes in the best prices and depths on the limit order book have a significant impact on the posted price schedule. The effects of transactions and other market events (e.g. public liquidity providers placing limit orders, and changes in the trading environment), on the other hand, are secondary. 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 as regressors the characteristics of the trades occurring between quote observations. Their specification allows them to show that the dynamics of 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. In addition, they find that various trade-related and liquidity shocks are able to explain the movements in bid and ask quotes. Furthermore, Escribano and Pascual (2006) model the bid and ask quotes instead of using the quote midpoint to show that bid and ask quotes do not move symmetrically and buys and sells are not equally informative. These studies demonstrate the linkages between liquidity and trade-related information, and the quote dynamics of an asset in single markets.

In this paper, we assess whether the above relations exist across different markets and what mechanisms underlie such linkages. In the case of securities that are cross-listed and traded in more than one stock market, prices are cointegrated, and changes in price in one market become the source of price movement in another. Since bid and ask quotes make up prices, one can therefore expect that quotes in one market are linked to quotes in another market. With this in mind, 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 quotes, of which the quotes are cointegrated process 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 as a priori, and therefore sets a very general parameterization of the model. Furthermore,it is flexible enough to accommodate further extension, such as a multimarket application. This will be discussed further in the next section.

3 Dual-Market Quote Dynamics

In this section, we present the model for dual-market quote dynamics. We extend the VECM into a dual-market setting and represent the bid and ask quotes in the two markets as simultaneous equations in the joint system. Such setting is versatile and allows us to test various concepts in market microstructure research. In the interest of this paper, we follow the specification of Engle and Patton (2004) and allow the quote revisions as a function of liquidity and trade-related variables, both of which reflect the mechanism of which information is aggregated and disseminated into quote dynamics.

We specify the model in terms of log-differences, of which the log levels of the bid and ask quotes in each market are cointegrated of order one. The model is defined in quote time which means there is a new observation 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 with $k \leq 3$. The function $l(t)$ counts the number of trades occuring between quote $t-1$ and quote t. The following equation is estimated using ordinary least squares and the standard errors are controlled for possible heteroskedasticity using White's (1980) correction.[5]

$$\begin{bmatrix} \Delta\log(ASK_t^A) \\ \Delta\log(BID_t^A) \\ \Delta\log(ASK_t^B) \\ \Delta\log(BID_t^B) \end{bmatrix} = c + \sum_{j=1}^{10} A_{(j)} \cdot \begin{bmatrix} \Delta\log(ASK_{t-j}^A) \\ \Delta\log(BID_{t-j}^A) \\ \Delta\log(ASK_{t-j}^B) \\ \Delta\log(BID_{t-j}^B) \end{bmatrix} + B \cdot \begin{bmatrix} SPR_{t-1}^A \\ SPR_{t-1}^B \end{bmatrix} + \Gamma_1 \cdot \begin{bmatrix} DPTH\_DIFF_{t-1}^A \\ DPTH\_DIFF_{t-1}^B \end{bmatrix}$$

$$+ \sum_{k=1}^{3} \Gamma_2^{(k)} \cdot \begin{bmatrix} BUY_{\tau(t)-k}^A \cdot 1 \\ BUY_{\tau(t)-k}^A \cdot V_{\tau(t)-k}^{A,med} \\ BUY_{\tau(t)-k}^A \cdot D_{\tau(t)-k}^A \\ BUY_{\tau(t)-k}^B \cdot 1 \\ BUY_{\tau(t)-k}^B \cdot V_{\tau(t)-k}^{B,med} \\ BUY_{\tau(t)-k}^B \cdot D_{\tau(t)-k}^B \end{bmatrix} + \sum_{k=1}^{3} \Gamma_3^{(k)} \cdot \begin{bmatrix} SELL_{\tau(t)-k}^A \cdot 1 \\ SELL_{\tau(t)-k}^A \cdot V_{\tau(t)-k}^{A,med} \\ SELL_{\tau(t)-k}^A \cdot D_{\tau(t)-k}^A \\ SELL_{\tau(t)-k}^B \cdot 1 \\ SELL_{\tau(t)-k}^B \cdot V_{\tau(t)-k}^{B,med} \\ SELL_{\tau(t)-k}^B \cdot D_{\tau(t)-k}^B \end{bmatrix}$$

$$+ \Gamma_4 \cdot \begin{bmatrix} \sum_{k=1}^{l(t)} BUY_{\tau(t)-k}^A \\ \sum_{k=1}^{l(t)} SELL_{\tau(t)-k}^A \\ \sum_{k=1}^{l(t)} BUY_{\tau(t)-k}^B \\ \sum_{k=1}^{l(t)} SELL_{\tau(t)-k}^B \end{bmatrix} + \sum_{d=1}^{7} \Gamma_5^{(d)} \cdot \left[DIURN_t^d \right] + \varepsilon_t. \qquad (1)$$

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 (4×1) vector of innovations.

Microstructure data such as the changes in quote often show evidence of negative serial correlation (Stoll, 2000). The inclusion of lags of the dependent variables and the trade variables will capture this serial correlation. We employ ten lags of the dependent variables and find that they are sufficient to control for serial correlation. Both variables SPR and $DPTH\_DIFF$ represent liquidity shocks potentially affecting quote revisions. The log-levels of the bid and ask series are generally accepted to be cointegrated, with the log-spread being stationary. Naturally, the lagged spread is chosen as an error-correction term for the bid and ask quotes. In addition, the difference between the depth

[5] The description of the variables considered for this model are listed in Appendix (A.1).

at the ask and the depth at the bid is often taken as a measure of liquidity and conveys information through the signalling and barrier effects as explained in the previous section.

Trade-related information such as trade direction, size, duration, and order flow lead to revisions in bid and ask quotes. Market microstructure theory suggests that a buy has a positive impact on both the bid and ask quotes, whereas a sell has a negative impact. We include BUY and $SELL$ variables 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 as a buy, while if the trade price is lower than the mid-quote, the trade is considered as a sell. Trade that occurred exactly at the mid-quote is considered indeterminate and given a value of zero.

With regard to trade size, studies show that medium volume trades drive most of the stock price movements since informed traders break up their trades so as to remain inconspicuous. To represent the medium size trades, we include a volume indicator, V^{med} which returns 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 trade since they are extremely rare for our sample stocks (refer to Table 2 on the summary statistics). Studies have also shown that short durations signal news events while long durations signal neither bad nor good news. To capture the impact of trading intensity, we include trade duration variable, D, which is calculated as the difference in seconds between two successive trade time stamps. 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 the previous quotes, and represent order flow in the market which has been shown to be informative. Finally, to capture any deterministic component of the intra-day dynamics, we follow the commonly used approach to control for diurnality effect by including a piece-wise linear splines, $DIURN$ into the model, to reflect the time of the day that the observation falls into.[6]

[6] see for example Dufour and Engle (2000), Engle and Patton (2004).

4 Data

Our sample consists of 64 cross-listed stocks and spans eleven months from February 1, 2011 to December 31, 2011. This sample selection constitutes all Canadian stocks listed in both the Toronto Stock Exchange and the New York Stock Exchange, which are readily tradeable in both markets over the sample period, of which data is available in the database. We use tick level data from TRTH (Thomson Reuters Tick History) database maintained by SIRCA.[7] Specifically, we obtain the time stamp (to the microseconds) of bid and ask quotes, bid and ask depths, trade prices, and trade volumes for each of the stocks in each market over the 225 trading days. For each of these variables, we use data from the market consolidated tape to ensure that our analysis captures the quote dynamics in the two markets accurately. In addition, we also obtain CAN/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.[8]

INSERT TABLE 1 HERE.

Table 1 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. This is 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 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 comes under 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, of which 41 out of 64 stocks report higher percentage spread in the U.S. than in Canada. The trend in spread in each market is consistent with the literature; trades are relatively less (more) frequent when the spread is wide (tight), indicating the effect of liquidity on 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

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

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

least frequently traded stocks in their respective markets. Finally, if we look at the 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 analysis, we discard any transactions and quotes that occured outside trading hours between 9.35AM to 16.00PM.[9] 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) of the quote prices 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 and as for the volume, we summed the total volume of the trades, attributed it to the first trade, and then removed the other trades from the sample.

The challenge in using tick data from both markets is to synchronise the data. Since microsecond data is so precise, we observe that most of the time, trading in the U.S. and Canada are conducted at slightly different time (a fraction of a second different). Therefore, to combine the U.S. and Canada datasets, we first compile a series of quote time using the time stamps from both markets. Once a combined time stamps is constructed, we link the data in each market according to the time stamps. If there is no data for any one market at a particular time stamp, we assign zero.[10]

5 Empirical Results

5.1 Quote Dynamic Model

In this section, we present the results for our quote model. We estimate Equation (1) daily for each of the 64 stocks. This totals to 14,400 estimated days. The average $R^2(adj)$ statistics for the U.S.

[9] 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.

[10] 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.

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 was significantly positive and negative at 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 quotes at the beginning of the trading day in both markets. From 9.30AM to 10AM especially, the diurnal variables show a significant positive coefficients on the ask quotes and significant negative coefficients on the bid quotes 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).

5.1.1 Lags of Dependent and Liquidity Variables

We report the coefficients for the first lag of the dependent variables in Panel A of Table 2.[11] We observe strong negative serial correlation between the dependent variables and their first lags in the home market as documented in the literature such as Stoll (2000) and Engle and Patton (2004). This indicates that bid and ask quotes mean-revert to restore the spread to its long-run equilibrium value. Across market, we observe reactions to changes in the lagged quotes. Specifically, the coefficient for the lagged ask quote in one market on the ask dependent variable of the other market is significantly positive, and significantly negative on the bid dependent variable. An increase in the ask quote in one market leads to an increase in the ask quote and a decrease in the bid quote of the other market in the following period. The opposite is true for the lagged bid quote. The fact that quotes in the two markets are driven by the changes in quotes in any of the market indicates a direct link between quotes in the two markets.

INSERT TABLE 2 HERE.

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

With regard to the role of 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 a wide spread in one market will narrow the spread in another 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 2 show the impact of the lagged spread on quotes in both markets. A high 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 quotes react to changes in spreads, indicating error-correcting behavior of the spread. 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, due to liqudity shocks. 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 market the same way they affect home market quotes. Quotes in both markets react to the changes in spreads such that the spread will return to their respective equilibriums in the following period. Particularly, an increase in spreads in the U.S. (Canada) leads to a decrease in the ask price and an increase in the bid price in Canada (U.S.). We conjecture this result to the competition between market makers in 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 is 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 2, of which 41 out of 64 stocks report higher percentage spreads in the U.S. than in Canada. This is consistent with Jang and Venkatesh (1991) and Escribano and Pascual (2006) who suggest that the responses of the bid and ask quotes are greater when the bid-ask spread is wide than when the spread is narrow. Overall, our findings suggest that quotes of cross-listed stocks are directly driven by spreads.

Next, we investigate the depth difference as a measure of market liquidity. Depth is the log difference between the depth at the ask and the depth at the bid prices. Huang and Stoll (1994) suggest that the difference between the depth at the ask and the depth 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. Furthermore, the barrier effect suggests that excess depth means less volume is required before a downward movement than an upward movement. Both effects lead to less buyers and more sellers, thus lowering the ask and increasing the bid quotes. Similarly, we expect quotes in host market will adjust to changes in the home market and leads to lower ask and bid quotes.

Panel C of Table 2 reports the coefficients of the lagged depth difference on the bid and ask quotes. We observe that an increase in depth difference in the U.S. leads to strong decrease in the home market bid and ask quotes. For example, the coefficients for $DEPTHDIFF_{t-1}^{US}$ are negative in 91% (91%) of the time for the U.S. ask and bid dependent variables, respectively. The same applies to the depth difference in Canada, of which the coefficients are negative in 83% (84%) of the time for the Canadian ask and bid dependent variables, respectively. This is a strong evidence for the signalling and barrier effects which lead to lower bid and ask quotes. The cross-market impact, however, is almost negligible and unobservable. These results suggest that depth difference as one measure of liquidity only affects bid and ask quotes in the home market.

5.1.2 The Importance of Trade-related Information

Another important concept in market microstructure is that trades by informed agents convey information and therefore cause a persistent impact on the long-run value of a stock. Trade-related activities such as direction, size, duration, and order flow are known to be informative and may cause revisions in market quotes.

INSERT TABLE 3 HERE.

Panel A of Table 3 reports the coefficients of the trade direction variables on the bid and ask quotes. Our findings on the impact of trade on home market bid and ask quote are 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 quotes, while the seller-initiated trade lowers the quotes. These quotes tend to be revised in the same direction, but not by the same amount. Ask and bid quotes do not respond symmetrically after trade-related shocks. Buyer-initiated trades are more important to the ask quote, while seller-initiated trades are more important to the bid quote, in either market. Across market, however, the impacts of trade direction appears negligible with magnitudes of almost close to 0, indicating that the two markets are still informationally fragmented.

Our empirical results reported in the Panel B of Table 3 indicate that medium trade size matters only to a small extent.[12] The coefficients $BUYVMED$ ($SELLVMED$) are only significant in 11% (11%) for the ask (bid) price in the U.S., and 16% (16%) for the ask (bid) price in Canada despite their relatively large magnitudes. These coefficients, however, have the priori expected signs: where a $BUYVMED$ variables all have positive signs on the bid and ask quotes while $SELLVMED$ all have negative signs. Panel C on Table 3 reports the coefficients on the interaction between the bid and ask quotes and the trade duration. We find that the trade duration coefficients are insignificant in most cases. A buy transaction arriving after a long time interval has very little impact on quotes. This is consistent with the findings of Easley and O'Hara (1992), that longer durations are likely to be associated with no news. Similarly, Engle and Patton (2004) find that the long duration variable tends to be insignificant, and even if they are, the coefficient is usually the opposite sign to the coefficient on the trade direction variables. This finding suggests that a trade that occurs after long duration is likely to be liquidity rather than information-driven.

Panel D on Table 3 reports our empirical findings on the importance of order flow on the bid and ask quotes. We find that order flow is highly significant in explaining informational asymmetries in the market. We observe that $TOTALBUY$ strongly increases both ask and bid prices in their respective markets, while $TOTALSELL$ strongly decreases them. This suggests that market makers set quotes based on the observations of the current and past aggregate quantities traded in

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

the market. We do not observe any effects of trading activity across markets. Overall, all of the above findings suggest that trade-related information only affects quotes in the same market. We therefore conclude that despite prices in the two markets being cointegrated, the two markets are still informationally fragmented.

5.2 Implied Model for Spreads, Midpoint of Quotes, and Price Premium

Next, the linkage between quote revisions and liquidity shocks and trade-related information are assessed using the quote model in the previous section. Based on this model, we can derive an implied VAR model for various market microstructure variables such as the spread in each market, mid-quote between markets, as well as the cross-market difference in mid-quotes. The impact of trades on the spread is of particular interest as the spread represents a key measure of the magnitude of friction in the market. The impact of liquidity and trades on the mid-quote between markets is also important as the mid-quote represents the implied efficient price of the cross-listed stock. Particularly, we are able to test whether the long-term value of the stock varies according to buyer and seller-initiatied trades, as well as liquidity shocks. Finally, the cross-market difference in midquotes represents the relative premium of trading in one market over another.

Equation (1) is rotated and restructured into a more desirable model of the log spread in each market, SPR^A_{t-j} and SPR^B_{t-j}, the log difference in the mid-quote from both markets, $\Delta \log(MQ_{t-j})$, and the cross-market difference in log mid-quotes, $\log(MQ^{A-B}_{t-j})$ as specified below.

$$
\begin{bmatrix} SPR_t^A \\ SPR_t^B \\ \Delta\log(MQ_t) \\ \log(MQ_t^{A-B}) \end{bmatrix} = \widetilde{c} + \sum_{j=1}^{10} \widetilde{A}_{(j)} \cdot \left(T_1 \cdot \begin{bmatrix} SPR_{t-j}^A \\ SPR_{t-j}^B \\ \Delta\log(MQ_{t-j}) \\ \log(MQ_{t-j}^{A-B}) \end{bmatrix} - T_2 \cdot \begin{bmatrix} SPR_{t-(j+1)}^A \\ SPR_{t-(j+1)}^B \\ \Delta\log(MQ_{t-(j+1)}) \\ \log(MQ_{t-(j+1)}^{A-B}) \end{bmatrix} \right)
$$

$$
+ \left(K + \widetilde{B} \cdot T_3\right) \cdot \begin{bmatrix} SPR_{t-1}^A \\ SPR_{t-1}^B \\ \Delta\log(MQ_{t-1}) \\ \log(MQ_{t-1}^{A-B}) \end{bmatrix} + \widetilde{\Gamma}_1 \cdot \begin{bmatrix} DPTH\_DIFF_{t-1}^A \\ DPTH\_DIFF_{t-1}^B \end{bmatrix}
$$

$$
+ \sum_{k=1}^{3} \widetilde{\Gamma}_2^{(k)} \cdot \begin{bmatrix} BUY_{\tau(t)-k}^A \cdot 1 \\ BUY_{\tau(t)-k}^A \cdot V_{\tau(t)-k}^{A,med} \\ BUY_{\tau(t)-k}^A \cdot D_{\tau(t)-k}^A \\ BUY_{\tau(t)-k}^B \cdot 1 \\ BUY_{\tau(t)-k}^B \cdot V_{\tau(t)-k}^{B,med} \\ BUY_{\tau(t)-k}^B \cdot D_{\tau(t)-k}^B \end{bmatrix} + \sum_{k=1}^{3} \widetilde{\Gamma}_3^{(k)} \cdot \begin{bmatrix} SELL_{\tau(t)-k}^A \cdot 1 \\ SELL_{\tau(t)-k}^A \cdot V_{\tau(t)-k}^{A,med} \\ SELL_{\tau(t)-k}^A \cdot D_{\tau(t)-k}^A \\ SELL_{\tau(t)-k}^B \cdot 1 \\ SELL_{\tau(t)-k}^B \cdot V_{\tau(t)-k}^{B,med} \\ SELL_{\tau(t)-k}^B \cdot D_{\tau(t)-k}^B \end{bmatrix}
$$

$$
+ \widetilde{\Gamma}_4 \cdot \begin{bmatrix} \sum_{k=1}^{l(t)} BUY_{\tau(t)-k}^A \\ \sum_{k=1}^{l(t)} SELL_{\tau(t)-k}^A \\ \sum_{k=1}^{l(t)} BUY_{\tau(t)-k}^B \\ \sum_{k=1}^{l(t)} SELL_{\tau(t)-k}^B \end{bmatrix} + \sum_{d=1}^{7} \widetilde{\Gamma}_5^{(d)} \cdot \left[DIURN_t^d \right] + \widetilde{\varepsilon}_t. \qquad (2)
$$

where T_1, T_2, and T_3 are rotation matrices. The derivation of this model can be found in Appendix (A.2).

The coefficients for our implied model are obtained through linear combination of the parameters estimated in Equation (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 the 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's (1980) robust standard errors in our estimations to correct for possible heteroskedasticity. Consistent with the finding in the previous section, we find that spreads in both markets are higher at the beginning of the day compared to the other periods. We find no evidence of an increase in average spreads towards the end of the day.

5.2.1 Lags of Dependent and Liquidity Variables

We first assess whether the implied variables such as the spreads, midpoint returns, and price premium are persistent. We also assess whether these variables are affected by liquidity variables such as the bid-ask spread and depth difference. We report the results in Table 4.

INSERT TABLE 4 HERE.

The change in midpoint shows persistence as reported in Panel A of Table 4. Past returns in midpoint predict subsequent midpoint returns. This appears to refute the efficient market hypothesis where one would expect the quotes of the specialist and limit orders to adjust to past returns. However, 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 adjusting limit orders to information contained in prices may explain such predictive power. The negative coefficient on the price premium suggests that positive return in midpoint price leads to a greater increase in Canadian prices compared to U.S. prices, thus a decrease in price premium. The price premium appears to be persistent especially for the first lag with highly positive and significant coefficients. This finding suggests a positive premium in the U.S. tends to be positively and serially correlated. The price premium also has a positive and significant impact on the price midpoint. An increase in premium suggests the midquote in the U.S. increases more than the midquote in Canada, leading to an increase in overall price midpoint. We do not observe any impact of price premium on the spreads in any of the two markets.

Panel B of Table 4 reports the coefficients of the bid-ask spreads on the implied model. The spreads do not seem to have significant impact on price midpoint and premium. They do, however, affect the spreads in the subsequent period, both in the home market, as well as across market. $SPREAD_{t-1}^{US}$ leads to a decrease in Canadian spread in the following period while $SPREAD_{t-1}^{CAN}$ leads to a decrease in the U.S. spread in the following period. Since high spread leads to a decrease in the ask and an increase in the bid, it will move the spread toward its equilibrium value. Therefore, it is expected that the coefficients for $SPREAD_{t-1}$ to be negative for the spread equations of the other market.

Panel C of Table 4 reports the coefficients of the lagged depth difference on the implied model. We do not observe any impact of the depth difference on spreads. However, the impact on price midpoint is negative and highly significant. Both $DEPTHDIFF^{US}_{t-1}$ and $DEPTHDIFF^{CAN}_{t-1}$ report strong negative coefficients on the price midpoint. This, again, is consistent with the signalling and barrier effects discussed in the previous section. The result can therefore be interpreted as large depth difference indicates oversupply of assets traded, thus suggesting that the stock is overpriced, leading to less buying and more selling by investors, hence both the ask and bid prices will decrease. Therefore, when the depth difference either in the U.S. or in Canada is large, the midpoint tend to be lower. The impact on the price premium is negative and significant for $DEPTHDIFF^{US}_{t-1}$ and positive and significant for $DEPTHDIFF^{CAN}_{t-1}$. This is consistent with the results in Section (5.1.1), because $DEPTHDIFF^{US}_{t-1}$ lowers only the U.S. bid and ask prices and not Canadian bid and ask prices, thus lowering the difference in prices in the two markets. $DEPTHDIFF^{CAN}_{t-1}$ on the other hand, lowers Canadian bid and ask prices, and not the U.S. quotes. As a consequence, the difference in prices in the two markets increases. In terms of magnitude, the impact of U.S. depth difference is greater (in absolute terms) on the price midpoint and price premium, compared to the impact of Canada depth difference, indicating asymmetric reactions by investors the two markets.

5.2.2 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 shows that trade direction has very little impact on spreads. We observe positive relationship between buyer and seller-initiated trades and the bid-ask spread in the U.S. However, the positive coefficients are only significant 19% of the time. While the asymmetric impacts of buys and sells on the ask and bid quotes are apparent as shown in Section (5.1.2), it is not easily detectable in a model for the spread. We observe similar relationship between trades and spread in Canada, in which the coefficients are positive, but they are not statistically significant. We do not observe a noticable impact of trades on spreads across market.

INSERT TABLE 5 HERE.

In terms of the implied efficient price, both an increase in purchases in the U.S. and Canada lead to an increase in the midpoint, whereas an increase in sells from either market will lead to a decrease. This is consistent with the findings in Panel A of Table 3 because both ask and bid prices increase following a purchase and decrease following a sell. Engle and Patton (2004) interpret this as trade increases the uncertainty about the true price of the stock, leading to not only the bid and ask prices to increase, but also the mid-quote to rise. As for the price premium, purchases in the U.S. lead to an increase in the price premium, 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 the U.S. trades compared to Canadian trades on midpoint and premium indicate strong evidence of information asymmetry between the two markets.

Our empirical results, Panel B of Table 5, indicate that medium-sized trades do not affect spreads in either market. They do, whoever, to a small extent affect price midpoint and price premium. For the price 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. As for trade duration, results reported in Panel C on Table 5 shows that trade duration coefficients are small and almost negligible in most cases.

The impact of order flow is highly apparent, as shown in Panel D of Table 5, particularly on the price midpoint and price premium. On the midpoint, $TOTALBUY$ from both markets strongly increase the midpoint of prices between the two markets. $TOTALSELL$ strongly lowers the price midpoint. This is clear evidence of the importance of order flow on the revisions of the efficient price of the cross-listed stocks which is in line with the study of Kyle (1985). As for the market premium, and increase in $TOTALBUY^{US}$ increase the price premium even further. Expectedly, $TOTALSELL^{US}$ lowers the price premium as the price of the stock in the U.S. decreases. Inversely, $TOTALBUY^{CAN}$ lowers the premium, while $TOTALSELL^{CAN}$ further increases the price premium between markets.

6 Conclusion

In this paper, we study the dynamics of quotes for cross-listed stocks. We specify a model to represent the quote revisions in each market and use as regressors a variety of liquidty and trade-related variables commonly used in the literature. From the empirical perspective, this paper represents an extension to the VECM model introduced by Engle and Patton (2004) by jointly modelling the time series dynamics of the revisions of bid and ask quotes from two fully-synchronised markets. Thus, it expands the empirical studies in this area such as those of Kavajecz and Odders-White (2001), Engle and Patton (2004), and Escribano and Pascual (2006). Another feature of this model is it enables us to extract the implied model for several microstructure variables such as the bid-ask spreads, the midpoint of prices between markets, and the price premium, in a VAR framework.

Application of our model using data from Canadian cross-listed stocks in the U.S. leads to several interesting findings. First, quote dynamics in the two markets are driven by liquidity shocks measured by the bid-ask spread. Bid and ask quotes converge when the spread is wide and diverge when the spread is narrow. This is a strong evidence of the the error-correcting mechanism of spread on the bid and ask quotes. Changes in spread in one market is likely to cause adjustments in quotes in another market. We attribute this to competition between market makers in both markets which keeps spreads in the two markets comparable. Second, the difference in depth affects only the quotes in the home market, and not across market. This suggests that depth difference only conveys information in the home market, indicating that the only form of liquidity affecting quotes across market is the bid and ask spread.

Third, trade-related information, are shown to have a direct effect on quotes in the home market, but not across market. This signifies that even though prices in the two markets are cointegrated, the markets are still informationally fragmented in terms of trades. The implied efficient price and the price premium, on the other hand, are driven by trades from either markets, indicating that trade-related information affects quotes across market indirectly through the movements it causes on the home market quotes. Finally, we observe that reactions of the U.S. quotes to liquidity shocks are stronger than the reactions of the Canadian quotes. Furthermore, U.S. trades have greater impact on the price midpoint and price premium than the Canadian trades. This suggests that liquidity and trade-related information play a greater role in the U.S than in Canada.

The above findings describe the mechanism of how liquidity and trade-related information get incorporated into prices for cross-listed stocks through the impact they have on quotes. We show how quote dynamics in two different markets are driven by liquidity. The prominence of the impact of bid and ask spread on quotes suggests that liquidity is an important direct channel of information to multiple markets. We also show that the fundamentals of cross-listed stocks such as the efficient price and relative premium are not only driven by liquidity shocks, but also buyer and seller-initiated trades, from any of the two markets. These results suggest that both liquidity and trade-related information provide investors with valuable information source on the fundamental values of cross-listed stocks.

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8 Appendix

Appendix A.1. Description of Variables

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 $t-1$.
SPR_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.
$BUY^i_{\tau(t)-k}$	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.
$SELL^i_{\tau(t)-k}$	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.
$V^{i,med}_{\tau(t)-k}$	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.
$D^i_{\tau(t)-k}$	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.

Appendix A.2. 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 $\Delta Y_t = \begin{bmatrix} \Delta \log(ASK_t^A) \\ \Delta \log(BID_t^A) \\ \Delta \log(ASK_t^B) \\ \Delta \log(BID_t^B) \end{bmatrix}$, $spread_{t-1} = \begin{bmatrix} SPR_{t-1}^A \\ SPR_{t-1}^B \end{bmatrix}$, 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 $\Delta \widetilde{Y}_t = T \cdot \Delta Y_t = \begin{bmatrix} \Delta SPR_t^A \\ \Delta SPR_t^B \\ \Delta \log(MQ_t) \\ \Delta \log(MQ_t^{A-B}) \end{bmatrix}$, 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 $\widetilde{Z}_t = \begin{bmatrix} SPR_t^A \\ SPR_t^B \\ \Delta \log(MQ_t) \\ \log(MQ_t^{A-B}) \end{bmatrix}$, $T_1 = \begin{bmatrix} 0.5 & 0 & 1 & 0.5 \\ -0.5 & 0 & 1 & 0.5 \\ 0 & 0.5 & 1 & -0.5 \\ 0 & -0.5 & 1 & -0.5 \end{bmatrix}$, $T_2 = \begin{bmatrix} 0.5 & 0 & 0 & 0.5 \\ -0.5 & 0 & 0 & 0.5 \\ 0 & 0.5 & 0 & -0.5 \\ 0 & -0.5 & 0 & -0.5 \end{bmatrix}$, $T_3 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$, 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:

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

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

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

Writing Equation (A7a) out, we get:

$$\begin{aligned}
\begin{bmatrix} SPR^A_t \\ SPR^B_t \\ \Delta\log(MQ_t) \\ \log(MQ^{A-B}_t) \end{bmatrix} = \widetilde{c} + \sum_{j=2}^{10} \widetilde{A}_{(j)} \cdot \left(T_1 \cdot \begin{bmatrix} SPR^A_{t-j} \\ SPR^B_{t-j} \\ \Delta\log(MQ_{t-j}) \\ \log(MQ^{A-B}_{t-j}) \end{bmatrix} - T_2 \cdot \begin{bmatrix} SPR^A_{t-(j+1)} \\ SPR^B_{t-(j+1)} \\ \Delta\log(MQ_{t-(j+1)}) \\ \log(MQ^{A-B}_{t-(j+1)}) \end{bmatrix} \right) \\
+ \Big(K \cdot \widetilde{B} \cdot T_3\Big) \cdot \begin{bmatrix} SPR^A_{t-1} \\ SPR^B_{t-1} \\ \Delta\log(MQ_{t-1}) \\ \log(MQ^{A-B}_{t-1}) \end{bmatrix} + \widetilde{\Gamma}_1 \cdot \begin{bmatrix} DPTH_DIFF^A_{t-1} \\ DPTH_DIFF^B_{t-1} \end{bmatrix} \\
+ \sum_{k=1}^{3} \widetilde{\Gamma}^{(k)}_2 \cdot \begin{bmatrix} BUY^A_{\tau(t)-k} \cdot 1 \\ BUY^A_{\tau(t)-k} \cdot V^{A,med}_{\tau(t)-k} \\ BUY^A_{\tau(t)-k} \cdot D^A_{\tau(t)-k} \\ BUY^B_{\tau(t)-k} \cdot 1 \\ BUY^B_{\tau(t)-k} \cdot V^{B,med}_{\tau(t)-k} \\ BUY^B_{\tau(t)-k} \cdot D^B_{\tau(t)-k} \end{bmatrix} + \sum_{k=1}^{3} \widetilde{\Gamma}^{(k)}_3 \cdot \begin{bmatrix} SELL^A_{\tau(t)-k} \cdot 1 \\ SELL^A_{\tau(t)-k} \cdot V^{A,med}_{\tau(t)-k} \\ SELL^A_{\tau(t)-k} \cdot D^A_{\tau(t)-k} \\ SELL^B_{\tau(t)-k} \cdot 1 \\ SELL^B_{\tau(t)-k} \cdot V^{B,med}_{\tau(t)-k} \\ SELL^B_{\tau(t)-k} \cdot D^B_{\tau(t)-k} \end{bmatrix} \\
+ \widetilde{\Gamma}_4 \cdot \begin{bmatrix} \sum_{k=1}^{l(t)} BUY^A_{\tau(t)-k} \\ \sum_{k=1}^{l(t)} SELL^A_{\tau(t)-k} \\ \sum_{k=1}^{l(t)} BUY^B_{\tau(t)-k} \\ \sum_{k=1}^{l(t)} SELL^B_{\tau(t)-k} \end{bmatrix} + \sum_{d=1}^{7} \widetilde{\Gamma}^{(d)}_5 \cdot \Big[DIURN^d_t\Big] + \widetilde{\varepsilon}_t. \quad \text{(A7b)}
\end{aligned}$$

Table 1. Summary Statistics

Table 1 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 quotes. *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 1. Continued

Symbol	Company Name	US N	US Volume	US Sml	US Med	US Big	US %Spread	US Duration	CAN N	CAN Volume	CAN Sml	CAN Med	CAN Big	CAN %Spread	CAN 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

Table 2. Coefficients of the first lagged dependent variables on the quote model

Table 2 reports the mean of the estimated coefficients for the first lag of the dependent variables (coefficients $A_{(1)}$, B and Γ_1 in Equation 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}
$DEPTHDIFF^{US}_{t-1}$	**-0.663**	**-0.662**	0.000	-0.002
Sig + / - (in %)	**0 / 91**	**0 / 91**	5 / 7	6 / 7
$DEPTHDIFF^{CAN}_{t-1}$	0.001	0.000	**-0.338**	**-0.347**
Sig + / - (in %)	9 / 8	8 / 10	**0 / 83**	**0 / 84**

Table 3. Coefficients of the trade-related variables on the quote model

Table 3 reports the average of the estimated coefficients for the first lag of the trade-related variables (coefficients $\Gamma_2^{(1)}, \Gamma_3^{(1)}$ and Γ_4 in Equation 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**

Table 4. Coefficients of the first lagged dependent and liquidity variables on the implied model

Table 4 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**

Panel B: Bid-Ask Spread

	$SPREAD^{US}$	$SPREAD^{CAN}$	$\Delta MIDPOINT$	$PREMIUM$
$SPREAD^{US}_{t-1}$	**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

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

Table 5. Coefficients of the trade-related variables on the implied model

Table 5 reports the mean of the estimated coefficients for the first lag of the trade-related variables (Coefficients $\widetilde{\Gamma}_2^{(1)}, \widetilde{\Gamma}_3^{(1)}$, and $\widetilde{\Gamma}_4$ in Equation 4). "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**