Information Flow and Price Discovery in Canadian and U.S. Stock Markets

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Abstract

In this paper, we consider the dynamics and complexity of price discovery of the same underlying assets traded in synchronous markets in two different countries. We extend the existing literature by studying the complex but realistic market conditions that are not jointly considered before: (1) Each country's market is exposed to both internal and external shocks of different sizes. (2) Information channels may be complex and vary over the trading day. (3) Each market may absorb external shocks with a unique (long or short) lag. (4) Sampling data across different frequencies may be necessary to avoid data truncation. Therefore, we propose a new approach and a new dynamic price discovery measure to study price discovery. In this paper, we use this research strategy to examine the 109 stocks listed and traded in both the Canadian and U.S. markets across intraday data of different frequencies from minute-by-minute to the end-of-day. We find the different behaviors of the two markets in incorporating innovations from within and across the markets, different information transmission channels across the markets, the dynamics for innovations to be absorbed in these markets, and distinguishable features of the information efficiency across a range of key market characteristics. This paper offers some fresh insight to the complexity and dynamics of price discovery.

JEL Codes: C5, F3, G1

Keywords: stock markets, pricing errors, information transmission, price discovery, dynamics

Theme Keywords: Market Microstructure, Financial Econometrics, Financial Mathematics

1 Introduction

In this paper, we study price discovery process for the stocks that are listed and traded in both the Canadian and U.S. stock markets using the methodology that accommodates complex two-way interactions among the two markets in two different countries. The complexity is characterized by a number of realistic considerations: (1) The two markets may be exposed, respectively, to internal and external shocks that arrive at different frequencies and are of different sizes. (2) The information channels between the two markets may be complex and vary over the trading day. (3) Each market may absorb the shock from the other market with a unique (long or short) lag. (4) The sampling method using intraday data of varying frequencies, therefore, matters in the sense it minimizes the opportunity of data truncation. The complexity discussed above undoubtedly invites a more comprehensive research strategy, which includes a more general structural model, an empirical research strategy of using intraday data of multiple frequencies, a new price discovery measure that captures the dynamics of price discovery, and a panel model linking the price discovery measures to some identifiable key market factors.

In the existing literature, some authors (see Hasbrouck (1995) and Harris, et al. (2002)) have studied price discovery for the stocks that are traded in multiple markets in a country while some other authors (Werner and Kleidon (1996), Hupperets and Menkveld (2002) , Eun and Sabherwal (2003), Grammig, Melvin, and Schlag (2005), Menkveld (2008), Otsubo (2014), and Frijns et al. (2015a, 2015b) for example) have studied price discovery for the stocks that are traded in multiple markets across countries. Among the latter, some authors (Werner and Kleidon (1996), Hupperets and Menkveld (2002) and Grammig, Melvin, and Schlag (2005), Menkveld (2008), and Otsubo(2014) for example) focus on the non-synchronous markets across countries but some (Eun and Sabherwal (2003), Frijns et al. (2015a, 2015b) for example) examine the synchronous markets that share many commonalities. This paper also focuses on the synchronous markets of this kind as in Eun and Sabherwal (2003) and Frijns et al. (2015a, 2015b) but allows for other complex and realistic situations.

The capital markets in the U.S. and Canada are synchronous and highly integrated. First, both capital markets are open to foreign investors and foreign corporations. Second, the two economies are highly integrated. The U.S. is the largest goods trading partner of

Canada.[1] The Canada is also the largest goods trading partner of the U.S.[2] Third, the two countries share a longest international border and share time zones. Fourth, the news media in the U.S. and Canada is also quite integrated due to the common language (English).[3] Fifth, the stock exchanges in the two countries use the decimal pricing system.[4] Finally, these U.S. and Canadian stock exchanges have the identical open time (9:30 EST or 14:30 UTC) and close time (16:00 EST or 21:00 UTC). The historical and current similarities and proximities of the Canadian and U.S. stock markets provide a fertile environment to study price discovery in two markets for the same stocks without dealing with non-synchronous issues. Because these two markets are ideal for studying price discovery a relatively simple context, some researchers (Eun and Sabherwal (2003), and Frijns et al. (2015a, 2015b)) offer some interesting insight to the Canada-U.S. cross-listed stocks in particular and broad cross-listed securities in general.

This paper focuses on price discovery for the same stocks (primarily Canadian stocks) traded in both the Canadian and U.S. markets but considers the kind of complexity noted early. Due to the fact that the stocks traded in the Canadian and U.S. markets are primarily issued by the companies with head offices in Canada, relative to the shocks in the U.S. market, the shocks in the Canadian market may arrive at a different frequency, be of different size, and be absorbed at a different speed in the U.S. market. Local/company news may appear more frequently in Canada while general/industry news may appear less frequently in the U.S. market. This may affect information channels between the two markets over the trading day. The shocks in Canada may be relatively smaller in size while those in the U.S. may be relatively greater in size. While the stock prices in the Canadian and U.S. markets are exposed to shocks sourced from the two markets, the stock price in one market may have a faster or slower absorption speed for the shock coming from the other market.

This complexity has not been dealt within the existing literature. From the theoretical perspective, Putnins (2013) notes that the existing literature assumes that the two market prices of the same stock are driven by the same common stochastic factor and that different market shocks arrive contemporaneously. Under this framework, the information share (IS) measure proposed by Hasbrouck (1995) and the component share (CS) measure proposed by

[1] See Table 4-1 in Canada's State of Trade: Trade and Investment Update 2013; see www.international.gc.ca/economist-economiste/performance/index.aspx?lang=eng

[2] Top Trading Partners - December 2013; see https://www.census.gov/foreign-trade/statistics/highlights/top/top1312yr.html

[3] Quebec's official language is French while English and French are official languages in Canada.

[4] The Canadian exchanges adopted the decimal pricing on April 15, 1996. The NASDAQ adopted decimal pricing by March 12, 2001. The NYSE adopted the decimal quotation system by September 11, 2001.

Booth et al. (1999), Chu et al. (1999) and Harris, et al. (2002) are defined in terms of a reduced form vector error correction model (VECM) but the interpretation of these measures are often dependent on the underlying structural model of prices. Yan and Zivot (2010) address the challenge by combining IS with CS to obtain the information leadership share measure (ILS). Although Yan and Zivot (2010) extend the structural model by including one permanent and one transitory shocks, their work are still built on the assumption that shocks arrive contemporaneously. Putnins (2013) shows that the IS and CS measures may vary subject to the relative noise levels in two markets while the ILS is robust in the presence of different noise levels in two markets but it is only for two price series, for a parameterization of one permanent and one transition shock, and uncorrelated reduced form VECM errors. Otsubo (2014) proposes a structural model and three price discovery measures based on the structural model but this structural model is only suitable to non-overlapping markets. Otsubo (2014) also notes the speed of information absorption and size of innovation in two non-overlapping markets but does not consider information channels between two synchronous markets. Frijns et al. (2015a) use the dynamic panel model to identify persistence in price discovery in the sense that strong price discovery appears persistent overtime while their price discovery measure per se (CS) is not a dynamic one. Frijns et al. (2015b) distinguish the speed of innovation arrival and that of innovation absorption and use macro announcement to differentiate price discovery but information channels for various shocks are not of a major concern. The complex and realistic situations considered in this paper are more general than those in the literature. In summary, our structural model allows the two markets to be exposed, respectively, to internal and external shocks that arrive at different frequencies and are of different sizes. Our empirical study examines the information channels between the two markets over the trading day. We entertain the possibility that each market may absorb the shock from the other market with a unique (long or short) lag. Considering the complex and realistic situations, we believe that the sampling method using intraday data of varying frequencies matters in the sense it minimizes the opportunity of data truncation.

This paper will propose a more comprehensive research strategy to study the complexity.

First, we propose a structural model with the following characteristics: (1) The two market prices of the same underlying stock are determined by the same common stochastic factor and the two different market specific shocks. (2) The different market specific shocks may be of different sizes and arrive at different frequencies. (3) Each market price of the same underlying stock may have a different absorption speed for the shock coming from the other market. This model shows how error correction coefficients in the reduce form VECM would change if the arriving frequencies, sizes and absorption speeds of the shocks change.

Second, because of the recognized complexity, we focus on the different roles played by the Canadian and U.S. market across (1) the intraday data of different frequencies started from time 9:30 EST, (2) the intraday data of different frequencies with the starting time shifting from 9:30 EST to 10:00 EST minute by minute, and (3) the intraday data during the opening/closing 30 minutes and that during the rest of the trading day. The in-depth analysis of the intraday data of these characteristics gives us a more insight to price discovery and the roles of the two markets.

Third, because we need to explore the different market shocks that may arrive at different points in time, we use the reduced form VECM for the price data and the SVAR models for residuals of that VECM using the intraday data of various frequencies. We are also able to identify information channels for shocks to be transmitted across the Canadian and U.S. markets. In this setting, we propose a dynamic price discovery measure (D) based on Wu, Meng, and Xu (2015) . Using this measure, we can find how fast these shocks transmit instant information from one stock market to another and how long it takes for these shocks to vanish over time. We also propose a summary evaluation measure (S) for price discovery with which we are able to identify the characteristics of price discovery across the two markets in the intraday data.

Finally, the objective of the paper is to study price discovery dynamics for the same stocks listed and traded in both the Canadian and U.S. markets to find the time duration needed for information absorption. To do so, we analyze the data over different frequencies—from the minute-by-minute data to the end-of-day data. We recognize that the real data generating process is, in reality, unobservable and that we have to rely on sampling at some frequencies, which will reveal some observable data but will inevitably omit some unobservable data. Hasbrouck (1995) studies price discovery within the U.S. stock markets using second-by-second intraday data when the U.S. stock market used the 1/6 tick system. Harris, McInish, and Wood (2002) study the intermarket price adjustments of DJIA stocks using intraday data of frequency of 101.86 seconds (about 1.7 minutes) when the U.S. stock market used the 1/6 tick system. Eun and Sabherwal (2003) study price discovery for the 62 stocks listed and traded in the U.S. and Canadian stock markets using intraday data of frequency of 10 minutes. The study of Eun and Sabherwal (2003) is based on the data for the period when the U.S. stock market used the 1/6 tick system while the Canadian stock market uses the decimal pricing system. Frijns et al. (2015a) use the one minute data to study the U.S.-

Canada stock price discovery. Frijns et al. (2015b) rely on the twenty minute window to study macroeconomic announcement's impact on the price discovery. We examine not only more stocks that are listed and traded in the two markets with the more recent data but also price discovery dynamics over a wide range of intraday data frequencies from minute-by-minute to end-of-day.

In this paper, we wish to address the following research questions.

The first question is, under more complex situations, why it is important to examine the intraday data of multiple frequencies. We propose a structural model in which the Canadian and U.S. prices of the same underlying stock are subject to shocks from within and from other markets, possibly arriving not simultaneously and/or being of different sizes. In addition, given these complications, we also allow varying sampling methods of intraday price data assuming that the structural model of the prices prevails.

The second question is that considering more complex situations and, therefore, using varying sampling methods of intraday data of different frequencies, whether or not we will find the empirical evidence that is consistent with the existing empirical evidence (see Eun and Sabherwal (2003)). As reported in this paper, the relative size of the error correction coefficient for the Canadian price of a stock, in a cointegration system, can increase relative to that for the U.S. price of the same stock if the intraday prices at lower frequencies are examined. This illustrates that a more general structural model can make some reasonable predictions about the relative size of error correction coefficient for the Canadian price of the stock with reference to that for the U.S. price of the same stock.

The third question is whether or not that information transmission efficiency is different within and across the Canadian and U.S. markets with reference to a range of possible factors. Clearly, because we are dealing with the price discovery dynamics, we need to propose a dynamic price discovery measure so that we can analyze the dynamics of information within and across the markets. In addition, without any frictions, information transmission efficiency should be homogeneous within and across the markets. The reality is that there are a lot of frictions in the two markets and it is interesting to identify, at the micro level, systematic departures from the ideal world.

We have the following interesting findings.

Our theoretical work indicates that under the more complex situations, there is a merit to examine the intraday data of multiple frequencies. Following the theoretical guidance, we note that error correction coefficients from data of different frequencies vary significantly. Eun and Sabherwal (2003) note that the smaller (greater) relative size of error correction coefficients means the stronger (weaker) role of price discovery in the corresponding market. We find that in very high frequency intraday data the Canadian stock prices show relatively small error correction coefficients than their U.S. counterparts indicating that the Canadian stock prices absorb information more quickly than their U.S. counterparts. This is consistent with the existing literature (Eun and Sabherwal, 2003). However, as we lower the frequency of intraday data by varying degrees (from 1 minute to 65 minutes), the opposite phenomenon is observed. That is, in very low frequency intraday data the U.S. stock prices show relatively small error correction coefficients than their Canadian counterparts indicating that the U.S. stock prices absorb information more quickly than their Canadian counterparts. The changes of these coefficients across different frequencies provide additional insight to price discovery dynamics between the U.S. and Canadian markets.

Our finding indicates that over the years that the trading volume in the Canadian market drops below the 50% mark while the trading volume in the U.S. market increases beyond the 50% mark. However, our analysis of trading volume and information channels in the two markets indicate that the opening/closing period of the trading day has more trades and, therefore, contains more information. For example, we find that the U.S. market, at the opening period, transmits more information to the Canadian market. In addition, we find that the Canadian market releases more information than the U.S. market about these stocks during the within trading day period, the overwhelming majority of which are issued by Canadian corporations.

Using the intraday data of various frequencies and our price discovery measures, we find that the arriving information takes from 60 minutes (1 hour) to 120 minutes (2 hours) to get completely absorbed within and across the Canadian and U.S. markets. Our example for Barrick Gold shows that the price discovery measure has some advantages over the existing ones because it is applicable to a dynamic setting over time with different sampling frequencies and is able to capture the information transmission efficiency consistently across intraday data of different frequencies. We find some distinct features of the information transmission across the trading day. Because the majority of the companies studied in this paper are registered in Canada and the information in Canada tends to be released more frequently during the trading day while in the opening period (after the closing for a day), the information in the U.S. tends to attract more attention and the Canadian stock price often reacts to this information. We find that price discovery for Canadian stocks tends to be more efficient in the Canadian market. The higher (lower) medium trade (or smaller (greater) order size volatility) in the Canadian market makes the market more (less) efficient.

The higher (lower) trading volume in a market (either the Canadian or U.S. market) tends to make this market more (less) efficient. Price discovery for stocks in the basic materials sector is more efficient in the Canadian market but price discovery for stocks in the financial sector is less efficient if information transmits from the U.S. to Canada. Price discovery for stocks traded in NYSE Alternext and NASDAQ is more efficient within the U.S. market and from the U.S. to Canada.

The remainder of this paper is organized as follows. In Section 2, we explain our data. In Section 3, we discuss the methodology including our model and new measure of information transmission. Section 4 presents the empirical analysis. Section 5 concludes.

2 Background and Data

2.1 The Canadian and U.S. stock markets

Stock markets have been evolved over time and, more recently, seen rapid development and integration. According to Michie (2006), transferable securities appeared in Italian city-states in medieval times. Then Amsterdam became the key center for securities trading by the seventeenth century. In 1724, Paris had a formal stock exchange which was interrupted during the French revolution and Napoleonic Wars. Then the London Stock Exchange emerged and securities markets in the newly independent United States and Canada started to develop. In the United States, the New York Stock Exchange (NYSE) started to operate in 1792.[5] Canada also started its Toronto Stock Exchange (TSX) in 1861.[6] By the First World War, there existed a wide range of local stock exchanges in major cities around the world. The stock markets were interrupted by the First World War and then recovered. The 1929 financial crisis and the end of the gold standard once again interrupted this recovery, which was further put on hold by the Second World War. In 1933-34, the U.S. Government established the Securities and Exchange Commission to regulate security issuing and trading and the Glass–Steagall Act was passed to prohibit the commercial banks from dealing with securities. After the Second World War, the role of stock exchanges had been consolidated in the financial systems in most industrial countries with the exception of those socialist countries (such as former Soviet Union and China) who used the central planning system, rather than the capital market, to allocate resources. Since 1980s the stock exchanges have

[5] See http://en.wikipedia.org/wiki/New_York_Stock_Exchange

[6] See en.wikipedia.org/wiki/Toronto_Stock_Exchange

expanded their role and electronic revolution further internationalized stock market operation and institutions although national and local governments still regulate these stock markets and exchanges.[7]

Traditionally, stock exchanges were financial-institution-owned mutual organizations. More recently, we have observed demutualization of stock exchanges and integration of stock exchanges across continents. Demutualization of stock exchanges is a process by which financial-institution-mutually-owned stock exchanges become joint stock companies. These joint stock companies raise funds from independent investors rather than mutual owners/operators. The joint stock companies separate their ownership from management/operator and become for-profit companies. In 2000, NASDAQ went through the demutualization and is owned and operated by the NASDAQ OMX Group, the stock of which is listed and traded on its own stock exchange under the ticker symbol NDAQ. In 2001, the TSX was demutualized and is now owned by TMX Group, which is listed and traded on its own stock exchange under the ticker symbol X. In 2005, the NYSE was demutualized and is now owned by Intercontinental Exchange, an American holding company, which is listed and traded on its own stock exchange under the ticker symbol ICE. NYSE Alternext is an equity trading market that was opened on May 17, 2005 by its parent institution Euronext (now NYSE Euronext) to provide small to medium sized firms easier access to an equity market. Some of exchanges are stand-alone joint stock companies while others are jointly owned and operated under larger holding corporations, which integrate regional exchanges into national or international exchanges.[8]

We study the price discovery process for the stocks listed and traded in the NYSE, NYSE Alternext, NASDAQ and TSX, which are all in the North America. The NYSE, NYSE Alternext, NASDAQ, and TSE have electronic trading systems but the NYSE still maintain its trading floor.[9] According to the World Federation of Exchanges,[10] as of January 2015, the NYSE is by far the world's largest stock exchange by market capitalization (market cap hereafter) at U.S. $19.8 trillion, the NASDAQ is the world's second largest stock exchange

[7]One excellent example is that National Association of Securities Dealers Automated Quotations (NASDAQ) was founded in 1971 as the then largest electronic trading system.

[8]For example, other public traded companies which own exchanges are CBOE Holdings, Inc. (NASDAQ:CBOE), CME Group Inc. (NASDAQ:CME), and OTC Markets Group Inc. (OTCMKTS:OTCM).

[9]On 24 January 2007, the NYSE went from being strictly an auction market to a hybrid market that encompassed both the auction method and an electronic trading method that immediately makes the trade electronically. A small group of extremely high-priced stocks isn't on this trading system and is still auctioned on the trading floor. See `https://en.wikipedia.org/wiki/Open_outcry`.

[10]See `www.world-exchanges.org/statistics/monthly-reports`

by market cap at U.S. $6.8 trillion, and the TSX is ranked the 8th largest stock exchange by market cap at U.S. $ 1.9 trillion, about 1/10 of the capitalization of the NYSE. In addition, both the U.S. and Canada use English and have much shared media. The NYSE and NASDAQ are much more international than the TSX is. As of January 2015, 1,937 U.S. companies and 527 non-U.S. companies are listed and traded at the NYSE and NYSE Alternext, 2,432 U.S. companies and 354 non-U.S. companies are listed and traded at the NASDAQ, while 3,692 Canadian companies and 70 non-Canadian companies are listed and traded at the TSX. But the trading value in the TSX grew much faster from 2005 to 2015. In January 2005, the trading value at the TSX is about U.S. $ 61 billion but it grew to U.S. $ 120 billion in January 2015. This is a 95% increase in trading value. In January 2005, the trading value at the NYSE and NYSE Alternext is about U.S. $ 1,380 billion but it grew to U.S. $ 1,520 billion in January 2015. This is only a 10% increase in trading value. In January 2005, the trading value at the NASDAQ is about U.S. $ 834 billion but it grew to U.S. $ 1,183 billion in January 2015. This is a 42% increase in trading value.

Many Canadian companies are listed and traded in both the U.S. and Canadian exchanges but a small number of U.S. companies and other international companies are listed and traded in the exchanges in both countries. As the capital market in the U.S. is so much larger, when Canadian companies are listed and traded in the U.S. stock exchange, the U.S. institutional and individual investors have convenient access to these Canadian companies. Typically, Canadian stock brokers offer services for trading stocks listed on both the U.S. and Canadian stock exchanges but U.S. stock brokers often offer services for trading of stocks listed only on the U.S. stock exchanges. Hence, Canadian investors have an easy access to U.S. stocks within Canada but the U.S. investors only have easy access to Canadian stocks if these stocks are listed and traded in the U.S. exchanges. In addition, there is little incentive for Canadians to buy Canadian stocks via brokers from the U.S. stock exchanges. Because they can buy them via brokers from the Canadian stock exchanges at lower commissions.[11] This indicates that the U.S. exchanges may have a different clientele base relative to the Canadian exchange in terms of those predominantly Canadian companies listed and traded in both the U.S. and Canada.

[11] The commissions for the U.S. and Canadian stocks are of the same dollars in their respective currencies. As the Canadian dollar is lower in value for the most time historically, the commission for trading Canadian stocks is marginally lower.

2.2 Data

We have retrieved our data from several sources. First, we identify the security names of the Canadian stocks and non-Canadian stocks that are listed and traded simultaneously in the Canadian stock exchange (TSX) and the U.S. stock exchanges (NYSE, NYSE Alternext, and NASDAQ). These data on interlisted securities are retrieved from the TMX Group's Internet portal[12] on August 15, 2014. We obtained 190 names of the stocks that are listed and traded in both the Canadian stock exchange (TSX) and the US stock exchanges (NYSE, NYSE Alternext, and NASDAQ).

We obtain further corporation information of these stocks about the market in which the stock of a company is listed and traded in the U.S. (NYSE, NYSE Alternext, and NASDAQ), the country in which the company is incorporated, the sector in which the company operates, and market cap of the company. We are able to retrieve the above corporation information for 190 stocks from Finviz, a financial data visualization company on September 30, 2014. Out of these 190 companies, there are 156 Canadian companies, 27 American companies, 3 Bermudian companies, 1 Columbian company, 1 Hong Kong's company, 1 Israelis company, and 1 South African company.

These companies belong to various sectors as show in Table 1. They are populated across various sectors such as basic materials, consumer goods, financial, health care, industrial goods, services, technology, and utility. While these companies' stocks are listed and traded in the TSX, they are also listed and traded, respectively, in the NYSE, NYSE Alternext, and NASDAQ. Table 1 provides the total count of the companies and their average market cap in million dollars across sectors and US exchanges as of September 30, 2014.

Table 1 also shows that among 190 companies, there are 87 traded in the NYSE, 61 traded in the NYSE Alternext, and 42 traded in the NASDAQ. Out of the 190 companies, 110 companies are in the basic materials sector with the average capitalization of U.S. $ 5.6 billion. Almost half of these 110 companies are traded in the NYSE Alternext. There are many mid-cap and small-cap companies in the basic materials sector. However, there are only 17 large-cap companies in the financial sector with the average capitalization of U.S. $ 27.0 billion. Among these companies, 14 are traded in the NYSE, 2 are traded in the NYSE Alternext, and 1 is traded in the NASDAQ.

The end-of-day stock price and trading volume data are retrieved via quandl.com, an emerging data portal from July 3, 1997 to January 26, 2015. The S&P 500 and TSE market

[12] http://www.tmxmoney.com/en/market_activity/interlisted.html

indices and their trading volume data of the same period are also retrieved from quandl.com.

In order to investigate the intraday data of the due-listed stocks at different frequencies, we retrieve the intraday stock and stock market index data from google.com from December 8, 2014 to December 26, 2014.[13] We are able to retrieve intraday (time stamp, close, high, low, and open prices, and trading volume) data at 1 minute frequency, 5 minute frequency, and 10 minute frequency. The intraday data of even lower frequencies (such as 15, 30, and 65 minute frequencies) can be sub-sampled from intraday data of higher frequencies (such as 1, 5, and 10 minute frequencies). We select these frequencies as they will not omit the critical end of day trading in the whole day which has 390 trading minutes.[14]

As we work on stocks listed and traded in both the Canadian and U.S. stock exchanges, we need to first convert stock prices in two currencies into two prices in one currency. We obtain the tick-by-tick intraday US/CN exchange rate data for our sample period from GAIN Capital, which is a leading provider of online foreign exchange trading, asset management, and B2B Forex services. GAIN Capital archive contains historical tick-by-tick exchange rate data for several currencies. We use the ask-bid averages at the frequencies that match our intraday stock price data of varying frequencies.

In this paper, using the exchange rate we convert the stock prices and the market index in the Canadian stock market into the prices denominated in U.S. dollars and the U.S. dollar denominated Canadian market index so that all stock prices and market indices are comparable. In the research reported in this paper, we are able to subsample the raw data so that we have the intraday data of the following frequencies: 1 minute, 5 minutes, 10 minutes, 15 minutes, 30 minutes, and 65 minutes in addition to the end-of-day daily data.

3 Research Methodology

3.1 A simple model for information arrival and absorption across data frequencies

Our research questions are somewhat different from those of Eun and Sabherwal (2003). We ask the following questions: Would the statistical significance of the error correction coefficients[15]and their relative sizes change if we use the price data of more than one frequencies

[13]To get the high frequency intraday market index data, we use the TSX 60 ETF and S&P 500 ETF as the proxies for the market indices.

[14]These frequencies can be multiplied by an integer to match 390.

[15]These are α_{cn} α_{us} in Eun and Sabherwal (2003)

(say 10 minutes)? Would the conclusions about information arrival and absorption based on the intraday data of one frequency (say 10 minutes) differ from that based on the end-of-day data? Would the conclusions about the information arrival and absorption differ at the different hours in a day?

To answer these questions, we propose a structural model which may provide some theories for what we often observe across the intraday data of different frequencies. Assume that same stock is listed and traded in two different markets, one is the Canadian market (cn) and the other is the U.S. market (us). The price vector is $[p_{cn,t}, p_{us,t}]'$, where $p_{cn,t}$ is the price for the Canadian market of a stock and $p_{us,t}$ is the price for the U.S. market of the same stock. Assume that m_t is the efficient price (or true value) of the same stock and follows a random walk process.

Before we propose the structural model of ours, we note that the widely used structural model for price discovery is given by the following equations:

$$\begin{aligned} p_{cn,t} &= m_t + e_{cn,t}, \\ p_{us,t} &= m_t + e_{us,t}, \\ m_t &= m_{t-1} + \eta_t, \end{aligned} \tag{1}$$

where $e_{cn,t}$ ($e_{us,t}$) is the idiosyncratic noise in the Canadian (U.S.) market.[16] There idiosyncratic noise can be viewed as uninformative bid-ask bounce or reporting errors as noted by Hasbrouck (1995). η_t can be considered as the innovation that moves the efficient price. When studying price discovery using high-frequency data, it is valuable to find out which market incorporate the innovation η_t faster. When the Canadian market incorporates the innovation immediately while the U.S. market incorporates the innovation with a lag, we can model this situation as

$$\begin{aligned} p_{cn,t} &= m_t + e_{cn,t}, \\ p_{us,t} &= m_{t-1} + e_{us,t}, \\ m_t &= m_{t-1} + \eta_t. \end{aligned} \tag{2}$$

[16] For example, Stock and Watson (1988) write the price vector of markets 1 and 2 as $\mathbf{p}_t = [p_{1,t}, p_{2,t}]'$ as a function of the common stochastic trend (m_t) and market specific shocks ($\mathbf{e}_t = [e_{1,t}, e_{2,t}]'$): $\mathbf{p}_t = \mathbf{1}m_t + \mathbf{e}_t$, where $\mathbf{1} = [1, 1]'$ and $m_t = m_{t+1} + \eta_t$ with η_t being a random error for m_t. In addition, the dynamic structural models of Amihud and Mendeson (1987) and Hasbrouck and Ho (1987), the structural model of Lehman (2002), the tick time structural model of Frijns and Schotman (2009), and the satellite model of Yan and Zivot (2010) are all widely used in the price discovery literature.

This is a case where the Canadian market serves as the "core" market while the U.S. market serves as the "satellite" market.[17] Using the price changes to rewrite equations in (2) can be written as

$$\begin{aligned} p_{cn,t} &= p_{cn,t-1} + \eta_t + e_{cn,t} - e_{cn,t-1}. \\ p_{us,t} &= p_{us,t-1} + \eta_{t-1} + e_{us,t} - e_{us,t-1}. \end{aligned} \tag{3}$$

These alternative equations show that the Canadian market incorporates the innovation η_t immediately and contributes to price discovery while the U.S market only absorbs the old or stale information given in the innovation η_{t-1}.[18]

However, if the Canadian and U.S. markets are exposed to innovations of different countries at different frequencies, then the adjustment coefficient estimates obtained from the cointegration analysis may not have the straightforward interpretation as given above.[19] More specifically, when the Canadian market has continuous exposure to Canadian company news that could be more frequently released while the U.S. market has its exposure to the news that might impact on the company and could be released less frequently, we need a new perspective.

To illustrate this, we propose a new structural model in which two kinds of innovations arrive at different frequencies may have different sizes. The first kind of innovation in the Canadian market $\eta_{cn,t}$ is released at a much higher frequency, but the second kind of innovation in the U.S. market $\eta_{2,t}$ is released at a lower frequency and may be of the same size or a greater size.

In this structural model, both the Canadian and U.S. markets are sensitive to innovations released in their own markets. But each market may be slow, to a different degree, in absorbing the innovation from the other market. This slow speed is characterized by the lag that takes to absorb $\eta_{i,t}$ for $i = cn, us$. More specifically, the Canadian market responds to the innovation in the U.S. market with m lags while the U.S. market responds to the innovation in the Canadian market with n lags. We could further explain the situations

[17] It is likely for the Canadian stocks to treat their home as the "core" market.

[18] It is likely for the Canadian stocks that rely more on their own home market for price discovery.

[19] To study the contributions of the upstairs (an off-exchange market where buyers and sellers negotiate) and downstairs (the trading floor or electronic equivalent where trades occur anonymously) stock markets, Booth et al. (2002) posit a microstructural model, in which the efficient price m_t is driven by two kinds of innovations $u_{1,t}$ and $u_{2,t}$. $u_{1,t}$ and $u_{2,t}$ portray the information revealed through trading in the upstairs and downstairs, respectively. However, they do not consider how the relative size of different innovations, the different speed of information absorption, and the different sampling frequencies affect the error correction coefficients in the equilibrium relation.

using the following model:

$$p_{cn,t} = p_{cn,t-1} + \eta_{cn,t} + \eta_{us,t-m} + e_{cn,t} - e_{cn,t-1}, \quad (4)$$
$$p_{us,t} = p_{us,t-1} + \eta_{cn,t-n} + \eta_{us,t} + e_{us,t} - e_{us,t-1},$$

where $p_{cn,t}$, $t = 1, 2, 3, \ldots$ while for $p_{us,t}$, $t = b, 2b, 3b, \ldots$ where b is a positive integer. $\eta_{cn,t}$ represents the high frequency innovation in the Canadian market and $\eta_{us,t}$ the low frequency innovation in the U.S. market. As we can see from equations (4), as t changes at a relatively high frequency, the innovation $\eta_{cn,t}$ can be immediately incorporated into the price in the Canadian market, while, as t changes at a relatively low frequency, the innovation $\eta_{us,t}$ can also be immediately incorporated into the price in the U.S. market, implying that different markets are sensitive to different kinds of innovations. If we set the data generating processes for both $p_{cn,t}$ and $p_{us,t}$ at the same frequency ($b = 1$), the U.S. market can pick up the innovation in the Canadian market after n lags, $\eta_{cn,t-n}$, while the Canadian market can pick up the innovation in the U.S. market after m lags, $\eta_{us,t-m}$. If $m > n$, the Canadian market responds slowly to the innovations revealed in the U.S. market, while the U.S. market responds quickly to the innovations revealed in the Canadian market. Compared with the traditional structural model in (3), the model in (4) can describe more complex scenarios for innovations for the Canadian stocks traded in both the Canadian and U.S. markets.

This structural model allows us to use the Monte Carlo simulations[20] to investigate what cause changes in error correction coefficients.[21] The Monte Carlo simulations show that when two kinds of innovations arriving at different points in time across two markets, the relative sizes of these error correction coefficients[22] will be affected by the timing of the information arrival, the speed of information absorption, sizes of these innovations, and the sampling method that may or may not miss any innovations in the data.

3.2 The role of each market in price discovery process

Now we consider the reduced-form model to make sense of the underlying structure of the data. When the same stock is listed and traded in different markets in the same country (see Hasbrouck, 1995 and Harris et al., 1995) and in different markets in different countries (see Eun and Sabherwal, 2003), there is at least one common factor (fundamental value) within

[20]see Appendix.

[21]In Eun and Sabherwal (2003), they are α_{cn} and α_{us}

[22]In Eun and Sabherwal (2003), it is $\left(\frac{|\alpha_{cn}|}{|\alpha_{us}|}\right)$

the two different prices. Other factors may be at play to make two prices depart each other temporarily. These other factors may reveal interesting patterns of price discovery dynamics.

When we study each underlying stock, we have four ($n = 4$) time series. At time t, $p_{cn,t}$ is the stock price in the Canadian stock market,[23] $p_{us,t}$ is the stock price in the U.S. stock market, $p_{idcn,t}$ is the Canadian stock market index (TSX),[24] and $p_{idus,t}$ is the U.S. stock market index (S&P 500). We use a vector

$$\mathbf{p}_t = [p_{cn,t}, p_{us,t}, p_{idcn,t}, p_{idus,t}]' \tag{5}$$

to denote the stock and market prices (in log), which, according to a vast empirical and theoretical literature, follow some geometric Brownian motion and have unit roots.[25] Hence, the stock and stock market index returns, $\Delta\mathbf{p}_t = \mathbf{p}_t - \mathbf{p}_{t-1}$, can be cast in a vector autoregressive (VAR) model of order k, which has an equivalent vector error correction model (VECM) representation:

$$\Delta\mathbf{p}_t = \mathbf{\Pi}\mathbf{p}_{t-1} + \sum_{j=1}^{k-1} \mathbf{\Gamma}_j \Delta\mathbf{p}_{t-j} + \mathbf{e}_t, \tag{6}$$

where $\mathbf{\Pi} = \alpha\beta'$, β is $4 \times r$ and has $rank(\beta) = r$, and α is $4 \times r$ and has $rank(\alpha) = r$. $\mathbf{\Gamma}_j$ is 4×4, with ith row denoted by γ_{ij}. $\mathbf{e}_t$ is 4×1 and is defined by $\mathbf{e}_t = [e_{cn,t}, e_{us,t}, e_{idcn,t}, e_{idus,t}]'$. We say that β contains r independent cointegration relations. We call α loading matrix which gives the weights to the r cointegration relations. In our paper, we expect that $r = 1$ and β is a 4×1 vector defined as $\beta = [\beta_{cn}, \beta_{us}, \beta_{idcn}, \beta_{idus}]'$. We normalize β_{cn} to 1. Then we expect $\beta = [\beta_{cn}, \beta_{us}, \beta_{idcn}, \beta_{idus}]' = [1, -1, 0, 0]'$ based on the law of one price of the same stock and the fact that the two broad stock market indices represent different underlying assets and hence have different prices. These restrictions also unite the structural model we propose and the cointegration model we use in estimation. We expect that α is a 4×1 vector such that it is defined as $\alpha = [\alpha_{cn}, \alpha_{us}, \alpha_{idcn}, \alpha_{idus}]'$. $\beta'\mathbf{p}_{t-1}$ is $I(0)$. Both $\Delta\mathbf{p}_t$ and $\mathbf{e}_t$ are also $I(0)$. To make sense of parameters α's and β's, we can define the cointegration residual, $\hat{\epsilon}_t$,

[23] The price is converted into the U.S. dollar price from the Canadian dollar price using the exchange rate.

[24] This market index is converted into the U.S. dollar denominated Canadian stock market index.

[25] That is, the price p can be characterized by

$$\frac{dp}{p} = \mu dt + \sigma dB,$$

where μ is a percentage drift, σ is the percentage volatility, and B is a Wiener process or Brownian motion.

from the regression of $p_{cn,t} + \beta_{us} p_{us,t} + \beta_{idcn} p_{idcn,t} + \beta_{idus} p_{idus,t} = \epsilon_t$ and write the VECM as

$$\Delta p_{cn,t} = \alpha_{cn} \hat{\epsilon}_t + \sum_{j=1}^{k-1} \gamma_{1j} \Delta \mathbf{p}_{t-j} + e_{cn,t}, \tag{7}$$

$$\Delta p_{us,t} = \alpha_{us} \hat{\epsilon}_t + \sum_{j=1}^{k-1} \gamma_{2j} \Delta \mathbf{p}_{t-j} + e_{us,t}, \tag{8}$$

$$\Delta p_{idcn,t} = \alpha_{idcn} \hat{\epsilon}_t + \sum_{j=1}^{k-1} \gamma_{3j} \Delta \mathbf{p}_{t-j} + e_{idcn,t}, \tag{9}$$

$$\Delta p_{idus,t} = \alpha_{idus} \hat{\epsilon}_t + \sum_{j=1}^{k-1} \gamma_{4j} \Delta \mathbf{p}_{t-j} + e_{idus,t}, \tag{10}$$

where γ_{ij} is the i-th row of $\mathbf{\Gamma}_j$. According to Eun and Sabherwal (2003), the statistical significance of α_{cn} (or α_{us}) and the relative size of α_{cn} (or α_{us}) contain critical information about the role of each market in price discovery. This is because $p_{cn,t}$ and $p_{us,t}$ must respond to each other to maintain the market equilibrium and the law of one price. According to equations (7) and (8), $p_{cn,t}$ and $p_{us,t}$ have to adjust to the broad market indices in the two countries. More specifically, when $\alpha_{cn} \neq 0$ and $\alpha_{us} \neq 0$, this is viewed in the existing literature, as the evidence that the Canadian (U.S.) market makes adjustments to the U.S. (Canadian) market. When $\alpha_{cn} = 0$ and $\alpha_{us} \neq 0$, this is viewed as the evidence of the U.S. market plays a role of a "satellite" of the Canadian market not a "core" market itself. When $\frac{|\alpha_{cn}|}{|\alpha_{us}|} < 1$, this is viewed as the evidence that, relative to the U.S. market, the Canadian market makes a more contribution to price discovery (the U.S. market must catch up with the Canadian market). When $\frac{|\alpha_{cn}|}{|\alpha_{us}|} > 1$, this is viewed as the evidence that, relative to Canadian market, the U.S. market makes a more contribution to price discovery (the Canadian market must catch up with the U.S. market). When $\alpha_{idus} = 0$ and $\alpha_{idcn} = 0$, according to equations (9) and (10), the broad market indices in the two markets do not adjust to the individual stock price prices $p_{cn,t}$ and $p_{us,t}$ in the two countries.

Our structural model considers more complex situations where (1) market innovations arrive at different frequencies, (2) market innovations and may be of different sizes, (3) these innovations may be absorbed in other markets at different speeds, and (4) sampling methods adopted may or may not miss some innovations. Our Monte Carlo simulations show that when two kinds of innovations arriving at different points in time across two markets, the relative size of these two alphas $\left(\frac{|\alpha_{cn}|}{|\alpha_{us}|}\right)$ will be affected by the timing of the information arrival, the speed of information absorption, and sizes of these innovations. More specifically, $|\frac{\alpha_{cn}}{\alpha_{us}}|$ will be *greater* than one in value when the Canadian market takes *many lags* ($m = 18$) to absorb the U.S. market's innovation under the condition that, relative to the Canadian market's innovation, the U.S. market's innovation is of much *lower* frequencies. These simulations also indicate that $|\frac{\alpha_{cn}}{\alpha_{us}}|$ will be *greater* than one in value even when the Canadian market takes only *one* lag ($m = 1$) to absorb the U.S. market's innovation under the condition that, relative to the Canadian market's innovation, the U.S. market's innovation is *substantially greater* in size, and of *lower* frequencies. Our Monte Carlo simulations also show that under the condition that, relative to the Canadian market's innovation, the U.S. market's innovation is of much *lower* frequencies, if the sampling method has no lag or does not miss any of the U.S. market's innovations in the sample, we will observe $|\frac{\alpha_{cn}}{\alpha_{us}}| > 1$. But using some sampling methods that have lags or miss the U.S. market's innovations in the sample, we may observe $|\frac{\alpha_{cn}}{\alpha_{us}}| < 1$. Therefore, when the two markets have their own innovations and absorb the other market innovations at different speeds, $|\frac{\alpha_{cn}}{\alpha_{us}}| < 1$ could be a result of omissions of observations with some sampling methods. Under this circumstance, it is critical to examine $|\frac{\alpha_{cn}}{\alpha_{us}}|$ across the intraday of different frequencies.

3.3 Contemporary information transmission

We could further evaluate contemporary information transmission using the data generating process for $\mathbf{p}_t$. The VAR model (or VECM) for $\mathbf{p}_t$ has a multivariate moving average (MA) or Wold representation:

$$\Delta\mathbf{p}_t = \mathbf{\Psi}(L)\mathbf{e}_t = \mathbf{e}_t + \mathbf{\Psi}_1\mathbf{e}_{t-1} + \mathbf{\Psi}_2\mathbf{e}_{t-2} + \cdots , \tag{11}$$

where $\mathbf{\Psi}(L) = \sum_{k=0}^{\infty}\mathbf{\Psi}_k L^k$ with $\mathbf{\Psi}_0 = \mathbf{I}$. $\mathbf{\Psi}(L)$ is a 4×4 polynomial matrix in lag operator L. The error terms in $\mathbf{e}_t$ are, in general, not orthogonal to each other.

We can relate combinations of i.i.d. structural innovations $\mathbf{v}_t$ to error terms in $\mathbf{e}_t$ in the VAR model (or VECM) for $\mathbf{p}_t$. Causal chains among structural innovations can be characterized as another structural vector autoregressive (SVAR) model by $\mathbf{A}\mathbf{e}_t = \mathbf{B}\mathbf{v}_t$. Here $\mathbf{A}$ and $\mathbf{B}$ are both 4×4 matrices, which are to be identified logically and estimated empirically. Then we can substitute $\mathbf{e}_t = \mathbf{A}^{-1}\mathbf{B}\mathbf{v}_t$ into equation (11) yields

$$\Delta\mathbf{p}_t = \mathbf{\Psi}(L)\mathbf{e}_t = \mathbf{\Psi}(L)\mathbf{A}^{-1}\mathbf{B}\mathbf{v}_t. \tag{12}$$

Typically, by imposing some reasonable prior restrictions on this SVAR model, we are able to identify the paths of contemporary information transmission reflected by the elements of $\mathbf{A}$, given that $\mathbf{B}$ is a diagonal matrix with the diagonal elements being the standard deviations of structural innovations. First, it is noted that the first 30 minutes (9:30AM-10:00AM, EST) and final 30 minutes (3:30PM-4:00PM, EST) would have higher trading volume. To differentiate these periods with other time periods, we impose additional restrictions on the elements of $\mathbf{A}$ of the SVAR model to infer contemporaneous information transmission across the two stock prices to differentiate the opening/closing trading periods from the rest of the trading day. Second, individual stock prices may be contemporaneously influenced by stock market indices because optimistic or pessimistic market conditions can affect individual stocks prices but individual stocks prices will not do so contemporaneously. To reflect this reality, we also use these restrictions in our identification of the SVAR model.

3.4 A price discovery measure for information transmission efficiency

Recall that the stock prices and broad market index prices are expressed in the 4×1 price vector $\mathbf{p}_t$ and that the cointegration with rank $r = 1$ if $\mathbf{\Psi}(1)$ is of rank $(4 - r) = 3$, and there exist two 4×1 matrices, α and β, both of rank $r = 1$, such that $\beta'\mathbf{\Psi}(1) = \mathbf{0}$ and $\mathbf{\Psi}(1)\alpha = \mathbf{0}$. The column of β is the cointegrating vector and the column of α contains the error correction coefficients.[26]

Now we identify the long-run impact of a shock and the pricing error based on the characterization of the data generating process. Define $\mathbf{G} = \begin{bmatrix} \alpha'_\perp \\ \beta' \end{bmatrix}$, where β' is a 1×4 matrix and $\alpha'_\perp$ is a 3×4 matrix satisfying $\alpha'_\perp \alpha = \mathbf{0}$. Using $\mathbf{G}$, we can express $\Delta\mathbf{p}_t$ as

$$
\begin{aligned}
\Delta\mathbf{p}_t &= \mathbf{\Psi}(L)\mathbf{G}^{-1}\mathbf{G}\mathbf{A}^{-1}\mathbf{B}\mathbf{v}_t \qquad (13)\\
&= \begin{bmatrix} \mathbf{D}_1(L) & \mathbf{D}_2(L) \end{bmatrix} \begin{bmatrix} \alpha'_\perp \\ \beta' \end{bmatrix} \mathbf{A}^{-1}\mathbf{B}\mathbf{v}_t \\
&= \mathbf{D}_1(L)\alpha'_\perp\mathbf{A}^{-1}\mathbf{B}\mathbf{v}_t + \mathbf{D}_2(L)\beta'\mathbf{A}^{-1}\mathbf{B}\mathbf{v}_t \\
&= \underbrace{\mathbf{D}_1(1)\alpha'_\perp\mathbf{A}^{-1}\mathbf{B}\mathbf{v}_t}_{\text{long-run impact denoted as } \mathbf{\Phi}\mathbf{v}_t} + \underbrace{[\mathbf{D}_1(L)\alpha'_\perp\mathbf{A}^{-1}\mathbf{B} - \mathbf{D}_1(1)\alpha'_\perp\mathbf{A}^{-1}\mathbf{B} + \mathbf{D}_2(L)\beta'\mathbf{A}^{-1}\mathbf{B}]\mathbf{v}_t}_{\text{pricing error denoted as } \mathbf{\Phi}^*(L)\mathbf{v}_t \text{ with } \mathbf{\Phi}^*(1)\mathbf{v}_t = \mathbf{0}},
\end{aligned}
$$

[26]Note that the cointegration relations under consideration in this study have no deterministic components, which lie outside the cointegrating space in the sense of Johansen (1992).

where $\mathbf{D}_1(L)$ contains the first 3 columns of $\mathbf{\Psi}(L)\mathbf{G}^{-1}$ and $\mathbf{D}_2(L)$ contains the last 1 column. We decompose $\Delta\mathbf{p}_t$ into the long-run impact component and the pricing error component. The initial impact of $\mathbf{v}_t$ on $\Delta\mathbf{p}_t$ is $\mathbf{\Phi}\mathbf{v}_t+\mathbf{\Phi}^*(0)\mathbf{v}_t$, and the long-run impact is $\mathbf{\Phi}\mathbf{v}_t$ as $\mathbf{\Phi}^*(1)\mathbf{v}_t = \mathbf{0}$. Thus, $\mathbf{\Phi}^*(0)\mathbf{v}_t$ measures the initial pricing error which can be corrected if given a long-enough period.[27]

Based on equation (13), we propose a new price discovery measure on how efficiently information would transmit from market j to market i in period t:

$$D_{i,j,t} = \frac{\mathbf{\Phi}_{i,j} + \mathbf{\Phi}^*(t)_{i,j}}{\mathbf{\Phi}_{i,j}}, \tag{14}$$

for $t = 0, 1, 2, \ldots$, where $\mathbf{\Phi}_{i,j}$ ($\mathbf{\Phi}^*(t)_{i,j}$) is the i, j-th element of $\mathbf{\Phi}$ ($\mathbf{\Phi}^*(t)$). This information efficiency measure is based on the coefficients in the Wold representation of the stock prices and broad stock market index prices. It is the ratio of the combination of long-term impact on price and pricing error in market i caused by market j to the long-term impact on price in market i caused by market j. Pricing errors can cause this ratio to be either great than 1 or less than 1. But when pricing errors vanish, this measure approaches to 1.

If the information efficiency measure $D_{i,j,t}$ approaches 1 rapidly (or slowly) as t gets greater, then it indicates the higher (lower) efficiency of information transmission from market j to market i. Hence, the efficiency benchmark of $D_{i,j,t}$ is 1 when t increases. If the information efficiency measure $D_{i,j,t}$ approaches 1 slowly, it remains interesting to see if $D_{i,j,t}$ shrinks over time t. If it does, it is a sign of low efficiency in information transmission over time. A $D_{i,j,t}$ value greater than 1 implies an over-reaction of market i to the shock from market j in period t, while a $D_{i,j,t}$ value greater than 0 and less than 1 implies an under-reaction in period t. Sometimes a negative $D_{i,j,t}$ value does occur. It shows that market i responds to the shock from market j in the opposite direction in period t, implying markets i and j do not share short-run common price movements in period t. If we apply this measure for a large number of stocks that are listed and traded in market i and market j, we would report the average of estimated $D_{i,j,t}$'s across those stocks as well the standard error of the corresponding estimated $D_{i,j,t}$'s.

Because $D_{i,j,t}$'s do not converge to 1 at the same speed, it is desirable to measure how quickly these $D_{i,j,t}$'s for $t = 1, 2, \ldots, T \leq \infty$ converges to 1. We could calculate the standard error (*std.err*) of $D_{i,j,t}$'s over $t = 1, 2, \ldots, T \leq \infty$. Intuitively, the smaller (greater) the standard error, the more (less) efficient information transmits. We propose a summary

[27] For the detailed proof, see Wu et al. (2015).

evaluation measure for $D_{i,j,t}$'s over $t = 1, 2, \ldots, T \leq \infty$, which is inversely related to the standard error ($std.err$). Let the collection of $D_{i,j,t}$'s over $t = 1, 2, \ldots, T \leq \infty$ be $\mathbf{D}_{i,j}$, then following Vives (1993, 1997) we define the summary evaluation measure $S_{i,j}$ as

$$S_{i,j} = \frac{1}{std.err(\mathbf{D}_{i,j})}. \tag{15}$$

The interpretation of $S_{i,j}$ is that the greater (smaller) the value for $S_{i,j}$ is, the more (less) efficient the information transmits from market j to market i or pricing errors vanish more quickly in market i in response to innovations in market j. In the empirical research we specify $T = 200$ minutes, which is about the time when pricing errors would vanish, as the cutoff point.

3.5 Panel analysis of summary evaluation measures

In this research, we follow a collection of many stocks over time at different time frequencies. For each stock, we observe the country where the company has its head office, the market cap of the company, the number of years being listed, the exchange where the stock is traded in the U.S. (NYSE, NYSE Alternext, and NASDAQ), the sector in which the company operates, the stock price time series, and the trading volume time series. In addition, for each stock, we have four summary evaluation measures for information transmission efficiency across both Canada and the U.S. ($\log(S_{cn,cn})$, $\log(S_{us,cn})$, $\log(S_{cn,us})$, $\log(S_{us,us})$).[28]) at different time frequencies under different regimes of the trading day (there appear some differences between the within trading day period and the opening/closing period in terms of trading volume as shown below). It is known that the greater (smaller) the value for $S_{i,j}$ is, the more (less) efficient the information transmits from market j to market i. If we are interested in the efficiency of information transmission across different time frequencies for this collection of stocks and the determinants (such as country, capitalization, the number of years listed, the size of medium trades, trading volume, sector, and market) of this efficiency, we need to pay attention to the panel nature of the data and implement the fixed effect panel data model (in the form of the least squares dummy variable model) to test if there is any difference in price discovery in the U.S. relative to that in Canada, if trading volume affects price discovery, in which sector(s) price discovery is more (less) efficient, and if the exchange where a stock is listed and traded affects price discovery. Consider the cluster nature of the panel data, we

[28]We use the logarithmic transformation to ensure the monotonic transformation and a possible better model fitting.

need to use the fixed effect panel data model with the standard errors of the Arellano and Bond type to do statistical inference.

4 Empirical Analysis

4.1 Behaviors of two markets at various frequencies

In the sample of 190 stocks listed and traded in both the U.S. and Canada stock exchanges, we are able to identify 172 stocks whose high frequency intraday data are available. Out of the 172 stocks, only 143 stocks are not thinly traded and have enough observations.[29] We evaluate the cointegration relations of the prices of the same stock in the two markets and find that only 109 stocks maintain their cointegration relations.[30] Among the 109 companies, there are 99 Canadian companies while there are only 10 U.S. companies.

The cointegration model includes four time series in $\mathbf{p}_t = [p_{cn}, p_{us}, p_{idcn}, p_{idus}]'$ as explained previously. All prices in Canadian dollars are converted into ones in US dollars. $[\beta_{cn}, \beta_{us}, \beta_{idcn}, \beta_{idus}]'$ is the cointegration vector, and $[\alpha_{cn}, \alpha_{us}, \alpha_{idcn}, \alpha_{idus}]'$ is the adjustment coefficient vector. We normalize β_{cn} to 1, and expect β_{us}, β_{idcn} and β_{idus} be equal to -1, zero and zero, respectively. The results in Table 2 show that, β_{us} is very close to -1, β_{idcn} and β_{idus} are very close to zero.

In section 3.1 and Appendix, we suggest that market innovation arrival frequencies, the size of innovations, the absorption speed of innovations from one market into another market, and different sampling methods of different frequencies will affect what we will observe about the underlying data generating process. If the innovation in the Canadian market occurs more frequently than that in the U.S. market as the companies are primarily Canadian companies but the innovation sizes do not differ significantly in the two markets, we would see that when the absorption speed in the Canadian market for the U.S. market's innovations is about the same as that in the U.S. market for the Canadian market's innovations, the Canadian and U.S. markets behave similarly in adjusting to the market equilibrium prices. Otherwise, the two markets would behave differently. This would affect the relative size of the error correction coefficients in the cointegration system.

In Table 2, we report the average estimates of cointegration vectors and adjustment

[29] The sample size is great than 100 observations over 12 days of the minute-by-minute data. During some minutes, there are no trades and hence no data.

[30] The irregular and non-synchronized trading of some thinly traded stocks does not provide good data in analyzing cointegration relations.

coefficient vectors. For each average estimate for the 109 stocks, we also report the 5% and 95% percentiles of the statistically significant coefficient estimates in the parentheses.[31] The average estimates of α_{idcn} and α_{idus} are very close to zero as expected. The coefficients of main interest are α_{cn} and α_{us}. Eun and Sabherwal (2003) note that if both α_{cn} and α_{us} are statistically significant, then the prices in the two different markets respond to a departure from equilibrium and contribute to price discovery.

Our analysis confirms the findings of Eun and Sabherwal (2003). In Table 2, the 10-minute column shows statistically significant α_{cn} and α_{us} estimates. These indicate that for the stocks listed and traded in both the U.S. and Canadian stock exchanges, price discovery takes place not only in one market but also in the other market. In addition, as shown in the 10-minute column of Table 2, the absolute value of average α_{us} estimate is greater than that of average α_{cn} estimate reflecting a larger contribution from the Canadian market to price discovery overall because the price in the U.S. market must, on average, adjust more to the innovations from the Canadian market. At the limit, if $\alpha_{cn} = 0$ and $\alpha_{us} \neq 0$, the U.S. market is a "satellite" market of the Canadian market for those stocks. We do not observe any evidence for any market serving as a "satellite" market.

In this paper, we extend the analysis of Eun and Sabherwal (2003) to include a further analysis of intraday data at higher frequencies at 1 minute and 5 minute intervals and at lower frequencies at 15 minutes, 30 minutes, and 65 minutes.[32] This extension allows us to explore the market equilibrium at different data frequencies to check the robustness of the previous findings and identify any new findings.

The additional estimation results for the data at the 1-, 5-, 15-, 30-, and 65-minute frequencies can be compared with those at the 10-minute frequency. When we compare the average α_{cn} (or α_{us}) estimates from the 1-minute to 1-day frequencies, we note that the absolute value of the average α_{cn} estimate is getting greater as the frequency is getting lower while the absolute value of the average α_{us} estimate rises to its peak at the 30 minute frequency and then fall back as we lower the frequency . The relative sizes of these two quantities also change as the frequency is getting lower. More specifically, $\frac{|\alpha_{cn}|}{|\alpha_{us}|}$ is less than 1 from the 1-minute to 30-minute frequency but it becomes greater than 1 at the 65-minute frequency. The implication of these observations suggests that the price in the Canadian market tends to adjust more than its counterpart in the U.S. market using the intraday data

[31]We use the 10% significant level for the normal distribution to find the critical values.

[32]These time frequencies are selected because these frequencies can divide 390 minutes in a trading day from 9:30 EST to 16:00 EST into even time intervals.

at lower frequencies.

To confirm the finding that the price in the Canadian market tends to adjust more than its counterpart in the U.S. market at a lower frequency, we further analyze the end-of-day data and the estimation results of this analysis are listed in the 1-day column of Table 2. The end-of-day data differ from the intraday data with frequencies less than one day in that the end-of-day data may incorporate more information and typically have a large sample size.[33] The finding from the end-of-day data shows that, indeed, the price in the Canadian market tends to adjust more than its counterpart in the U.S. market at the lowest intraday frequency.

4.2 Information arrival and absorption in intraday data

Our simulation results in Appendix indicate that it is possible to find what we have observed, the ratio $\frac{|\alpha_{cn}|}{|\alpha_{us}|}$ changes from a value less than one to a value great than one if innovations in another market arrive at different intervals and if each market absorbs innovations in another market with its own unique number of lags.

We need to analyze the sensitivity of our observation to different initial sampling times for the intraday data of different frequencies. In addition to the observation from the end-of-day data, we need to learn more about the market behaviors in the first 30 minutes. We use the following strategy to achieve the above two aims. We select three frequencies—the 60-minute, 30-minute and 15-minute frequencies. For the 60-minute frequency, we wish to check if $\frac{|\alpha_{cn}|}{|\alpha_{us}|} > 1$ as noted previously for the 65-minute frequency in Table 2. For the 30- and 15-minute frequencies, we wish to check $\frac{|\alpha_{cn}|}{|\alpha_{us}|} < 1$ as noted for the 30-minute and 15-minute frequencies in Table 2. We select the shifting step to be 1 minute. When we use the intraday data of the 60-minute frequency, we shift the first sampling time from 9:30 EST to 9:31 EST, 9:32 EST, ..., 10:00 EST, respectively, and the last sampling time from 15:30 EST to 15:31 EST, 15:32 EST, ..., 16:00 EST for thirty shifts. We could do the same for the intraday data for the 30-minute and 15-minute frequencies, respectively.[34] The resulting samples have the following features: (1) as the initial sampling time shifts into the future, each sample has less

[33] While the intraday data of high frequencies only cover the period from December 8, 2014 to December 23, 2014, the end-of-day data cover the period from July 3, 1997 to January 12, 2015. We are able to obtain the end-of-day data for 172 stocks among the 190 stocks and 126 stocks data are not thinly traded and maintain cointegration relations in their U.S. and Canadian prices. That is, the end-of-day data offer a larger sample size and more stocks than the intraday data do.

[34] In the case of the 15-minute frequency, we are able to have 15 1-minute shifts and beyond that 15 shifts, the new sample will overlap other samples overwhelmingly. In the case of the 30-minute frequency, we are able to have 30 1-minute shifts.

exposure to the first (few) minute(s) of the trading day but more exposure to the last (few) minute(s) of the trading day and (2) due to different sampling frequencies, the samples of the 60-minute frequency contain proportionally more information of the markets in the first 30 minutes while the samples of the 30- and 15-minute frequencies contain proportionally less information of the markets in first 30 and 15 minutes, respectively.

With these properties in mind, we can examine Figures 1, 2, and 3. Figure 1 shows when we use the intraday data of the 60-minute frequency, $\frac{|\alpha_{cn}|}{|\alpha_{us}|} > 1$ in the first 10 minutes in the earlier trading while in Figures 2 and 3, we observe $\frac{|\alpha_{cn}|}{|\alpha_{us}|} < 1$ when we use the intraday data of the 30- and 15-minute frequencies, respectively. Because the intraday data of the 60-minute frequency have more exposure to the first (few) minute(s) of the trading day than their 30-minute and 15-minute counterparts, we can view the evidence in Figure 1 confirm the finding that the Canadian price tends to make more adjustments, at the beginning of the trading day, to reflect the U.S. price which absorbs more information overnight. Throughout the rest of the trading day, the U.S. price tends to make more adjustments to reflect the Canadian price which absorbs more information.

Our Monte Carlo simulations show that $|\frac{\alpha_{cn}}{\alpha_{us}}|$ will be *greater* than one in value when the Canadian market takes *many lags* ($m = 18$) to absorb the U.S. market's innovation under the condition that, relative to the Canadian market's innovation, the U.S. market's innovation is of much *lower* frequencies. These simulations also indicate that $|\frac{\alpha_{cn}}{\alpha_{us}}|$ will be *greater* than one in value even when the Canadian market takes only *one* lag ($m = 1$) to absorb the U.S. market's innovation under the condition that, relative to the Canadian market's innovation, the U.S. market's innovation is *substantially greater* in size, and of *lower* frequencies. Our Monte Carlo simulations also show that under the condition that, relative to the Canadian market's innovation, the U.S. market's innovation is of much *lower* frequencies, if the sampling method has no lag or does not miss any U.S. market's innovations in the sample, we will observe $|\frac{\alpha_{cn}}{\alpha_{us}}| > 1$. But using some sampling methods that have lags or miss the U.S. markek's innovations in the sample, we may observe $|\frac{\alpha_{cn}}{\alpha_{us}}| < 1$. Therefore, when the two markets have their own innovations and absorb the other market innovations at different speeds, $|\frac{\alpha_{cn}}{\alpha_{us}}| < 1$ could be a result of omissions of observations with some sampling methods. Under this circumstance, it is critical to examine $|\frac{\alpha_{cn}}{\alpha_{us}}|$ across the intraday of different frequencies.

4.3 Volume analysis

We note that the previous analysis suggests that the price in the Canadian market tends to adjust more than its counterpart in the U.S. market using the intraday data at lower frequencies. In order to appreciate the role of each market. We analyze the daily trading volume of the 109 stocks from July 3, 1997 to January 12, 2015 across four sector groups (basic materials, financial, technology, and others) and across different U.S. exchanges (NYSE & Alternext and NASDAQ). The average trading volume in Canada (the U.S.) and the ratio of the trading volume in Canada (the U.S.) to the total trading volume are reported in Table 3. Overall, about 63.8% of the total trading volume for 109 stocks occurs in the U.S. About 67.7% of the trading volume for 69 stocks in the basic materials sector occurs in the U.S. as well. About 57.1% of the trading volume for 25 stocks in the "other" sectors (consumer goods, health care, industrial goods, services, and utilities) occurs in the U.S. However, about 75.7% of the trading volume for 7 stocks in the financial sector and 60.8% of the trading volume for 8 stocks in the technology sector occur in the Canada. In addition, out of the 109 stocks, about 63.1 % of the trading volume for 87 stocks occurs in the U.S. NYSE & Alternext and about 75.8% of the trading volume for 22 stocks occurs in the U.S. NASDAQ. In summary, we see a significant role of the U.S. market in trading volume.

Having analyzed the role of each market, we could examine the time trend of the trading volume from July 3, 1997 to January 12, 2015. On one hand, Figure 4 shows that the average daily trading volume of the 109 stocks in Canada as a percentage of the total average daily trading volume of these stocks in both Canada and the U.S. has been decreasing from July 3, 1997 to January 12, 2015. Starting from 2003, the percentage is lower than 50%. On the other, following the downward trend of the trading volume in Canada, some large departures of the trading volume trend occur from time to time. These departures from the trend may carry some information and hence move prices in one way or the other.

Finally, we should examine the trading volume within the trading day. In Figure 5, we plot the average minute-by-minute trading volume of the 109 stocks in Canada and that in the U.S. over the sample period from December 8, 2014 to December 23, 2014. We find that the trading volume of these stocks is higher in the U.S. than in Canada and that heavy trading often occurs in the opening/closing period when trading dynamics is different from that during the rest of the trading day.

4.4 Information channels

As noted in our previous section, trading volume tends to be greater in the opening/closing period of the trading day in both the Canadian and U.S. markets. In particular, during these periods, the Canadian market prices tend to make greater adjustments towards the U.S. market prices. But what are the information channels during the trading day excluding the brief opening and closing periods, which we call it the "within trading day period"? Although it is known that the U.S. market prices tend to make greater adjustments towards the Canadian market prices during the within trading day period, would the information channels in this period differ from those in the opening/closing period?

In order to detect the contemporary information transmission, we can conduct the SVAR analysis through a suitable structural decomposition for the residuals from the cointegration model in the form of the VECM. The residuals from the cointegration model are given by $\mathbf{e}_t = [e_{cn}, e_{us}, e_{idcn}, e_{idus}]'$ while innovations are given by $\mathbf{v}_t = [v_{cn}, v_{us}, v_{idcn}, v_{idus}]'$. We can relate the residuals to innovations by a suitably identified structure $\mathbf{Ae}_t = \mathbf{Bv}_t$ in a SVAR model. In our analysis, given the 4×4 matrix $\mathbf{B}$ is a diagonal matrix, the 4×4 matrix $\mathbf{A}$, when suitably identified, provides how information is transmitted contemporarily across the two markets.

To identify the structure of $\mathbf{Ae}_t = \mathbf{Bv}_t$ in different trading periods, we make the use of the within trading day period as regime 1 ($s1$) and the opening/closing period (from 9:30 EST to 10:00 EST and 15:30 EST to 16:00 EST) as regime 2 ($s2$). We are interested in learning if the two identified and estimated parameter matrices $\mathbf{A}_{s1}$ and $\mathbf{A}_{s2}$ are statistically different and provide concrete information about information channels (directions and sizes) in each regime.

We can further impose additional 0 and 1 restrictions on $\mathbf{A}$. We assume that the prices of the two broad stock market indices can affect the market prices of the stock comtemporarily but not the other way around because all individual stocks are exposed to the systematic risk captured by the prices of the stock market indices but the price of an individual stock cannot affect the price of the stock market index, in which the individual stock is one of the many members of the stock market index. If each $\mathbf{A}$ ($\mathbf{A}_{s1}$ or $\mathbf{A}_{s2}$) is partitioned into four 2×2 submatrices, $\mathcal{A}_{i,j}$'s for $i, j = 1, 2$, then we can set $\mathcal{A}_{2,1}$ to be a null matrix $\mathbf{0}$. This implies that 0 restrictions are imposed on the cells of $\mathbf{A}$ at the $[3, 1], [3, 2], [4, 1], [4, 2]$ positions. In addition, 1 restrictions are imposed on all diagonal elements of matrix $\mathbf{A}$ based on the argument of normalization. The resulting matrix $\mathbf{A}$ looks like

$$\mathbf{A} = \begin{bmatrix} \mathcal{A}_{1,1} & \mathcal{A}_{1,2} \\ \mathcal{A}_{2,1} & \mathcal{A}_{2,2} \end{bmatrix} = \begin{bmatrix} 1 & A_{cn,us} & A_{cn,idcn} & A_{cn,idus} \\ A_{us,cn} & 1 & A_{us,idcn} & A_{us,idus} \\ 0 & 0 & 1 & A_{idcn,idus} \\ 0 & 0 & A_{idus,idcn} & 1 \end{bmatrix}, \tag{16}$$

where the element $A_{i,j}$ captures the contemporary information transmission from price j to price i, for $i = cn, us, idcn, idus$. Since the elements $A_{i,j}$ and $A_{j,i}$ are not generally the same, we cannot impose any restrictions of symmetry on matrix $\mathbf{A}$. We find that the just identified SVAR models with various estimated $\mathbf{A}$'s have the same log-likelihood function value and that we cannot find any model that is superior to another. To find the model specification which may give a higher log-likelihood function value, we further explore all 16 over-identified structures for matrix $\mathbf{A}$ below. We use 0s and 1s to indicate 0 and 1 restrictions and use the symbol "Na" to indicate a free parameter. Then we use the intraday data of various frequencies to test which is more plausible.

$$\mathbf{A}_1 = \begin{bmatrix} 1 & Na & Na & 0 \\ 0 & 1 & Na & Na \\ 0 & 0 & 1 & Na \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad \mathbf{A}_2 = \begin{bmatrix} 1 & Na & Na & 0 \\ 0 & 1 & Na & Na \\ 0 & 0 & 1 & 0 \\ 0 & 0 & Na & 1 \end{bmatrix}, \quad \mathbf{A}_3 = \begin{bmatrix} 1 & 0 & Na & 0 \\ Na & 1 & Na & Na \\ 0 & 0 & 1 & Na \\ 0 & 0 & 0 & 1 \end{bmatrix},$$

$$\mathbf{A}_4 = \begin{bmatrix} 1 & 0 & Na & 0 \\ Na & 1 & Na & Na \\ 0 & 0 & 1 & 0 \\ 0 & 0 & Na & 1 \end{bmatrix}, \quad \mathbf{A}_5 = \begin{bmatrix} 1 & Na & 0 & Na \\ 0 & 1 & Na & Na \\ 0 & 0 & 1 & Na \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad \mathbf{A}_6 = \begin{bmatrix} 1 & Na & 0 & Na \\ 0 & 1 & Na & Na \\ 0 & 0 & 1 & 0 \\ 0 & 0 & Na & 1 \end{bmatrix},$$

$$\mathbf{A}_7 = \begin{bmatrix} 1 & 0 & 0 & Na \\ Na & 1 & Na & Na \\ 0 & 0 & 1 & Na \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad \mathbf{A}_8 = \begin{bmatrix} 1 & 0 & 0 & Na \\ Na & 1 & Na & Na \\ 0 & 0 & 1 & 0 \\ 0 & 0 & Na & 1 \end{bmatrix}, \quad \mathbf{A}_9 = \begin{bmatrix} 1 & Na & Na & Na \\ 0 & 1 & 0 & Na \\ 0 & 0 & 1 & Na \\ 0 & 0 & 0 & 1 \end{bmatrix},$$

$$\mathbf{A}_{10} = \begin{bmatrix} 1 & Na & Na & Na \\ 0 & 1 & 0 & Na \\ 0 & 0 & 1 & 0 \\ 0 & 0 & Na & 1 \end{bmatrix}, \quad \mathbf{A}_{11} = \begin{bmatrix} 1 & 0 & Na & Na \\ Na & 1 & 0 & Na \\ 0 & 0 & 1 & Na \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad \mathbf{A}_{12} = \begin{bmatrix} 1 & 0 & Na & Na \\ Na & 1 & 0 & Na \\ 0 & 0 & 1 & 0 \\ 0 & 0 & Na & 1 \end{bmatrix},$$

$$\mathbf{A}_{13} = \begin{bmatrix} 1 & Na & Na & Na \\ 0 & 1 & Na & 0 \\ 0 & 0 & 1 & Na \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad \mathbf{A}_{14} = \begin{bmatrix} 1 & Na & Na & Na \\ 0 & 1 & Na & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & Na & 1 \end{bmatrix}, \quad \mathbf{A}_{15} = \begin{bmatrix} 1 & 0 & Na & Na \\ Na & 1 & Na & 0 \\ 0 & 0 & 1 & Na \\ 0 & 0 & 0 & 1 \end{bmatrix},$$

$$\mathbf{A}_{16} = \begin{bmatrix} 1 & 0 & Na & Na \\ Na & 1 & Na & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & Na & 1 \end{bmatrix}.$$

Each $\mathbf{A}_i$ in the above can be viewed as consisting of four 2×2 submatrices, $\mathcal{A}^i_{k,l}$, where $i = 1, 2, \ldots, 16$ and $k, l = 1, 2$, such that

$$\mathbf{A}_i = \begin{bmatrix} \mathcal{A}^i_{1,1} & \mathcal{A}^i_{1,2} \\ \mathcal{A}^i_{2,1} & \mathcal{A}^i_{2,2} \end{bmatrix}. \tag{17}$$

The matrix $\mathcal{A}^i_{1,1}$ describes the relationship between the two market prices of the same underlying stock while the matrix $\mathcal{A}^i_{2,2}$ describes the relationship between the prices of the two broad stock market indices. The matrix $\mathcal{A}^i_{1,2}$ contains the relationships between the prices of the two broad stock market indices and the two prices of the same stock. In the matrix $\mathcal{A}^i_{1,2}$, the 0 restriction is used to accommodate the possibility that one specific broad stock market index may not affect one specific price of the underlying stock. The matrix $\mathcal{A}^i_{2,1}$ is a null matrix indicating that no prices of any individual stock have any impact on the prices of the two broad stock market indices. The changes of $\mathbf{A}_i$ in the 16 over-identified structures can be viewed as rotating the 0 restriction in $\mathcal{A}^i_{1,1}$, $\mathcal{A}^i_{1,2}$, and $\mathcal{A}^i_{2,2}$, respectively, at different positions of each 4×4 matrix $\mathbf{A}_i$.

Our focal point is on the statistical significance of elements $A_{us,cn}$ and $A_{cn,us}$ in $\mathcal{A}^i_{1,1}$, which is a submatrix in $\mathbf{A}_i$, as these elements indicate the channels of information transmission between the Canadian price and the U.S. price of the same underlying stock. If $A_{us,cn}$ ($A_{cn,us}$) is statistically significant, it indicates that innovations arrive systematically from the Canadian market (the U.S. market) to the U.S. market (the Canadian market). In addition, we are interested in learning if $A_{us,cn}$ and $A_{cn,us}$ differ across regime 1 ($s1$) and regime 2 ($s2$) or not.

In our econometric analysis on the intraday data of each frequency (1 minute, 5 minutes, 10 minutes, 15 minutes, 30 minutes, and 65 minutes), we adopt the following testing strategy.

First, we need to be certain that in the U.S. and Canadian markets the within trading day period and the opening/closing period behave differently. We therefore test if $\mathbf{A}_{s1}$ and $\mathbf{A}_{s2}$ are element-wise identical for the best fitted model with both $\mathbf{A}_{s1}$ and $\mathbf{A}_{s2}$ adopting one of the 16 over-identified structures of $\mathbf{A}$. We first select the best fitted model for each stock and find out which one of the 16 over-identified structures for $\mathbf{A}_{s1}$ and $\mathbf{A}_{s2}$, under the assumption of element-wise equalities across the two matrices, is selected. We then compare the best fitted model with an unrestricted and just-identified model for all stocks and at all frequencies. The just-identified unrestricted structures of $\mathbf{A}_{s1}$ and $\mathbf{A}_{s2}$ can be jointly estimated in the unrestricted SVAR model as

$$\mathsf{A} = \begin{bmatrix} \mathbf{A}_{s1} & \mathbf{0} \\ \mathbf{0} & \mathbf{A}_{s2} \end{bmatrix} = \begin{bmatrix} 1 & Na & Na & Na & 0 & 0 & 0 & 0 \\ 0 & 1 & Na & Na & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & Na & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & Na & Na & Na \\ 0 & 0 & 0 & 0 & 0 & 1 & Na & Na \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & Na \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}, \tag{18}$$

while each of the 16 over-identified $\mathbf{A}_{s1}$ and $\mathbf{A}_{s2}$, under the assumption of element-wise equalities, can be jointly estimated in the restricted SVAR model as

$$\mathsf{A}_r = \begin{bmatrix} \mathbf{A}_0 & \mathbf{0} \\ \mathbf{0} & \mathbf{A}_0 \end{bmatrix}, \tag{19}$$

where $\mathbf{A}_{s1} = \mathbf{A}_{s2} = \mathbf{A}_0$, where $\mathbf{A}_0$ is one of the 16 over-identified structures. The likelihood ratio (LR) test for over-identification and element-wise equalities can be implemented for the best fitted model with one of the 16 over-identified structures. The LR test statistic for the SVAR model with a restricted and over-identified structure has 7 degrees of freedom, two of which are for the two zero restrictions for over-identification and five of which are for element-wise equalities. For each stock and its intraday data at each frequency, we first select the best fitted model with one of the 16 over-identified structure, under the assumption of element-wise equalities, that gives the highest log-likelihood value and then implement the over-identification test on that best fitted model with reference to the unrestricted and just-identified counterpart. It turns out that for all 109 stocks with their intraday data of various frequencies, we must reject the over-identification restrictions. In other words, we cannot conclude that the parameters in two regimes ($s1$ and $s2$), $\mathbf{A}_{s1}$ and $\mathbf{A}_{s2}$, are element-wise identical. This is an overwhelming evidence for differentiating regime 1 from regime 2.

Second, given the recognized differences between regimes 1 and 2, we need to know further that under such regime differences, whether or not the U.S. and Canadian markets still share similar information channels. If so, what are the information channels? Now we relax the assumption of element-wise equalities but still assume that $\mathbf{A}_{s1}$ and $\mathbf{A}_{s2}$ maintain the same structure—adopting one of the 16 over-identified structures with the parameters being freely estimated. In this setting, the model with the unrestricted and just-identified structure has A as given in equation (18). The model with a restricted and over-identified structure has $\mathbf{A}_{s1}$ and $\mathbf{A}_{s2}$ adopting one of the 16 over-identified structures. We select the best fitted model with one of the 16 over-identified structures that gives the highest log-likelihood value and then implement the LR test for this model with reference to the model with the unrestricted and just-identified structure. This LR test statistics has 2 degrees of freedom, which represents two additional zero restrictions imposed on $\mathbf{A}_{s1}$ and $\mathbf{A}_{s2}$. Panel A of Table 4 shows that the information channels across two regimes ($s1$ and $s2$) are shared by some stocks but vary a lot across stocks and the intraday data of different frequencies. Our testing results indicate that no stock based on the intraday data of various frequencies satisfies the over-identified structures given in Section 4.4 such as $\mathbf{A}_2$, $\mathbf{A}_4$, $\mathbf{A}_6$, $\mathbf{A}_8$, $\mathbf{A}_{10}$, $\mathbf{A}_{12}$, $\mathbf{A}_{14}$, and $\mathbf{A}_{16}$. However, the other over-identified structures given in Section 4.4 such as $\mathbf{A}_1$, $\mathbf{A}_3$, $\mathbf{A}_5$, $\mathbf{A}_7$, $\mathbf{A}_9$, $\mathbf{A}_{11}$, $\mathbf{A}_{13}$, and $\mathbf{A}_{15}$ are suitable for some stocks at some frequencies but for not other stocks at some other frequencies. The Panel A of Table 4 gives, based on the LR tests, the numbers of stocks satisfy some $\mathbf{A}_i$'s ($i = 1, 3, 5, 7, 9, 11, 13, 15$) at some particular frequencies (1 minute, 5 minutes, 10 minutes, 15 minutes, 30 minutes, and 65 minutes) and the total numbers of stocks that satisfies all $\mathbf{A}_i$'s ($i = 1, 3, 5, 7, 9, 11, 13, 15$) at some particular frequencies (1 minute, 5 minutes, 10 minutes, 15 minutes, 30 minutes, and 65 minutes). Among these over-identified structures, $\mathbf{A}_{11}$ is the one which suits most stocks. As noted previously, $\mathbf{A}_{11}$ has 0 restrictions on the cells of $\mathbf{A}_{11}$ at the $[1, 2]$ and $[2, 3]$ positions. These indicate that the Canadian price of a stock transmits information to the U.S. price of the same stock but the Canadian stock market index cannot affect the latter. If we look at the total numbers of stocks across frequencies, we find that, in Panel A of Table 4 , based on the intraday data of the 1-minute frequency, 69 stocks satisfy some over-identified structure; based on the data of the 5-minute frequency, 80 stocks appear; based on the data of the 10-minute frequency, 95 stocks appear; based on the data of the 15 minute frequency, 104 stocks appear; and, finally, based on the data of the 30- and 65-minute frequencies, all 109 stocks appear.

Third, in view of some stocks do not share the same information channels based on the intraday data of the 1-minute, 5-minute, 10-minute, and 15-minute frequencies as shown in Panel A of Table 4 , we further explore alternative information channels. We relax the previous assumption that although the over-identified structures $\mathbf{A}_{s1}$ and $\mathbf{A}_{s2}$ are not element-wise identical, they share the same structure in one of the 16 over-identified structures given in Section 4.4. Now we allow the structures to differ across regimes 1 and 2. Regime 1 represents the within trading day period, which is much longer and hence is subject to more variations than regime 2 is. Regime 2, which is the opening/closing period, however, tends to absorb more information across the Canadian and U.S. markets. Hence, in our econometric work, we allow $\mathbf{A}_{s1}$ adopts one of the 16 over-identified structures given in Section 4.4 while keeping $\mathbf{A}_{s2}$ as unrestricted and just-identified. In $\mathbf{A}_{s2}$, $A_{cn,us}$ and $A_{us,cn}$ give out the important information on "the channel from the U.S. market to the Canadian market" and "the channel from the Canadian market to the U.S. market," respectively. There are 16 over-identified structures for $\mathbf{A}_{s1}$ and 2 just-identified structures for $\mathbf{A}_{s2}$. Combining the 16 over-identified structures for regime 1 with each just-identified structure for regime 2, we end up 32 over-identified A's for both regimes 1 and 2. We could group these 32 over-identified structures into four categories: "Up-Up", "Up-Down", "Down-Up", and "Down-Down". The "Up"s and "Down"s refer to $A_{cn,us}$ (from the U.S. to Canada) and $A_{us,cn}$ (from Canada to the U.S.), respectively, in $\mathbf{A}_{s1}$ and $\mathbf{A}_{s2}$. For example, "Up-Down" refers to the situation where, in regime 1, $A_{cn,us}$ is statistically significant and, in regime 2, $A_{us,cn}$ is statistically significant. We can implement the LR test for the model with one of these more relaxed but still restricted and over-identified structures against the model with the unrestricted and just-identified structure. The LR test statistics has 1 degree of freedom representing an additional 0 restriction on one of the element in $\mathbf{A}_{s1}$. We implement the LR tests on the stocks at the frequencies that do not satisfy the shared information channel assumption. In Panel B of Table 4 , the less restricted over-identified structures are suitable for all remaining stocks that do not satisfy the more restricted over-identification structures—the stocks share the same information channels in regimes 1 and 2.

Fourth, given the results of Panels A and B in Table 4 , we wish to further classify the information transmission channels into either "from Canada to the U.S." or "from the U.S. to Canada." Recall that we are interested in finding out if $A_{cn,us}$ and $A_{us,cn}$ are statistically significant. $\mathbf{A}_3$, $\mathbf{A}_7$, $\mathbf{A}_{11}$, and $\mathbf{A}_{15}$ in Panel A and "Down-Down" in Panel B represent "from Canada to the U.S.". By the same logic, "from the U.S. to Canada" can be likewise classified. There are some cases in Panels B that are not easily classified. The examples of such cases are "Up-Down" and "Down-Up" cases where information channels do change across regimes 1 and 2. Overall, Panel C in Table 4 shows that there are slightly more information channels from Canada to the U.S. rather than from the U.S. to Canada. The interpretation is that the Canada market releases more information than the U.S. market about these stocks, the overwhelming majority of which are issued by Canadian corporations.

4.5 Price discovery process

4.5.1 Empirical evidence for price discovery measure $D_{i,j,t}$

In the Tables 5–10, we report the price discovery measures for information transmission efficiency within the Canadian market ($D_{cn,cn,t}$), across the Canadian and U.S. markets ($D_{us,cn,t}$ and $D_{cn,us,t}$), and within the U.S. market ($D_{us,us,t}$). The measure $D_{us,cn,t}$ ($D_{cn,us,t}$) captures how the U.S. (the Canadian) market price incorporates innovations from the Canadian (U.S.) market based on the intraday data of different frequencies (1 minute, 5 minutes, 10 minutes, 15 minutes, 30 minutes, and 65 minutes). In each of Tables 5–10, we report the average price discovery measures of $D_{cn,cn,t}$, $D_{us,cn,t}$, $D_{cn,us,t}$, and $D_{us,us,t}$ for the 109 stocks and their corresponding standard errors in parentheses at various lags and across the two regimes. We use t to represent the number of lags of the intraday data of a particular frequency. The averages in the bold font are those that first reach 1 ± 0.01 in each regime as t increases. For example, in Table 5, the average price discovery measures are obtained from the intraday data of the 1-minute frequency, $t = 60$, 90, and 120 represent the lags of 60, 90, and 120 times, respectively. The two regimes are the within trading day period as regime 1 and the opening/closing period (from 9:30 EST to 10:00 EST and 15:30 EST to 16:00 EST) as regime 2, respectively. When the price discovery measure approaches 1, it implies that pricing errors vanish. In Table 5, we find that pricing errors vanish starting from 60 minutes according to the intraday data of the 1-minute frequency. Across regimes, there are some minor differences. But regimes are not a deterministic factor in information transmission over time. For 60 minutes or more, pricing errors vanish over time.

When we examine the estimates in Tables 6–10 based on the intraday data of lower frequencies, we find the similar evidence of vanishing pricing errors albeit that at lower frequencies, pricing errors can be more persistent and can take a longer time (in minutes) to vanish. For example, in Table 6, we find that pricing errors start to vanish at 150 minutes (30 lags $\times$ 5 minutes = 150 minute). In Table 10, we find that pricing errors start to vanish at 130 minutes (2 lags $\times$ 65 minutes = 130 minutes.)

4.5.2 A case study of $D_{us,cn,t}$: Barrick Gold (ABX)

Tables 5–10 present the aggregate price discovery for the 109 stocks based on the intraday data of different frequencies. To supplement these aggregate results, we focus on a well-known Canadian company and the world largest gold mining company, Barrick Gold (Ticker Symbol: ABX for both the NYSE and TSX), which is listed and traded in both the Canadian and U.S. markets. We focus only on the dynamics of $D_{us,cn,t}$, which shows how the U.S. price of ABX absorbs the innovations from its Canadian price as t increases.

As shown in Figures 6–8, the price discovery measure converges to 1 over time and is eventually at 1 at about 120 minutes based on the intraday data of the 15-, 5-, and 1-minute frequencies. Although the intraday data are sampled at different frequencies, the convergence of the price discovery measure $D_{us,cn,t}$ to 1 will not be affected too much and is robust across the intraday data of different frequencies. In other words, there is a strong evidence for the efficiency of the U.S. market in pricing the Barrick Gold in response to the innovations in the Canadian market.

This example for Barrick Gold also shows that the price discovery measure has some advantages over the existing ones because it is applicable to a dynamic setting over time with different sampling frequencies and is able to capture the information transmission efficiency consistently across intraday data of different frequencies.

4.5.3 Empirical evidence for summary evaluation measure $S_{i,j}$

Tables 11–15 provide the summary of the summary evaluation measures and their pairwise correlations at the 1-, 5-, 10-, and 15-minute frequencies, respectively. As shown in Table 11, information transmission is more efficient in regime 2 (the opening/closing period) within the Canadian market, or from the Canadian to the U.S. markets, or from the U.S. to Canadian markets based on the minute-by-minute data.

We find that the Canadian market is more efficient in absorbing the innovations from within the Canadian market ($S_{cn,cn}$) across the intraday data of the 1-, 5-, 10- and 15-minute frequencies in regimes 1 and 2. But it is less efficient in absorbing the innovations across the markets ($S_{cn,us}$ across the intraday data of various frequencies in regimes 1 and 2. The U.S. market is less efficient in absorbing the innovations from within ($S_{us,us}$) across the intraday data of various frequencies in regimes 1 and 2. But it is more efficient in absorbing the innovations from the Canadian market ($S_{us,cn}$). As shown in Tables 12–15, $S_{cn,cn}$ and $S_{us,cn}$ in regime 1 and $S_{cn,us}$ and $S_{us,us}$ in regime 2 are highly and positively correlated for the data of the 5-, 10-, and 15-minute frequencies although $S_{cn,cn}$ and $S_{us,cn}$ in regimes 1 and 2 are highly and positively correlated for the data of the 1-minute frequency. This indicates that, in regime 1 (the within trading day period), the information transmission efficiency within the Canadian market and from the Canadian market to the U.S. market are highly and positively correlated while, in regime 2 (the opening/closing period), the information transmission efficiency within the U.S. market and from the U.S. market to the Canadian market are highly and positively correlated. Why do we observe the above? One of the most likely explanations is that the vast majority of the companies are registered in Canada and information tends to be released more frequently (hence in regime 1) within the Canadian market while at the opening period (hence in regime 2) it is often the time when the information in the U.S. is being reported and the Canadian stock price reacts to this information.

To further explore how the summary evaluation measures within and across the two markets are determined, we wish to examine the panel data for $\log(S_{i,j})$'s within and across the two markets for the 109 stocks[35] over 1, 5, 10, and 15 minute frequencies[36] under two different regimes of the trading day. Regime 1 is the within trading day period while regime 2 is the opening/closing period. It is known that the greater (smaller) the value for $\log(S_{i,j})$ ($S_{i,j}$) is, the more (less) efficient the information transmits from market j to market i.[37] We use the fixed effect panel data model in the form of the least squares dummy variable model for $\log(S_{i,j})$'s to learn if there is any difference in efficiency of price discovery in the U.S. relative to that in Canada, if trading volume affects the efficiency of price discovery, if price discovery is more (less) efficient in some sectors than others, and if price discovery is more (less) efficient in some stock exchange than others.

In the fixed effect panel data model, we first discuss some dummy variables to explore the summary evaluation measures. First, we introduce dummy variables for summary evaluation measures of various types. We let the summary evaluation measure from Canada to Canada $\log(S_{cn,cn})$ be the baseline case by introducing 3 dummy variables for other summary evaluation measures. Let $D_{S_{us,cn}} = 1$ if $\log(S_{i,j})$ is $\log(S_{us,cn})$ and $D_{S_{us,cn}} = 0$ otherwise. Let $D_{S_{cn,us}} = 1$ if $\log(S_{i,j})$ is $\log(S_{cn,us})$ and $D_{S_{cn,us}} = 0$ otherwise. Let $D_(S_{us,us}) = 1$ if $\log(S_{i,j})$ is $\log(S_{us,us})$ and $D_{S_{us,us}} = 0$ otherwise. Second, we introduce a dummy variable for country where the company has its head office. We let the U.S. be the baseline case by setting Country = 0 for the U.S. and Country = 1 for Canada.[38] Third, we use a dummy variable for trading regime and let regime 1 (the within trading day period) be the baseline case by setting Regime = 0 for regime 1 and Regime = 1 for regime 2 (the opening/closing

[35] $k = 1, 2, \ldots, 109$.

[36] $t = 1, 2, 3, 4$.

[37] As the logarithmic transformation is a monotonic transformation, $S_{i,j}$ and $\log(S_{i,j})$ represent the same information given that $S_{i,j}$ is always positive. It turns out that from the modeling point of the view, the latter is more desirable in terms of goodness of fit.

[38] Recall that, among the 109 companies, there are 99 Canadian companies while there are only 10 U.S. companies.

trading period). Fourth, we also introduce dummy variables for exchange types. We let the NYSE be the baseline case by introducing two dummy variables for NYSE Alternext and NASDAQ. We let Alternext = 1 if the exchange is NYSE Alternext and Alternext = 0 otherwise. We let NASDAQ = 1 if the exchange is NASDAQ and NASDAQ = 0 otherwise. Fifth, we also introduce three sector dummies for basic materials (or "Basic"), technology (or "Technology"), and financial (or "Financial") while companies in all other sectors (consumer goods, health care, industrial goods, services, and utilities) serve as the baseline case. We let Basic = 1 if the sector is basic materials and Basic = 0 otherwise. Other two dummy variables Technology and Finance are defined similarly.[39]

In the fixed effect panel data model, we also consider some continuous variables that might be correlated with the summary evaluation measures $\log(S_{i,j})$'s $(i, j = cn, us)$. In order to appreciate these continuous variables, we report their basic statistics in Table 16. The average number of shares traded per minute (for either Canada or the U.S.) is the cross-sectional average of the overtime average numbers of shares traded per minute (in either the Canadian or U.S. market) from 9:30 EST (or 14:30 UTC) to 16:00 EST (or 21:00 UTC) (391 data points per trading day) across the 109 stocks. The standard deviation of the number of shares traded per minute (or either Canada or the U.S.) is the standard deviation of the overtime averages. The minute-by-minute trading volume, on average, is about 75% higher in the U.S. than in Canada but the dispersion of the trading volume is much higher in Canada than in the U.S.

The number of shares traded per minute (for either Canada or the U.S.) and its standard deviation for regime 1 or 2, in Table 16, are defined similarly across regimes 1 and 2. For regime 1, the corresponding time is from 10:01 EST (or 15:01 UTC) to 15:29 EST (or 20:29 UTC) (329 data points per trading day) while, for regime 2, the corresponding time is from 9:30 EST (or 14:30 UTC) to 10:00 EST (15:00 UTC) and from 15:30 EST (or 20:30 UTC) to 16:00 ES (or 21:00 UTC) (62 data points per trading day). Clearly, regime 2 (the open/closing period) has, on average, a higher trading volume and a higher standard deviation of the trading volume than regime 1 (the within trading day period) does. This reflects a more important role of regime 2, the open/closing period of the trading day.

[39]In our data, we have 8 sectors. Among these sectors, there are 69 companies in the basic materials sector, there are 8 companies in the technology sector, 7 companies in the financial sector, and 25 companies in the other five sectors (consumer goods, heath care, industrial goods, services, and utilities). In Eun and Sabherwal (2003), the sectors do not affect price discovery significantly. In our preliminary analysis, some sectors such as the basic materials and financial sectors affect price discovery while some others such as the technology sector do not affect price discovery.

In Table 16, the number of shares traded in the sample period refers to (for either Canada or the U.S.) the cross-sectional average of the total numbers of shares traded over the sample period (12 trading days) across the 109 stocks. The standard deviation of the number of shares traded in the sample is the cross-section deviation of the total numbers of shares traded in the sample across the 109 stocks. In the sample of the intraday trading, we find the total trading, on average, is much higher in the U.S. than in Canada among the 109 stocks.

The variable, MediumTrade, in Table 16 is the average of the standard deviations of the minute-by-minute trading volumes for the 109 stocks and is a measure for the proportion of medium trades. The smaller (greater) the MediumTrade value, the more medium trades dominate (more extreme (large or small) trades dominate). The standard deviation of MediumTrade is the standard deviation of the minute-by-minute trading volumes for the 109 stocks. The MediumTrade value is lower, in average and dispersion, in the U.S. than in Canada. This means that the size of medium trades, on average, is higher in the U.S. than in Canada and has lower dispersion in the U.S. than in Canada.

In Table 16, Capitalization is the average capitalization of the stocks in million U.S. dollars. The average capitalization is about US $ 9.5 billion but the size of the companies varies substantially.

When estimating the fixed effect panel data model, we include the logarithmic transformation of market cap (Market-cap) for each company in terms of million U.S. dollars,[40] the number of years of being listed (Yearslisted) in years, the logarithmic transformation of the standard deviation of trading volume within 1 minute to measure the median trade in Canada (MediumTrade$_{cn}$), the logarithmic transformation of the standard deviation of trading volume within 1 minute to measure the median trade in the U.S. (MediumTrade$_{us}$),[41] the logarithmic transformation of the aggregate trading volume (in the number of shares) in the Canadian market over the sample period (Volume$_{cn}$) , and the logarithmic transformation of the aggregate trading volume in the U.S. market over the same period (Volume$_{us}$) .

In our fixed effect panel data model, we allow each dummy variable to enter into the model not only alone to affect the intercept coefficient of the model but also as a cross-product of this dummy variable and each continuous variable (such as Market-cap, Yearslisted,

[40]The data are retrieved from Finviz as of September 30, 2014.

[41]Eun and Sabherwal (2003) use the trade-by-trade data while we use the minute-by-minute data. It is not possible for us to construct the median trade variable in the usual way. The second best is to look at the trading volume variation within a small window, say 1 minute, to get a sense of medium trades. When the variation is small, this is a reflection of less large orders and/or less small orders but more median orders.

MediumTrade_{cn}, MediumTrade_{us}, Volume_{cn}, and Volume_{us}) to affect the slope coefficient of the model. This gives the researcher enough flexibility to reveal the underlying data generating process.

The estimation results for the fixed effect panel data models for $\log(S_{i,j})$ and $S_{i,j}$ are presented in Tables 17 and 18, respectively. In both models, we use and report the standard errors of the Arellano and Bond type for statistical inference.

The panel data model for $\log(S_{i,j})$ in Table 17 has an overall better fit as it has a higher R^2, a higher log-likelihood function ($\log L$), a lower AIC value, and a lower BIC value than the model for $S_{i,j}$ in Table 18. We use the panel data model for $\log(S_{i,j})$ in Table 17 for our statistical inference.

The estimation results indicate that market cap, regime, the number of years being listed, and being in the technology sector do not affect the summary evaluation measures of information transmission efficiency ($\log(S_{i,j})$'s).

We find that, if a stock has its head office in Canada, the value of $\log(S_{cn,cn})$ tends to be higher while the value of $\log(S_{us,us})$ tends to be lower. This means that the information transmission efficiency within the Canadian market tends to be higher and that within the U.S. market tends to be lower. Therefore, we conclude that if a company has its head office in a country, then its stock tends to be priced more efficiently in the market of that country. This is, at the micro level, consistent with the hypothesis of home bias.

The empirical results also indicate that a greater (smaller) number of Canadian medium trades, which implies a smaller (greater) order size volatility measured by MediumTrade_{cn}, leads to a higher (lower) value of $\log(S_{cn,cn})$, which indicates a more (less) efficient Canadian market. But the number of the U.S. medium trades has no impact on other $\log(S_{i,j})$'s. Therefore, the greater (smaller) the number of the medium trades in Canada leads to more (less) efficient information transmission within the Canadian market. The trading volume in Canada is positively correlated with the value of $\log(S_{cn,cn})$ but less correlated with the values of $\log(S_{us,cn})$ and $\log(S_{us,us})$ with reference to the baseline case for $\log(S_{cn,cn})$. The trading volume in the U.S. is positively correlated with the values of $\log(S_{us,cn})$ and $\log(S_{us,us})$. Therefore, the higher (lower) the trading volume in a market makes the market more (less) efficient in information absorption. This is, at the micro level, consistent with the hypothesis that an increase in trading volume may be caused by new information.

We find that when a stock is in the basic materials sector, the value of $\log(S_{cn,cn})$ is higher but the values of $\log(S_{us,cn})$, $\log(S_{cn,us})$, and $\log(S_{us,us})$ are lower. Therefore, the Canadian market is more efficient in pricing stocks in the basic materials sector. This seems to be consistent, at the micro level, with the niche role of the Canadian stock exchange as a listing and trading center for stocks in the basic materials (mining and energy) sector in the world stock exchanges. However, when a company is in the financial sector, the value of $\log(S_{cn,us})$ is lower. That means that the price discovery due to the information transmission from the U.S. market to the Canadian market is less efficient relative to the baseline case for $\log(S_{cn,cn})$.

We also find that if stocks are traded at the NYSE Alternext as well as at the TSX, the value of $\log(S_{cn,cn})$ is lower and the information transmission within the Canadian market is less efficient. This appears to be consistent, at the micro level, with the fact that Canadian firms that are relatively junior and traded at the NYSE Alternext are mostly exposed to the U.S. market. When these stocks are traded in the NYSE Alternext, the values of $\log(S_{cn,us})$ and $\log(S_{us,us})$ are higher and the information transmission from the U.S. market to the Canadian market and within the U.S. stock market are more efficient. Once the information of these relatively junior companies is absorbed in the U.S. market, it would spread out efficiently within the U.S. market and to the Canadian market. If stocks are traded at the NASDAQ, the value of $\log(S_{cn,us})$ is higher and the information transmission from the U.S. market to the Canadian market is more efficient. This is because the Canadian stocks traded in the NASDAQ are typically in the basic materials and technology sectors, the information transmits more efficiently via the NASDAQ.

5 Concluding Remarks

In this paper, we propose a research strategy to study the price discovery in the Canadian and U.S. stock markets for the same stocks and apply it to the intraday data of various frequencies.

We note that the error correction coefficients estimated from the minute-by-minute intraday data show only a partial picture of price discovery. To show a more complete picture, we use the intraday data of multiple frequencies and find that error correction coefficients from data of different frequencies vary significantly. In very high frequency intraday data the Canadian stock prices show relatively small error correction coefficients than their U.S. counterparts indicating that the Canadian stocks absorb information more quickly than their U.S. counterparts. This is consistent with the existing literature (Eun and Sabherwal, 2003). However, as we lower the frequency of intraday data by varying degrees (from 1 minute to 65 minutes), the opposite phenomenon is observed. That is, in very low frequency intraday data the U.S. stocks show relatively small error correction coefficients than their Canadian counterparts indicating that the U.S. stocks absorb information more quickly than their Canadian counterparts.

We also note that over the years the trading volume in the Canada market drops below the 50% mark while the trading volume in the U.S. market increases beyond the 50% mark. However, our analysis of trading volume and information channels in the two markets indicate that the opening/closing period of the trading day has more trades and could potentially contain more information. In addition, we find that the Canadian market releases more information than the U.S. market about these stocks, the overwhelming majority of which are issued by Canadian corporations.

Using the intraday data of various frequencies and our price discovery measures, we find that the arriving information takes from 60 minutes (1 hour) to 120 minutes (2 hours) to get completely absorbed within and across the Canadian and U.S. markets. Our example for Barrick Gold also shows that the price discovery masure has some advantages over the existing ones because it is applicable to a dynamic setting over time with different sampling frequencies and is able to capture the information transmission efficiency consistently across intraday data of different frequencies. We also find some distinct features of the information transmission across the trading day. Because the majority of the companies studied in this paper are registered in Canada, the information about the companies from Canada tends to be released more frequently during the trading day while in the opening/closing period, the information about the external environment for the companies from the U.S. tends to be reported less frequently and the stock prices of these Canadian companies often reacts to the U.S. in the opening/closing period.

Price discovery for Canadian stocks tends to be more efficient in the Canadian market. The greater (smaller) number of medium trades in the Canadian market makes the market more (less) efficient. The higher (lower) trading volume in a market (either the Canadian or U.S. market) tends to make this market more (less) efficient. Price discovery for stocks in the basic materials sector is more efficient in the Canadian market but price discovery for stocks in the financial sector is less efficient if information transmits from the U.S. to Canada. Price discovery for stocks traded in NYSE Alternext and NASDAQ is more efficient within the U.S. market and from the U.S. to Canada.

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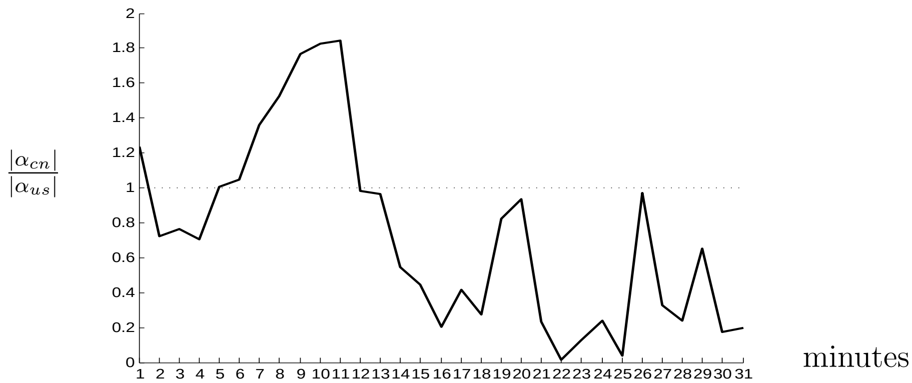
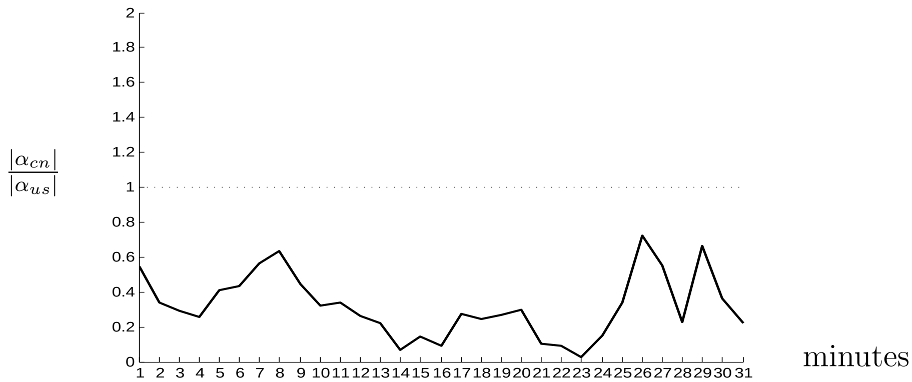
Figure 1: $\frac{|\alpha_{cn}|}{|\alpha_{us}|}$ for Intraday Data of 60-minute Frequency as Initial Sampling Time Shifts Minute by Minute



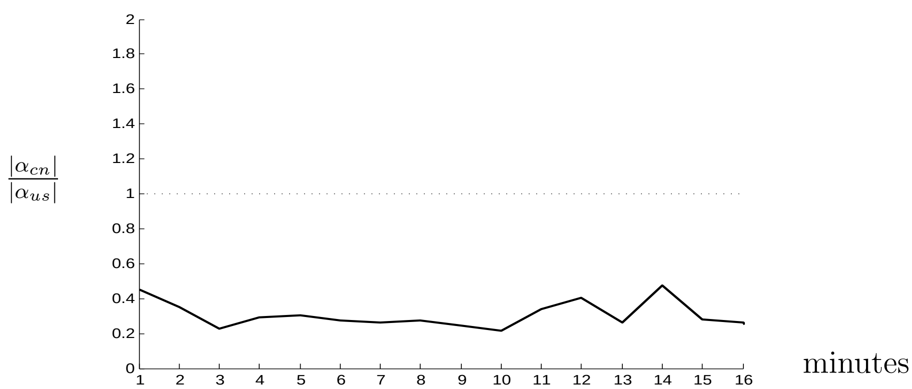
Note: Based on the intraday data of the 60-minute frequency, when the initial sampling time shifts by 1 minute a time, $\frac{|\alpha_{cn}|}{|\alpha_{us}|}$ is greater than 1 only in the earlier part of the first 10 minutes.

Figure 2: $\frac{|\alpha_{cn}|}{|\alpha_{us}|}$ for Intraday Data of 30-minute Frequency as Initial Sampling Time Shifts Minute by Minute



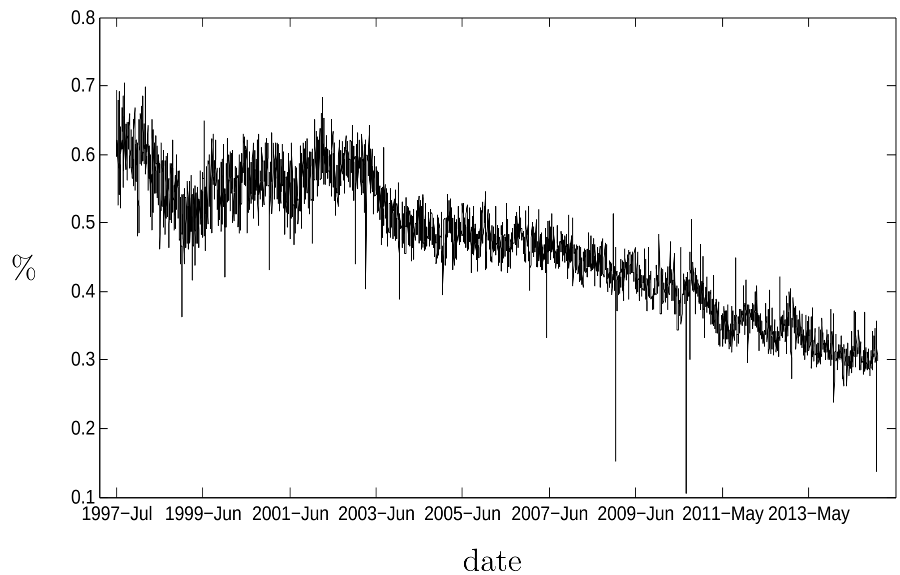
Note: Based on the intraday data of the 30-minute frequency, when the initial sampling time shifts by 1 minute a time, $\frac{|\alpha_{cn}|}{|\alpha_{us}|}$ is less than 1 throughout the first 30 minutes.

Figure 3: $\frac{|\alpha_{cn}|}{|\alpha_{us}|}$ for Intraday Data of 15-minute Frequency as Initial Sampling Time Shifts Minute by Minute



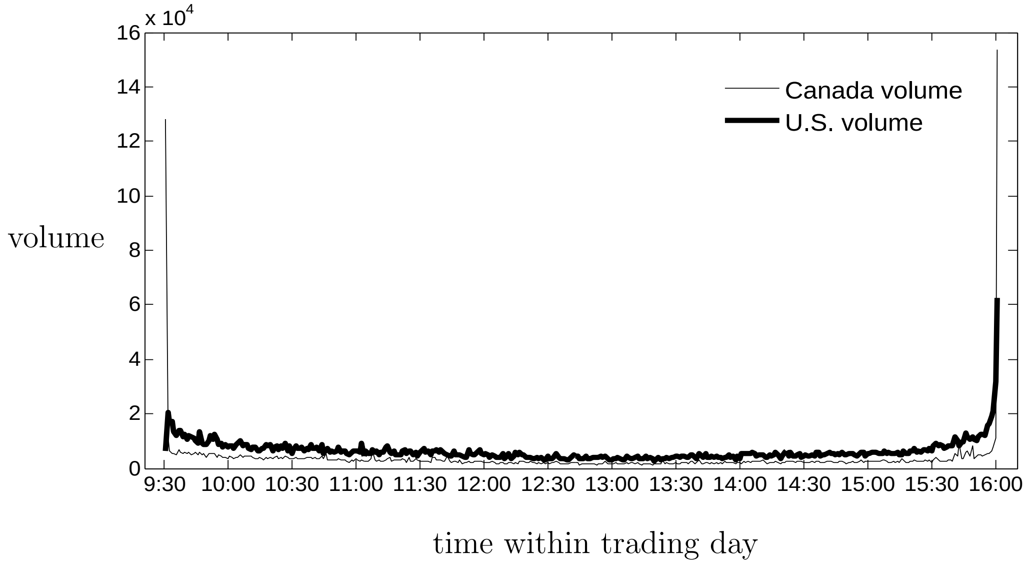
Note: Based on the intraday data of the 15-minute frequency, when the initial sampling time shifts by 1 minute a time, $\frac{|\alpha_{cn}|}{|\alpha_{us}|}$ is less than 1 for the first 15 minutes.

Figure 4: The Daily Trading Volume in Canada as a Percentage in the Total Daily Trading Volume in Both Canada and the U.S.



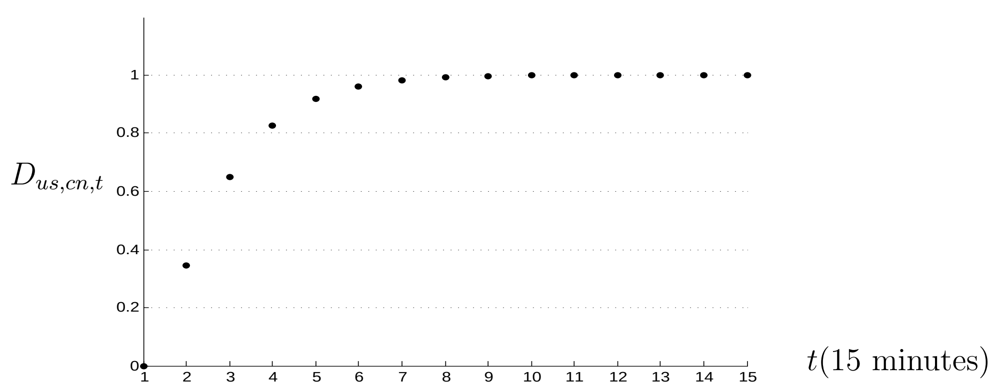
Note: The average daily trading volume of the 109 stocks in Canada as a percentage of the total average daily trading volume of these stocks in both Canada and the U.S. has been decreasing from July 3, 1997 to January 12, 2015.

Figure 5: Average Trading Volume in 1 Minute in Canada and the U.S.



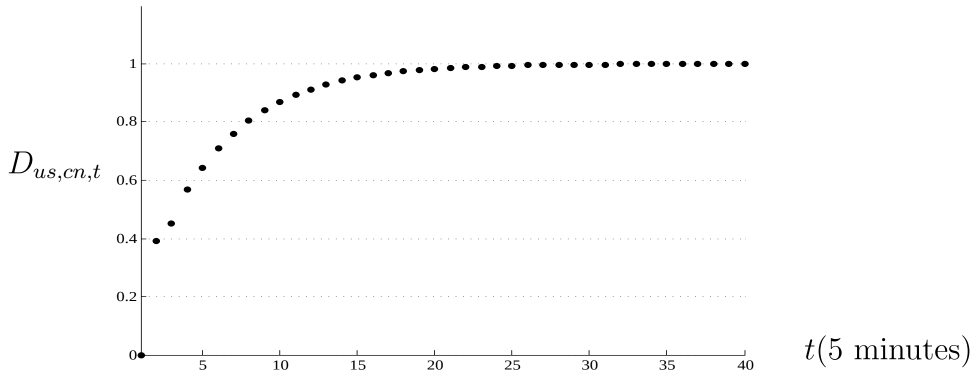
Note: The figure shows the average minute-by-minute trading volume of the 109 stocks in Canada and that in the U.S. over the sample period from December 8, 2014 to December 23, 2014. The trading activities are heavy at the beginning and end of the trading day.

Figure 6: Dynamics of Barrick Gold (ABX)'s $D_{us,cn,t}$ Based on Intraday Data of 15-minute Frequency



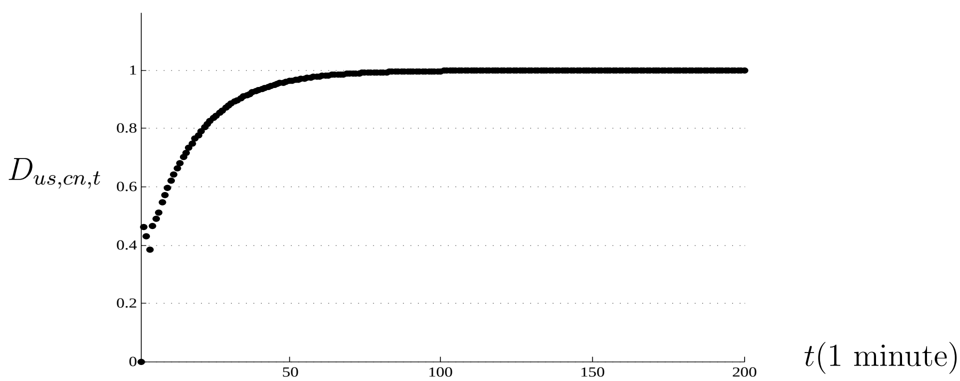
Note: The price discovery measure converges to 1 over time and eventually is at 120 minutes ($t = 8$).

Figure 7: Dynamics of Barrick Gold (ABX)'s $D_{us,cn,t}$ Based on Intraday Data of 5-minute Frequency



Note: The price discovery measure converges to 1 over time and eventually is at 120 minutes ($t = 24$).

Figure 8: Dynamics of Barrick Gold (ABX)'s $D_{us,cn,t}$ Based on Intraday Data of 1-minute Frequency



Note: The price discovery measure converges to 1 over time and eventually is at 120 minutes ($t = 120$).

Table 1: Basic Information of Stocks Listed in the U.S. and Canadian Stock Exchanges

		NYSE		NYSE Alternext		NASDAQ		Sector/Industry Subtotal	
Sector	Industry	Count	Average MktCap (Mil)	Count	Average MktCap (Mil)	Count	Average MktCap (Mil)	Count	Average MktCap (Mil)
Basic Materials	Agricultural Chemicals	2	19,575					2	19,575
	Copper			2	570			2	570
	Gold	13	4,538	21	396	2	5,537	36	2,177
	Independent Oil & Gas	5	24,296	3	859	2	221	10	12,450
	Industrial Metals & Minerals	9	3,515	22	129			31	1,112
	Major Integrated Oil & Gas	2	39,224	1	39,405			3	39,285
	Nonmetallic Mineral Mining	1	1,216	1	561			2	889
	Oil & Gas Drilling & Exploration	7	15,856	1	309			8	13,913
	Oil & Gas Equipment & Services	2	1,583					2	1,583
	Oil & Gas Pipelines	3	29,600					3	29,600
	Silver	3	2,739	5	265	2	1,005	10	1,155
	Specialty Chemicals					1	6,210	1	6,210
Basic Materials Total		47	11,534	56	1,009	7	2,820	110	5,621
Consumer Goods	Auto Parts					1	455	1	455
	Beverages - Soft Drinks	1	648					1	648
	Paper & Paper Products	2	1,934					2	1,934
	Processed & Packaged Goods					1	884	1	884
	Textile - Apparel Clothing	1	6,633					1	6,633
Consumer Goods Total		4	2,787			2	669	6	2,081
Financial	Asset Management			1	3,104			1	3,104
	Exchange Traded Fund			1	6,840			1	6,840
	Life Insurance	1	35,705					1	35,705
	Money Center Banks	5	69,609					5	69,609
	Property & Casualty Insurance	2	10,990					2	10,990
	Property Management					1	1,804	1	1,804
	Real Estate Development	5	7,884					5	7,884
	REIT - Office	1	2,269					1	2,269
Financial Total		14	31,958	2	4,972	1	1,804	17	27,010
Healthcare	Biotechnology					7	218	7	218
	Drug Delivery	1	43,548			1	72	2	21,810
	Drug Manufacturers - Other					3	3,679	3	3,679
	Medical Instruments & Supplies					1	31	1	31
	Medical Laboratories & Research					2	437	2	437
Healthcare Total		1	43,548			14	967	15	3,806
Industrial Goods	Aerospace/Defense Products & Services	1	3,237					1	3,237
	Industrial Electrical Equipment					2	291	2	291
	Waste Management	1	2,973					1	2,973
Industrial Goods Total		2	3,105			2	291	4	1,698
Services	Auto Parts Wholesale	1	20,460					1	20,460
	Business Services	2	2,740					2	2,740
	CATV Systems	1	11,457					1	11,457
	Consumer Services					1	510	1	510
	Entertainment - Diversified	1	1,801					1	1,801
	Marketing Services					1	930	1	930
	Publishing - Periodicals	1	29,876					1	29,876
	Railroads	2	47,239					2	47,239
	Restaurants	1	10,442					1	10,442
Services Total		9	19,333			2	720	11	15,948
Technology	Application Software					3	5,211	3	5,211
	Business Software & Services					1	1,043	1	1,043
	Communication Equipment					4	474	4	474
	Computer Based Systems					1	190	1	190
	Computer Peripherals			1	29			1	29
	Diversified Communication Services					1	4,974	1	4,974
	Internet Information Providers			1	173	1	259	2	216
	Internet Software & Services	1	9,436					1	9,436
	Medical Laboratories & Research					1	323	1	323
	Printed Circuit Boards	1	1,624					1	1,624
	Telecom Services - Domestic	1	35,480			1	438	2	17,959
	Wireless Communications	2	20,425					2	20,425
Technology Total		5	17,478	2	101	13	1,904	20	5,617
Utilities	Diversified Utilities	4	4,340	1	58	1	1,966	6	3,231
	Electric Utilities	1	276					1	276
Utilities Total		5	3,527	1	58	1	1,966	7	2,809
Grand Total		87	15,281	61	1,093	42	1,552	190	7,691

The authors' calculation based on the data retrieved from Finviz.com on September 30, 2014.

Table 2: Cointegration Analysis

	1 min	5 min	10 min	15 min	30 min	65min	1 day
β_{us}	-1.003	-1.005	-1.004	-1.005	-1.005	-1.012	-1.002
	(-1.053,-0.982)	(-1.029,-0.985)	(-1.026,-0.988)	(-1.029,-0.981)	(-1.030,-0.973)	(-1.073,-0.974)	(-1.033,-0.969)
β_{idcn}	-0.021	-0.008	-0.006	-0.004	0.006	-0.001	0.009
	(-0.060,0.000)	(-0.034,0.000)	(-0.056,0.000)	(-0.039,0.000)	(-0.043,0.037)	(-0.100,0.075)	(-0.019,0.029)
β_{idus}	0.006	0.004	0.002	0.002	-0.004	0.001	-0.011
	(-0.005,0.025)	(0.000,0.019)	(0.000,0.029)	(0.000,0.025)	(-0.028,0.024)	(-0.043,0.062)	(-0.054,0.032)
α_{cn}	**-0.078**	**-0.137**	**-0.162**	**-0.158**	**-0.249**	**-0.443**	**-0.410**
	(-0.195,0.000)	(-0.427,0.000)	(-0.586,0.158)	(-0.610,0.410)	(-1.147,0.414)	(-1.973,0.000)	(-0.935,0.000)
α_{us}	**0.133**	**0.258**	**0.396**	**0.476**	**0.583**	**0.384**	**0.178**
	(0.000,0.321)	(0.000,0.588)	(0.000,0.935)	(0.000,1.123)	(0.000,1.898)	(0.000,1.812)	(-0.012,0.550)
α_{idcn}	0.000	0.000	0.004	-0.002	-0.023	-0.093	-0.188
	(-0.009,0.004)	(0.000,0.000)	(-0.026,0.079)	(-0.040,0.009)	(-0.212,0.000)	(-0.833,0.105)	(-0.613,0.000)
α_{idus}	0.001	0.000	0.000	0.001	-0.003	-0.032	-0.029
	(0.000,0.005)	(0.000,0.000)	(0.000,0.000)	(0.000,0.000)	(0.000,0.000)	(-0.247,0.000)	(-0.169,0.000)

Note: The table reports the average estimates of cointegration vectors and adjustment coefficient vectors for the 109 stocks. Below each average estimate, the 5% and 95% percentiles of the statistically significant coefficient estimates are given in the parentheses.

Table 3: Daily Trading Volume Analysis

		Canada volume	U.S. volume	Canada ratio	U.S. ratio
Total (109 firms)	Average	1432080	2518635	36.2%	63.8%
	5th percentile	31993	91036	26.0%	74.0%
	95th percentile	4561502	8835753	34.0%	66.0%
Basic (69 firms)	Average	20805729	43607271	32.3%	67.7%
	5th percentile	824960	1984443	29.4%	70.6%
	95th percentile	62666020	170352975	26.9%	73.1%
Financial (7 firms)	Average	34867571	11213567	75.7%	24.3%
	5th percentile	7561190	1374118	84.6%	15.4%
	95th percentile	53282000	23732244	69.2%	30.8%
Technology (8 firms)	Average	9249575	5960965	60.8%	39.2%
	5th percentile	1716695	1434615	54.5%	45.5%
	95th percentile	26417510	11784564	69.2%	30.8%
Others (25 firms)	Average	4779824	6371592	42.9%	57.1%
	5th percentile	87020	796121	9.9%	90.1%
	95th percentile	17259340	15721434	52.3%	47.7%
NYSE & Alternext (87 firms)	Average	20758646	35444533	36.9%	63.1%
	5th percentile	616330	2106754	22.6%	77.4%
	95th percentile	57380080	152165186	27.4%	72.6%
NASDAQ (22 firms)	Average	3052650	9577264	24.2%	75.8%
	5th percentile	155370	739098	17.4%	82.6%
	95th percentile	7840015	40544492	16.2%	83.8%

Note: This table lists the daily average trading volume in terms of shares in the Canadian and U.S. stock markets across 109 stocks during the period of July 3, 1997–January 12, 2015. It also reports that the proportion of the daily average trading volume in one country in the total of the two countries. The daily average trading volume in the finance and technology tends to be higher in Canada than in the U.S.

Table 4: Numbers of Stocks Satisfying a Specific Over-identified A Based on LR Tests

	1 min	5 min	10 min	15 min	30 min	65min
Panel A: Over-identified structures that cannot be rejected by LR test						
$\mathbf{A}_1$	14	12	11	14	10	15
$\mathbf{A}_3$	2	13	15	17	16	20
$\mathbf{A}_5$	2	4	5	3	6	3
$\mathbf{A}_7$	4	1	2	2	4	9
$\mathbf{A}_9$	9	11	14	16	14	10
$\mathbf{A}_{11}$	19	18	27	24	20	17
$\mathbf{A}_{13}$	9	7	8	14	25	19
$\mathbf{A}_{15}$	10	14	13	14	14	16
Total number	69	80	95	104	109	109
Panel B: Over-identified structures that cannot be rejected by LR test						
Up-Up	4	0	2	1	0	0
Up-Down	23	12	4	2	0	0
Down-Up	2	3	0	0	0	0
Down-Down	11	14	8	2	0	0
Total number	40	29	14	5	0	0
Panel C: Total number of two key types of information channels						
From Canada to the U.S.	46	60	65	59	54	62
From the U.S. to Canada	38	34	40	48	55	47

Note: Panel A presents the results on the number of stocks sharing the initial information channels given by $\mathbf{A}_i$ at a certain frequency. Panel A shows that the information channels across two regimes ($s1$ and $s2$) are shared by some stocks but vary a lot across stocks and the intraday data of different frequencies. Our testing results indicate that no stock based on the intraday data of various frequencies satisfies the over-identified structures given in Section 4.4 such as $\mathbf{A}_2$, $\mathbf{A}_4$, $\mathbf{A}_6$, $\mathbf{A}_8$, $\mathbf{A}_{10}$, $\mathbf{A}_{12}$, $\mathbf{A}_{14}$, and $\mathbf{A}_{16}$. However, the other over-identified structures given in Section 4.4 such as $\mathbf{A}_1$, $\mathbf{A}_3$, $\mathbf{A}_5$, $\mathbf{A}_7$, $\mathbf{A}_9$, $\mathbf{A}_{11}$, $\mathbf{A}_{13}$, and $\mathbf{A}_{15}$ are suitable for some stocks at some frequencies but for not other stocks at some other frequencies. Although the over-identified structures $\mathbf{A}_{s1}$ and $\mathbf{A}_{s2}$ are not element-wise identical, they share the same structure in one of the 16 over-identified structures given in Section 4.4. Panel B presents the results on the number of stocks having different information channels across regimes 1 and 2. We allow $\mathbf{A}_{s1}$ adopts one of the 16 over-identified structures given in Section 4.4 while keeping $\mathbf{A}_{s2}$ as unrestricted and just-identified. Combining the 16 over-identified structures for regime 1 with each just-identified structure for regime 2, we end up 32 over-identified A's for both regimes 1 and 2. We could group these 32 over-identified structures into four categories: "Up-Up", "Up-Down", "Down-Up", and "Down-Down". The "Up"s and "Down"s refer to $A_{cn,us}$ (from the U.S. to Canada) and $A_{us,cn}$ (from Canada to the U.S.), respectively, in $\mathbf{A}_{s1}$ and $\mathbf{A}_{s2}$. For example, "Up-Down" refers to the situation where, in regime 1, $A_{cn,us}$ is statistically significant and, in regime 2, $A_{us,cn}$ is statistically significant. The less restricted over-identified structures are suitable for all remaining stocks that do not satisfy the more restricted over-identification structures—the stocks share the same information channels in regimes 1 and 2. Panel C summarizes the total numbers of two key types of information channels—Down–"from Canada to the U.S." and Up–"from the U.S. to Canada" and shows that overall that there are slightly more information channels from Canada to the U.S. rather than from the U.S. to Canada. The interpretation is that the Canada market releases more information than the U.S. market about these stocks, the overwhelming majority of which are issued by Canadian corporations.

Table 5: Information Transmission (Intraday Data of 1-minute Frequency)

	$t=0$		$t=30$		$t=60$		$t=90$		$t=120$	
	$s1$	$s2$	$s1$	$s2$	$s1$	$s2$	$s1$	$s2$	$s1$	$s2$
$D_{cn,cn,t}$	1.614	1.701	0.962	1.014	0.979	**0.993**	0.987	0.991	**0.991**	0.992
	(3.237)	(2.262)	(0.632)	(0.212)	(0.217)	(0.142)	(0.116)	(0.111)	(0.086)	(0.088)
$D_{us,cn,t}$	0.333	0.490	0.934	0.968	0.978	0.987	**0.991**	**0.993**	0.995	0.995
	(0.404)	(0.424)	(0.209)	(0.101)	(0.083)	(0.069)	(0.053)	(0.053)	(0.041)	(0.042)
$D_{cn,us,t}$	0.413	0.314	0.980	0.955	**0.990**	0.983	0.994	**0.992**	0.996	0.995
	(0.425)	(0.414)	(0.102)	(0.142)	(0.063)	(0.069)	(0.049)	(0.050)	(0.039)	(0.039)
$D_{us,us,t}$	2.169	2.863	1.039	1.069	**1.008**	1.011	1.001	**1.002**	0.999	1.000
	(5.101)	(5.967)	(0.160)	(0.298)	(0.051)	(0.073)	(0.026)	(0.030)	(0.017)	(0.018)

Note: t indicates the number of lags for the intraday data at a certain frequency. In order to convert a particular number of t lags into the number of lags in minutes for the intraday data, please multiply t by the intraday data frequency in minutes. $s1$ and $s2$ refer to regimes 1 and 2, respectively. $D_{i,j,t}$ is the price discovery measure for the long run impact in market i caused by market j. The price discovery measure is the average of all such measures for the 109 stocks. The numbers in the parentheses are standard errors. The numbers in the bold font are those price discovery measures of the same kind that first reach 1 ± 0.01 in each regime as t increases. When $D_{i,j,t}$ approaches 1, this indicates that there is no pricing error in market i caused by market j at lag in minutes what is equal to $t \times$ intraday data frequency in minutes.

Table 6: Information Transmission (Intraday Data of 5-minute Frequency)

	$t=0$		$t=10$		$t=20$		$t=30$		$t=40$	
	$s1$	$s2$	$s1$	$s2$	$s1$	$s2$	$s1$	$s2$	$s1$	$s2$
$D_{cn-cn,t}$	1.282	1.310	0.985	0.975	0.979	0.977	0.984	0.984	0.988	0.988
	(2.886)	(2.815)	(0.608)	(0.613)	(0.263)	(0.264)	(0.150)	(0.150)	(0.105)	(0.105)
$D_{us-cn,t}$	0.525	0.586	0.958	0.961	0.988	0.989	**0.992**	**0.992**	0.993	0.993
	(0.464)	(0.439)	(0.125)	(0.118)	(0.084)	(0.084)	(0.084)	(0.084)	(0.084)	(0.084)
$D_{cn-us,t}$	0.359	0.292	1.120	1.117	0.989	0.989	0.989	0.989	**0.991**	**0.991**
	(0.450)	(0.429)	(2.042)	(2.042)	(0.123)	(0.123)	(0.089)	(0.089)	(0.086)	(0.086)
$D_{us-us,t}$	12.332	12.527	1.362	1.362	1.045	1.045	**1.005**	**1.005**	0.997	0.997
	(80.547)	(80.605)	(2.551)	(2.557)	(0.432)	(0.432)	(0.131)	(0.131)	(0.090)	(0.090)

Note: t indicates the number of lags for the intraday data at a certain frequency. In order to convert a particular number of t lags into the number of lags in minutes for the intraday data, please multiply t by the intraday data frequency in minutes. $s1$ and $s2$ refer to regimes 1 and 2, respectively. $D_{i,j,t}$ is the price discovery measure for the long run impact in market i caused by market j. The price discovery measure is the average of all such measures for the 109 stocks. The numbers in the parentheses are standard errors. The numbers in the bold font are those price discovery measures of the same kind that first reach 1 ± 0.01 in each regime as t increases. When $D_{i,j,t}$ approaches 1, this indicates that there is no pricing error in market i caused by market j at lag in minutes what is equal to $t \times$ intraday data frequency in minutes.

Table 7: Information Transmission (Intraday Data of 10-minute Frequency)

	$t=0$		$t=5$		$t=10$		$t=15$		$t=20$	
	$s1$	$s2$	$s1$	$s2$	$s1$	$s2$	$s1$	$s2$	$s1$	$s2$
$D_{cn,cn,t}$	2.263	2.279	1.185	1.184	**1.002**	**1.001**	0.991	0.991	0.994	0.994
	(9.382)	(9.383)	(2.298)	(2.297)	(0.359)	(0.358)	(0.155)	(0.155)	(0.086)	(0.086)
$D_{us,cn,t}$	0.543	0.530	0.939	0.938	**0.990**	0.989	0.998	**0.997**	0.999	0.999
	(0.479)	(0.462)	(0.215)	(0.214)	(0.053)	(0.053)	(0.022)	(0.022)	(0.012)	(0.012)
$D_{cn,us,t}$	0.341	0.331	0.891	0.910	0.974	0.976	**0.991**	**0.991**	0.995	0.996
	(0.440)	(0.440)	(0.295)	(0.372)	(0.079)	(0.079)	(0.041)	(0.041)	(0.027)	(0.027)
$D_{us,us,t}$	1.986	2.339	1.118	1.161	1.026	1.027	1.012	1.012	**1.007**	**1.007**
	(8.798)	(10.024)	(1.291)	(1.447)	(0.256)	(0.259)	(0.103)	(0.103)	(0.069)	(0.069)

Note: t indicates the number of lags for the intraday data at a certain frequency. In order to convert a particular number of t lags into the number of lags in minutes for the intraday data, please multiply t by the intraday data frequency in minutes. $s1$ and $s2$ refer to regimes 1 and 2, respectively. $D_{i,j,t}$ is the price discovery measure for the long run impact in market i caused by market j. The price discovery measure is the average of all such measures for the 109 stocks. The numbers in the parentheses are standard errors. The numbers in the bold font are those price discovery measures of the same kind that first reach 1 ± 0.01 in each regime as t increases. When $D_{i,j,t}$ approaches 1, this indicates that there is no pricing error in market i caused by market j at lag in minutes what is equal to $t \times$ intraday data frequency in minutes.

Table 8: Information Transmission (Intraday Data of 15-minute Frequency)

	$t=0$		$t=4$		$t=6$		$t=8$		$t=10$	
	$s1$	$s2$	$s1$	$s2$	$s1$	$s2$	$s1$	$s2$	$s1$	$s2$
$D_{cn,cn,t}$	0.310	0.310	0.678	0.677	0.880	0.879	0.948	0.948	0.974	0.973
	(19.515)	(19.515)	(4.210)	(4.209)	(1.330)	(1.330)	(0.476)	(0.476)	(0.226)	(0.226)
$D_{us,cn,t}$	0.535	0.521	0.891	0.892	0.965	0.965	0.986	0.987	**0.994**	**0.994**
	(0.504)	(0.480)	(0.852)	(0.852)	(0.260)	(0.260)	(0.091)	(0.091)	(0.042)	(0.042)
$D_{cn,us,t}$	0.404	0.399	0.963	0.955	0.984	0.982	**0.993**	**0.992**	0.996	0.996
	(0.465)	(0.476)	(0.568)	(0.572)	(0.144)	(0.146)	(0.047)	(0.050)	(0.024)	(0.027)
$D_{us,us,t}$	0.749	1.058	**1.003**	1.019	0.985	0.989	0.993	**0.994**	0.997	0.997
	(24.698)	(24.956)	(2.915)	(2.923)	(0.787)	(0.789)	(0.221)	(0.222)	(0.065)	(0.065)

Note: t indicates the number of lags for the intraday data at a certain frequency. In order to convert a particular number of t lags into the number of lags in minutes for the intraday data, please multiply t by the intraday data frequency in minutes. $s1$ and $s2$ refer to regimes 1 and 2, respectively. $D_{i,j,t}$ is the price discovery measure for the long run impact in market i caused by market j. The price discovery measure is the average of all such measures for the 109 stocks. The numbers in the parentheses are standard errors. The numbers in the bold font are those price discovery measures of the same kind that first reach 1 ± 0.01 in each regime as t increases. When $D_{i,j,t}$ approaches 1, this indicates that there is no pricing error in market i caused by market j at lag in minutes what is equal to $t \times$ intraday data frequency in minutes.

Table 9: Information Transmission (Intraday Data of the 30-minute Frequency)

	$t=0$		$t=1$		$t=2$		$t=3$		$t=4$	
	$s1$	$s2$	$s1$	$s2$	$s1$	$s2$	$s1$	$s2$	$s1$	$s2$
$D_{cn,cn,t}$	1.352	1.423	0.931	0.951	0.972	0.971	**1.010**	**1.008**	1.005	1.005
	(4.257)	(4.273)	(1.463)	(1.470)	(0.413)	(0.414)	(0.317)	(0.317)	(0.190)	(0.190)
$D_{us,cn,t}$	0.584	0.576	0.853	0.864	0.964	0.965	**0.999**	**0.997**	1.000	1.000
	(0.533)	(0.548)	(0.875)	(0.879)	(0.172)	(0.172)	(0.101)	(0.100)	(0.065)	(0.065)
$D_{cn,us,t}$	0.419	0.392	0.796	0.780	**1.003**	**1.003**	1.014	1.017	0.997	0.998
	(0.492)	(0.481)	(0.587)	(0.589)	(0.122)	(0.121)	(0.064)	(0.065)	(0.032)	(0.031)
$D_{us,us,t}$	1.073	1.069	0.837	0.823	**1.008**	**1.009**	1.032	1.036	1.012	1.013
	(4.285)	(4.297)	(1.432)	(1.437)	(0.183)	(0.185)	(0.193)	(0.194)	(0.085)	(0.086)

Note: t indicates the number of lags for the intraday data at a certain frequency. In order to convert a particular number of t lags into the number of lags in minutes for the intraday data, please multiply t by the intraday data frequency in minutes. $s1$ and $s2$ refer to regimes 1 and 2, respectively. $D_{i,j,t}$ is the price discovery measure for the long run impact in market i caused by market j. The price discovery measure is the average of all such measures for the 109 stocks. The numbers in the parentheses are standard errors. The numbers in the bold font are those price discovery measures of the same kind that first reach 1 ± 0.01 in each regime as t increases. When $D_{i,j,t}$ approaches 1, this indicates that there is no pricing error in market i caused by market j at lag in minutes what is equal to $t \times$ intraday data frequency in minutes.

Table 10: Information Transmission (Intraday Data of 65-minute Frequency)

	$t=0$		$t=1$		$t=2$		$t=3$		$t=4$	
	$s1$	$s2$	$s1$	$s2$	$s1$	$s2$	$s1$	$s2$	$s1$	$s2$
$D_{cn,cn,t}$	0.586	0.725	1.053	1.071	1.032	1.036	0.952	0.957	**0.997**	**0.999**
	(2.876)	(2.948)	(1.647)	(1.660)	(0.241)	(0.266)	(0.349)	(0.352)	(0.045)	(0.049)
$D_{us,cn,t}$	0.581	0.511	0.984	0.989	**1.001**	**1.000**	0.969	0.968	0.993	0.991
	(0.524)	(0.489)	(1.624)	(1.629)	(0.236)	(0.244)	(0.329)	(0.331)	(0.056)	(0.059)
$D_{cn,us,t}$	0.442	0.417	0.863	0.876	1.046	1.051	0.986	0.986	**0.998**	**0.998**
	(0.521)	(0.525)	(0.906)	(0.919)	(0.389)	(0.391)	(0.096)	(0.096)	(0.052)	(0.053)
$D_{us,us,t}$	0.876	0.939	0.867	0.893	1.043	1.046	**1.007**	**1.005**	1.000	0.999
	(2.872)	(2.911)	(1.283)	(1.314)	(0.484)	(0.485)	(0.198)	(0.201)	(0.080)	(0.083)

Note: t indicates the number of lags for the intraday data at a certain frequency. In order to convert a particular number of t lags into the number of lags in minutes for the intraday data, please multiply t by the intraday data frequency in minutes. $s1$ and $s2$ refer to regimes 1 and 2, respectively. $D_{i,j,t}$ is the price discovery measure for the long run impact in market i caused by market j. The price discovery measure is the average of all such measures for the 109 stocks. The numbers in the parentheses are standard errors. The numbers in the bold font are those price discovery measures of the same kind that first reach 1 ± 0.01 in each regime as t increases. When $D_{i,j,t}$ approaches 1, this indicates that there is no pricing error in market i caused by market j at lag in minutes what is equal to $t \times$ intraday data frequency in minutes.

Table 11: Summary of $S_{i,j}$ at Various Frequencies in Different Regimes

	$S_{cn,cn}$		$S_{us,cn}$		$S_{cn,us}$		$S_{us,us}$	
	$s1$	$s2$	$s1$	$s2$	$s1$	$s2$	$s1$	$s2$
1min	54.979	76.840	40.184	56.950	44.811	51.179	30.238	30.891
5min	51.049	49.645	55.733	59.179	28.475	23.836	26.058	26.442
10min	59.787	47.463	47.262	35.126	31.540	27.286	20.628	25.795
15min	30.711	29.714	37.823	32.947	26.686	26.264	23.463	26.778

Note: $S_{i,j}$ is a summary evaluation measure for $D_{i,j,t}$. The interpretation of $S_{i,j}$ is that the greater (smaller) the value for $S_{i,j}$ is, the more (less) efficient the information transmits from market j to market i or pricing errors vanish more quickly in market i in response to innovations in market j. $s1$ ($s2$) refers to regime 1 (2).

Table 12: Correlations of $S_{i,j}$'s at 1 Minute Frequency in Different Regimes

	$S_{cn,cn}$		$S_{us,cn}$		$S_{cn,us}$		$S_{us,us}$	
	$s1$	$s2$	$s1$	$s2$	$s1$	$s2$	$s1$	$s2$
$S_{cn,cn}$	1.000	1.000						
$S_{us,cn}$	**0.605**	**0.474**	1.000	1.000				
$S_{cn,us}$	-0.035	-0.057	-0.211	-0.172	1.000	1.000		
$S_{us,us}$	-0.318	-0.274	-0.179	-0.181	0.146	0.259	1.000	1.000

Note: This table summarizes the averaged pair-wise correlations of $S_{i,j}$'s at 1 minute frequency. $s1$ ($s2$) refers to regime 1 (2).

Table 13: Correlations of $S_{i,j}$'s at 5 minute Frequency in Different Regimes

	$S_{cn,cn}$		$S_{us,cn}$		$S_{cn,us}$		$S_{us,us}$	
	$s1$	$s2$	$s1$	$s2$	$s1$	$s2$	$s1$	$s2$
$S_{cn,cn}$	1.000	1.000						
$S_{us,cn}$	**0.481**	0.450	1.000	1.000				
$S_{cn,us}$	-0.218	-0.257	-0.285	-0.222	1.000	1.000		
$S_{us,us}$	-0.342	-0.345	-0.285	-0.195	0.267	**0.539**	1.000	1.000

Note: This table summarize the averaged pair-wise correlations of $S_{i,j}$'s at 5 minute frequency. $s1$ ($s2$) refers to regime 1 (2).

Table 14: Correlations of $S_{i,j}$'s at 10 Minute Frequency in Different Regimes

	$S_{cn,cn}$		$S_{us,cn}$		$S_{cn,us}$		$S_{us,us}$	
	$s1$	$s2$	$s1$	$s2$	$s1$	$s2$	$s1$	$s2$
$S_{cn,cn}$	1.000	1.000						
$S_{us,cn}$	**0.532**	0.286	1.000	1.000				
$S_{cn,us}$	-0.147	-0.191	-0.289	-0.284	1.000	1.000		
$S_{us,us}$	-0.234	-0.255	-0.341	-0.246	0.261	**0.427**	1.000	1.000

Note: This table summarize the averaged pair-wise correlations of $S_{i,j}$'s at 10 minute frequency. $s1$ ($s2$) refers to regime 1 (2).

Table 15: Correlations of $S_{i,j}$'s at 15 Minute Frequency in Different Regimes

	$S_{cn,cn}$		$S_{us,cn}$		$S_{cn,us}$		$S_{us,us}$	
	$s1$	$s2$	$s1$	$s2$	$s1$	$s2$	$s1$	$s2$
$S_{cn,cn}$	1.000	1.000						
$S_{us,cn}$	**0.579**	0.342	1.000	1.000				
$S_{cn,us}$	-0.203	-0.250	-0.262	-0.263	1.000	1.000		
$S_{us,us}$	-0.231	-0.303	-0.261	-0.238	0.346	**0.531**	1.000	1.000

Note: This table summarize the averaged pair-wise correlations of $S_{i,j}$'s at 15 minute frequency. $s1$ ($s2$) refers to regime 1 (2).

Table 16: Basic Statistics for Continuous Variables in Panel Analysis

		Canada	U.S.
Number of shares traded per minute	Average	3,663	6,442
	Std.	9,982	4,181
	5th percentile	1,630	3,416
	95th percentile	5,558	12,118
Number of shares traded per minute in regime 1	Average	2,568	5,341
	Std.	793	1,447
	5th percentile	1,607	3,388
	95th percentile	4,163	8,239
Number of shares traded per minute in regime 2	Average	9582	12,398
	Std.	24,536	7,709
	5th percentile	2,780	7,715
	95th percentile	11,080	20,646
Number of shares traded in sample period	Average	17,184,959	30,223,617
	Std.	26,033,416	65,503,443
	5th percentile	383,920	1,092,427
	95th percentile	54,738,020	106,029,031
MediumTrade	Average	29,421	13,417
	Std.	49,422	31,688
	5th percentile	376	926
	95th percentile	108,315	48,641
Market cap in million U.S. $	Average	9,515	
	Std.	18,572	
	5th percentile	70	
	95th percentile	45,699	
YearsListed	Average	11	
	Std.	5	
	5th percentile	4	
	95th percentile	18	

Note: The average number of shares traded per minute (for either Canada or the U.S.) is the cross-sectional average of the overtime average numbers of shares traded per minute (in either the Canadian or U.S. market) from 9:30 EST (or 14:30 UTC) to 16:00 EST (or 21:00 UTC) (391 data points per trading day) across the 109 stocks. The standard deviation of the the number of shared traded per minute (or either Canada or the U.S.) is the standard deviation of the overtime averages. The number of shares traded per minute (for either Canada or the U.S.) and its standard deviation for regime 1 or 2 is defined similarly across regimes 1 and 2. For regime 1, the corresponding time is from 10:01 EST (or 15:01 UTC) to 15:29 EST (or 20:29 UTC) (329 data points per trading day) while, for regime 2, the corresponding time is from 9:30 EST (or 14:30 UTC) to 10:00 EST (15:00 UTC) and from 15:30 EST (or 20:30 UTC) to 16:00 ES (or 21:00 UTC) (62 data point per trading day). The number of shares traded in the sample period refers to (for either Canada or the U.S.) the cross-sectional average of the total numbers of shares traded over the sample period (12 trading days) across the 109 stocks. The standard deviation of the the number of shares traded in the sample is the cross-section deviation of the total numbers of shares traded in the sample across the 109 stocks. MediumTrade is the average of the standard deviations of the minute-by-minute trading volumes for the 109 stocks and is an approxy for the proportion of medium trades. The smaller (greater) the standard deviation, the more medium trades dominate (more extreme (large or small) trades dominate). The standard deviation of MediumTrade is the standard deviation of the standard deviations of the minute-by-minute trading volumes. Capitalization is the average capitalization of the stocks in million U.S. dollars.

Table 17: Panel Analysis—$\log(S_{i,j})$

Variable	Coef. (Std.)	Variable	Coef. (Std.)	Variable	Coef. (Std.)
Intercept	-0.462 (0.370)	MediumTrade$_{us}$	0.035 (0.106)	Technology	-0.053 (0.178)
Market-cap	-0.028 (0.062)	Regime*MediumTrade$_{us}$	0.017 (0.095)	Regime*Technology	-0.025 (0.146)
Regime*Market-cap	0.001 (0.052)	$D_{s_{us,cn}}$*MediumTrade$_{us}$	-0.077 (0.135)	$D_{s_{us,cn}}$*Technology	-0.034 (0.208)
$D_{s_{us,cn}}$*Market-cap	0.021 (0.072)	$D_{s_{cn,us}}$*MediumTrade$_{us}$	-0.083 (0.128)	$D_{s_{cn,us}}$*Technology	0.132 (0.196)
$D_{s_{cn,us}}$*Market-cap	0.035 (0.072)	$D_{s_{us,us}}$*MediumTrade$_{us}$	-0.119 (0.133)	$D_{s_{us,us}}$*Technology	0.376 (0.232)
$D_{s_{us,us}}$*Market-cap	0.093 (0.082)	Volume$_{cn}$	0.251*** (0.058)	Financial	0.099 (0.136)
Country	0.265* (0.137)	Regime*Volume$_{cn}$	-0.025 (0.052)	Regime*Financial	0.014 (0.134)
Regime*Country	-0.059 (0.100)	$D_{s_{us,cn}}$*Volume$_{cn}$	-0.196*** (0.071)	$D_{s_{us,cn}}$*Financial	0.071 (0.159)
$D_{s_{us,cn}}$*Country	-0.126 (0.152)	$D_{s_{cn,us}}$*Volume$_{cn}$	-0.065 (0.070)	$D_{s_{cn,us}}$*Financial	-0.360** (0.180)
$D_{s_{cn,us}}$*Country	-0.252* (0.153)	$D_{s_{us,us}}$*Volume$_{cn}$	-0.206*** (0.075)	$D_{s_{us,us}}$*Financial	-0.329 (0.207)
$D_{s_{us,us}}$*Country	-0.465*** (0.149)	Volume$_{us}$	-0.145 (0.090)	Alternext	-0.320*** (0.101)
YearsListed	-0.003 (0.007)	Regime*Volume$_{us}$	0.010 (0.077)	Regime*Alternext	0.071 (0.090)
Regime*YearsListed	-0.001 (0.007)	$D_{s_{us,cn}}$*Volume$_{us}$	0.231** (0.110)	$D_{s_{us,cn}}$*Alternext	0.125 (0.119)
$D_{s_{us,cn}}$*YearsListed	0.002 (0.009)	$D_{s_{cn,us}}$*Volume$_{us}$	0.144 (0.104)	$D_{s_{cn,us}}$*Alternext	0.414*** (0.121)
$D_{s_{cn,us}}$*YearsListed	-0.003 (0.009)	$D_{s_{us,us}}$*Volume$_{us}$	0.360*** (0.108)	$D_{s_{us,us}}$*Alternext	0.514*** (0.138)
$D_{s_{us,us}}$*YearsListed	-0.012 (0.010)	Basic	0.458*** (0.095)	NASDAQ	-0.045 (0.108)
MediumTrade$_{cn}$	-0.145** (0.064)	Regime*Basic	-0.055 (0.082)	Regime*NASDAQ	0.041 (0.089)
Regime*MediumTrade$_{cn}$	0.016 (0.044)	$D_{s_{us,cn}}$*Basic	-0.358*** (0.112)	$D_{s_{us,cn}}$*NASDAQ	-0.088 (0.124)
$D_{s_{us,cn}}$*MediumTrade$_{cn}$	0.027 (0.060)	$D_{s_{cn,us}}$*Basic	-0.509*** (0.116)	$D_{s_{cn,us}}$*NASDAQ	0.354*** (0.121)
$D_{s_{cn,us}}$*MediumTrade$_{cn}$	-0.059 (0.060)	$D_{s_{us,us}}$*Basic	-0.825*** (0.124)	$D_{s_{us,us}}$*NASDAQ	0.053 (0.138)
$D_{s_{us,us}}$*MediumTrade$_{cn}$	-0.053 (0.049)				
$R^2 = 0.220$	$\log L = -6263.928$	$AIC = 3.63$	$BIC = 3.73$		

Note: The fixed effect panel data model for $\log(S_{i,j})$. The higher the value of $\log(S_{i,j})$ is, the more efficient the information transmits from market j to market i. The robust standard errors of the Arellano and Bond type are reported in parentheses. $*** - p < 0.01$, $** - p < 0.05$, $* - p < 0.10$

Table 18: Panel Analysis of $S_{i,j}$

Variable	Coef. (Std.)	Variable	Coef. (Std.)	Variable	Coef. (Std.)
Intercept	-131.514*** (27.173)	MediumTrade$_{us}$	6.657 (10.400)	Technology	1.590 (9.013)
Market-cap	5.008 (5.849)	Regime*MediumTrade$_{us}$	-0.074 (10.659)	Regime*Technology	-1.341 (9.634)
Regime*Market-cap	1.559 (5.008)	$D_{s_{us,cn}}$*MediumTrade$_{us}$	4.601 (16.580)	$D_{s_{us,cn}}$*Technology	4.727 (14.619)
$D_{s_{us,cn}}$*Market-cap	-1.475 (7.161)	$D_{s_{cn,us}}$*MediumTrade$_{us}$	-13.225 (13.466)	$D_{s_{cn,us}}$*Technology	3.682 (11.744)
$D_{s_{cn,us}}$*Market-cap	1.151 (8.004)	$D_{s_{us,us}}$*MediumTrade$_{us}$	-19.264 (12.486)	$D_{s_{us,us}}$*Technology	20.679 (12.688)
$D_{s_{us,us}}$*Market-cap	-1.954 (6.258)	Volume$_{cn}$	16.478*** (5.105)	Financial	7.968 (12.721)
Country	23.055*** (6.003)	Regime*Volume$_{cn}$	-3.605 (5.280)	Regime*Financial	1.057 (10.907)
Regime*Country	-6.482 (6.680)	$D_{s_{us,cn}}$*Volume$_{cn}$	-5.952 (7.951)	$D_{s_{us,cn}}$*Financial	5.016 (16.917)
$D_{s_{us,cn}}$*Country	-8.131 (8.042)	$D_{s_{cn,us}}$*Volume$_{cn}$	-6.162 (7.206)	$D_{s_{cn,us}}$*Financial	-27.696 (18.035)
$D_{s_{cn,us}}$*Country	-19.036* (10.249)	$D_{s_{us,us}}$*Volume$_{cn}$	-11.961** (5.882)	$D_{s_{us,us}}$*Financial	-21.178 (14.503)
$D_{s_{us,us}}$*Country	-11.708 (7.535)	Volume$_{us}$	-6.100 (8.250)	Alternext	-21.435* (11.465)
YearsListed	-0.417 (0.638)	Regime*Volume$_{us}$	1.857 (8.392)	Regime*Alternext	2.820 (8.037)
Regime*YearsListed	0.211 (0.556)	$D_{s_{us,cn}}$*Volume$_{us}$	4.044 (13.183)	$D_{s_{us,cn}}$*Alternext	6.625 (13.441)
$D_{s_{us,cn}}$*YearsListed	0.401 (0.816)	$D_{s_{cn,us}}$*Volume$_{us}$	10.171 (10.388)	$D_{s_{cn,us}}$*Alternext	17.862 (12.147)
$D_{s_{cn,us}}$*YearsListed	-0.167 (0.801)	$D_{s_{us,us}}$*Volume$_{us}$	25.477*** (9.758)	$D_{s_{us,us}}$*Alternext	23.900** (11.584)
$D_{s_{us,us}}$*YearsListed	-0.680 (0.772)	Basic	36.062*** (7.752)	NASDAQ	-1.739 (9.606)
MediumTrade$_{cn}$	-9.560** (4.815)	Regime*Basic	-1.977 (6.854)	Regime*NASDAQ	2.437 (7.410)
Regime*MediumTrade$_{cn}$	2.957 (4.639)	$D_{s_{us,cn}}$*Basic	-27.764*** (9.962)	$D_{s_{us,cn}}$*NASDAQ	-0.167 (12.299)
$D_{s_{us,cn}}$*MediumTrade$_{cn}$	0.750 (7.262)	$D_{s_{cn,us}}$*Basic	-20.301* (10.461)	$D_{s_{cn,us}}$*NASDAQ	24.584** (10.325)
$D_{s_{cn,us}}$*MediumTrade$_{cn}$	5.431 (6.373)	$D_{s_{us,us}}$*Basic	-47.566*** (9.145)	$D_{s_{us,us}}$*NASDAQ	-6.646 (9.522)
$D_{s_{us,us}}$*MediumTrade$_{cn}$	-3.495 (5.208)				
$R^2 = 0.094$	$\log L = -19772.77$	$AIC = 11.310$	$BIC = 11.420$		

Note: The fixed effect panel data model for $S_{i,j}$. The higher the value of $S_{i,j}$ is, the more efficient the information transmits from market j to market i. The robust standard errors of the Arellano and Bond type are reported in parentheses. $***-p < 0.01$, $**-p < 0.05$, $*-p < 0.10$

APPENDIX

In this appendix, we report the simulation results which highlight different adjustment coefficients in cointegration analysis that may result from using the intraday data of different frequencies.

To be more generic, we assume that one underlying asset (stock) is traded in two different markets (markets 1 and 2). We could consider the Canadian market as the example of market 1 and the U.S. market as market 2. The price vector is $[p_{1,t}, p_{2,t}]'$, where $p_{1,t}$ is the price for market 1 and $p_{2,t}$ is the price for market 2. Assume that m_t is the efficient price (or true value) of the underlying asset and follows a random walk process.

The widely used structural model for price discovery is given by the following equations:

$$\begin{aligned} p_{1,t} &= m_t + e_{1,t}, \\ p_{2,t} &= m_t + e_{2,t}, \\ m_t &= m_{t-1} + \eta_t, \end{aligned} \tag{A-1}$$

where $e_{1,t}$ and $e_{2,t}$ are the idiosyncratic noise in the two markets. η_t can be considered as the innovation that drives the efficient price movement.

When studying price discovery using high-frequency data, it is valuable to find out which market incorporates the innovation η_t faster. When market 1 incorporates innovation immediately while maker 2 incorporates innovation with a lag, we can model this situation as

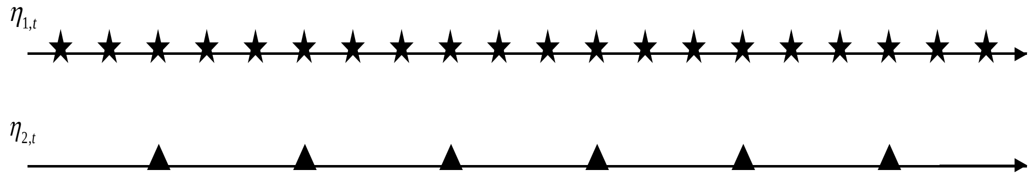
$$\begin{aligned} p_{1,t} &= m_t + e_{1,t}, \\ p_{2,t} &= m_{t-1} + e_{2,t}, \\ m_t &= m_{t-1} + \eta_t. \end{aligned} \tag{A-2}$$

This is a case where market 2 serves as a satellite market. Using the price changes to rewrite equations in (A-2) can be written as

$$\begin{aligned} p_{1,t} &= p_{1,t-1} + \eta_t + e_{1,t} - e_{1,t-1}. \\ p_{2,t} &= p_{2,t-1} + \eta_{t-1} + e_{2,t} - e_{2,t-1}. \end{aligned} \tag{A-3}$$

These alternative equations show that market 1 incorporates the innovation η_t immediately and contributes to price discovery while market 2 only absorb the old or stale information

Figure A-1: Two types of innovations with different arrival frequencies



Notes: Innovations in market 1, $\eta_{1,t}$ appear more frequently than innovations in market 2, $\eta_{2,t}$.

given in the innovation η_{t-1}.

However, if markets 1 and 2 incorporate innovations of different frequencies, then the adjustment coefficient estimates obtained from the cointegration analysis may not have the straightforward interpretation.

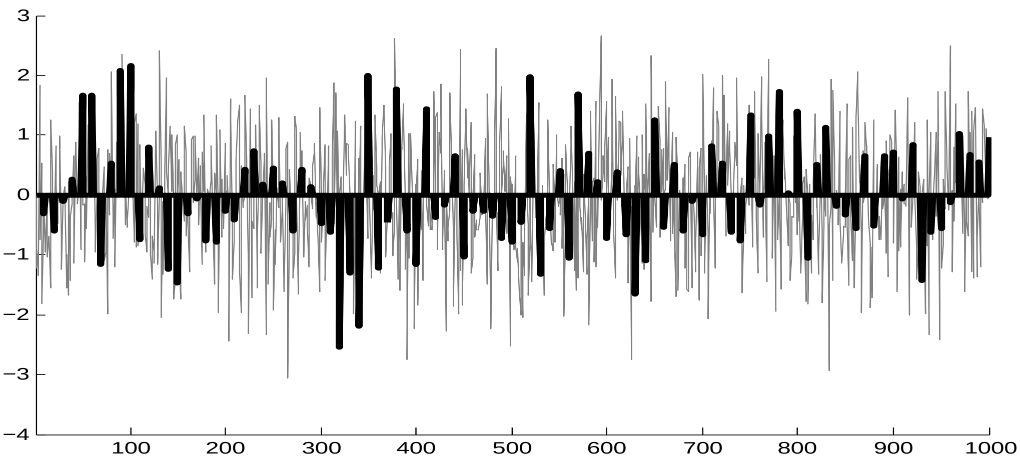
To illustrate this, we assume that there are two kinds of innovations arriving at different frequencies. As shown in Figure A-1, innovations in market 1, $\eta_{1,t}$, are released at a much higher frequency, but innovations in market 2, $\eta_{2,t}$, are released at a lower frequency. An example would be that the Canadian market (market 1), the home market of Canadian companies, has exposure to the more frequent Canadian local news while the U.S. market (market 2), the foreign market of these Canadian companies, has exposure to the less frequent U. S. news that may externally impact on the Canadian companies.

Assuming that both markets 1 and 2 are sensitive to innovations in the two markets $\eta_{1,t}$ and $\eta_{2,t}$. But each may be slow in absorbing the innovation from the other market with a lag. More specifically, market 1 responds to the innovation in market 2 with a lag m while market 2 responds to the innovation in market 1 with a lag n. We can further assume that market 1 is the home market and, hence, is more sensitive to innovations on its own than innovations on the other. We could further explain the situations using the following model:

$$
\begin{aligned}
p_{1,t} &= p_{1,t-1} + \eta_{1,t} + \eta_{2,t-m} + e_{1,t} - e_{1,t-1}, \\
p_{2,t} &= p_{2,t-1} + \eta_{1,t-n} + \eta_{2,t} + e_{2,t} - e_{2,t-1},
\end{aligned} \tag{A-4}
$$

where $\eta_{1,t}$ represents the high frequency innovation and $\eta_{2,t}$ the low frequency innovation. As we can see from equations (A-4), as t changes at a relatively high frequency, the innovation $\eta_{1,t}$ can be immediately incorporated into the price in market 1, while, as t changes at a relatively low frequency, the innovation $\eta_{2,t}$ can be immediately incorporated into the price

Figure A-2: Two kinds of innovations arriving at different frequencies



Notes: The black bars are for innovations arriving at every 10 time unit interval while the gray bars are for innovation arriving at every one time unit interval.

in market 2, implying that different markets are sensitive to different kinds of innovations. If we set the two data generating processes at the higher frequency, market 2 as the foreign market can pick up the more frequent market 1 innovation after n lags (e.g., n minutes), $\eta_{1,t-n}$, while market 1 as the home market can pick up the less frequent market 2 innovation after m lags (e.g., m minutes), $\eta_{2,t-m}$. If $m > n$, market 1 responds slowly to the innovations revealed in market 2, while market 2 responds quickly to the innovations revealed in market 1. Compared with the traditional structural model in (A-3), the model given in (A-4) can describe more complex scenarios for innovations.

In order to show how the relative magnitudes of m and n can influence the adjustment coefficient estimate obtained from cointegration analysis, we use the Monte Carlo simulation based on the model given in (A-4). First, we assume that $\eta_{1,t}$ is an innovation arriving at every one-time-unit interval, while $\eta_{2,t}$ is an innovation arriving at every ten-time-unit interval, and $\eta_{1,t}$ and $\eta_{2,t}$ are independently drawn from $N(0,1)$, at their respective time intervals as shown in Figure A-2. We normalize $n = 1$, implying that market 2 responds to the innovation in market 1 with only one lag. Then, by varying m from 1 to 30, we investigate the result from a very fast respond of market 1 to the innovation in market 2 to a very slow respond.

For each specific value of m, we are able to generate the two price series $p_{1,t}$ and $p_{2,t}$. Then we conduct the cointegration analysis, estimate the adjustment coefficients α_1 and α_2, and calculate the ratio $|\frac{\alpha_1}{\alpha_2}|$. In the literature, $|\frac{\alpha_1}{\alpha_2}| = 1$ is interpreted as the evidence for equal contributions from the two markets to price discovery. $|\frac{\alpha_1}{\alpha_2}| < 1$ is interpreted as the evidence that market 1 contributes more to price discovery than market 2 does due to the fact that market 1 needs a relatively smaller adjustment to market 2 than market 2 does to market 1. Table A-1 reports the estimate results of $|\frac{\alpha_1}{\alpha_2}|$ from 1000 Monte Carlo simulations.

Table A-1: Monte Carlo simulation for $|\frac{\alpha_1}{\alpha_2}|$ based on model (A-4) with different choice of m, $\eta_{2,t} \sim N(0, 1)$

	m=1	m=2	m=3	m=4	m=5	m=6	m=7	m=8	m=9	m=10
25th quantile	0.285	0.359	0.382	0.415	0.435	0.450	0.495	0.503	0.507	0.512
50th quantile	0.393	0.452	0.500	0.539	0.580	0.613	0.631	0.648	0.663	0.682
75th quantile	0.513	0.563	0.661	0.697	0.767	0.787	0.842	0.872	0.892	0.896
	m=11	m=12	m=13	m=14	m=15	m=16	m=17	m=18	m=19	m=20
25th quantile	0.497	0.503	0.516	0.515	0.515	0.507	0.498	0.503	0.487	0.497
50th quantile	0.684	0.687	0.665	0.687	0.686	0.680	0.681	0.685	0.689	0.684
75th quantile	0.919	0.943	0.940	0.923	0.937	0.957	0.996	1.015	1.057	0.919
	m=21	m=22	m=23	m=24	m=25	m=26	m=27	m=28	m=29	m=30
25th quantile	0.492	0.425	0.437	0.430	0.425	0.422	0.437	0.420	0.412	0.417
50th quantile	0.719	0.739	0.723	0.734	0.720	0.704	0.680	0.689	0.699	0.709
75th quantile	1.123	1.041	1.038	1.058	1.107	1.137	1.093	1.098	1.105	1.124

Recall our data generating process, all $\eta_{1,t}$'s are revealed by market 1 more frequently than all $\eta_{2,t}$'s are by market 2. Hence cumulatively, the sum of $\eta_{1,t}$ over 10 one-time-unit intervals is ten times greater than $\eta_{2,t}$ in 1 ten-time-unit interval. The price in market 2 must make greater adjustments to maintain the market equilibrium. Therefore it is quite understandable to see that $|\frac{\alpha_1}{\alpha_2}| < 1$. However, as shown in Table A-1, the ratio $|\frac{\alpha_1}{\alpha_2}|$ becomes greater as m increases. Hasbrouck (1995) explains which price/market first incorporate innovations as the evidence for price discovery. In our simulation, as m increases, although market 1 still incorporates most of innovations in market 1 first, market 1 responds innovations in market 2 more slowly. To get into the market equilibrium, as m increases, market 1 needs to make greater adjustments towards market 2 and, hence in the cointegration system, the error correction coefficient (α_1) for market 1's price becomes greater. This eventually leads to the ratio $|\frac{\alpha_1}{\alpha_2}|$ close to 1. In particular, when $m > 18$ lags (e.g., 18 minutes), the 75% quantile of $|\frac{\alpha_1}{\alpha_2}|$ is greater than 1. This simulation shows that price discovery can be difficult to analyze when innovations arrive at different time intervals.

In the above we assume that innovations in markets 1 and 2 follow the standard normal distribution. In order to see the role of innovation size, we set $\eta_{2,t} \sim N(0, 2)$ for new Monte Carlo simulations. That is, innovations $\eta_{2,t}$'s still arrive every ten-time-unit interval but it has a variance that is doubled. The Monte Carlo simulation result for $|\frac{\alpha_1}{\alpha_2}|$ is reported in

Table A-2.

Table A-2: Monte Carlo simulation for $|\frac{\alpha_1}{\alpha_2}|$ based on model (A-4) with different choice of m, $\eta_{2,t} \sim N(0, 2)$

	m=1	m=2	m=3	m=4	m=5	m=6	m=7	m=8	m=9	m=10
25th quantile	0.412	0.551	0.639	0.705	0.736	0.758	0.826	0.840	0.924	0.944
50th quantile	0.671	0.807	0.967	1.101	1.081	1.108	1.182	1.149	1.190	1.237
75th quantile	1.077	1.144	1.241	1.372	1.416	1.419	1.433	1.372	1.458	1.572
	m=11	m=12	m=13	m=14	m=15	m=16	m=17	m=18	m=19	m=20
25th quantile	0.956	0.926	0.899	0.908	0.887	0.879	0.888	0.896	0.887	0.880
50th quantile	1.171	1.165	1.147	1.124	1.147	1.124	1.118	1.105	1.142	1.166
75th quantile	1.860	1.867	1.881	1.918	1.996	1.887	1.908	1.881	1.992	1.921
	m=21	m=22	m=23	m=24	m=25	m=26	m=27	m=28	m=29	m=30
25th quantile	0.823	0.786	0.806	0.781	0.802	0.779	0.818	0.806	0.775	0.786
50th quantile	1.129	1.176	1.197	1.203	1.139	1.154	1.173	1.165	1.207	1.223
75th quantile	2.017	1.958	1.887	1.941	1.933	1.945	1.948	1.884	1.881	2.027

As we can see in Table A-2, when the variance of $\eta_{2,t}$ is greater than that of $\eta_{1,t}$, the cointegration analysis of the two prices produces a greater adjustment coefficient of α_1, leading to a greater $|\frac{\alpha_1}{\alpha_2}|$ even when market 1 responds to $\eta_{2,t}$ with a 1 period delay (at the 75th quantile).

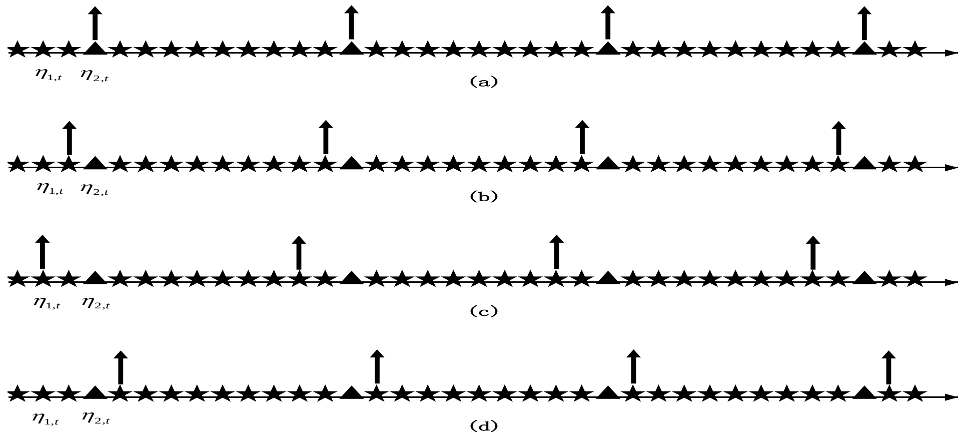
The above Monte Carlo simulations show that when two kinds of innovations exist in markets 1 and 2, the magnitude of $|\frac{\alpha_1}{\alpha_2}|$ is affected by both the speed of information absorption and the relative size of innovations. Under these situations, the size $|\frac{\alpha_1}{\alpha_2}|$ may not be easily interpreted as a reliable measure for price discovery without considering those other two factors.

In addition to the issues relating to the speed of information absorption and the relative size of innovations, we also examine the impact of the sampling frequency on the size of adjustment coefficients in cointegration analysis. The rationale behind this is that the real data generating process is, in real life, unobservable so that we have to sample the data. But sampling data at different frequencies may well represent the challenge posted by differences in the observables and unobservables. Since we have two kinds of innovations with different frequencies, and different markets incorporate innovations in different speed, different sampling frequency will give different estimates of adjustment coefficients, which may lead to the opposite conclusions.

We sample the price data at every ten-time-unit interval (e.g., 10 minutes), when $\eta_{2,t}$ arrives. Figure A-3 displays the different sampling methods.

With reference to the time when $\eta_{2,t}$ occurs, we use $lag = 0$, $lag = 1$, ..., $lag = 9$ to name

Figure A-3: Two kinds of innovations with different sampling methods



Note: Each horizontal line represents the time line. Each star represents an innovation $\eta_{1,t}$ while each triangle represents $\eta_{2,t}$. The upside arrows represent where the data points are sampled. With reference to the time when $\eta_{2,t}$ occurs, we use $lag = 0$, $lag = 1$, ..., $lag = 9$ to name the sampling methods. For example, the sampling method of $lag = 0$ corresponds to the time points of innovation $\eta_{2,t}$ without any lags; the sampling method of $lag = 1$ corresponds to the time points of $\eta_{2,t}$ lagged once. Sub-figures (a)-(d) describe the sampling methods of $lag = 0$, $lag = 1$, $lag = 2$ and $lag = 9$, respectively.

the sampling methods. For example, the sampling method of $lag = 0$ corresponds to the time points of innovation $\eta_{2,t}$ without any lags; the sampling method of $lag = 1$ corresponds to the time points of $\eta_{2,t}$ lagged once. Figure A-3 (a)-(d) describe the sampling methods of $lag = 0$, $lag = 1$, $lag = 2$ and $lag = 9$, respectively.

In our simulations, we set $m = 2, 5, 10$, $\eta_{1,t} \sim N(0, 1)$, and $\eta_{2,t} \sim N(0, 1)$. Then, we use different sampling methods ($lag = 0$ to $lag = 9$) to see how the sampling methods affect the size of adjustment coefficients. Table A-3 shows that when market 1 can fully respond to $\eta_{2,t}$ within 2 one-time-unit intervals ($m = 2$), the sampling method of $lag = 0$ could generate the ratio $|\frac{\alpha_1}{\alpha_2}|$ that is greater than 1 (1.719). When we use the sampling methods of $lag = 1$ to $lag = 8$, we see $|\frac{\alpha_1}{\alpha_2}| < 1$. However, when we use the sampling method of $lag = 9$, we see $|\frac{\alpha_1}{\alpha_2}| > 1(1.224)$.

We can resort to Figure A-3 to explain these observations. When we use the sampling method of $lag = 0$ to sample our data as in Figure A-3(a) , the points in time for sampling corresponds to when $\eta_{2,t}$ occurs. At these points in time, innovations, $\eta_{1,t}$'s, are revealed before being incorporated into prices in both markets and innovations, $\eta_{2,t}$'s, are also incorporated into the price in market 2. Therefore, at these points in time, only market 1 tends to absorb the $\eta_{2,t}$, and looks as if market 1 adjusts its price towards market 2, which gives a relatively large α_1 or $|\frac{\alpha_1}{\alpha_2}| > 1$.

For the sampling methods of $lag = 1$ to $lag = 8$, the price in Market 1 at these points in time has already fully absorbed the old $\eta_{2,t}$ and the new $\eta_{2,t}$ has not yet arrived. In these situations, the main character for the data sampled as such at these points in time is that market 2 attempts to absorb innovations $\eta_{1,t}$'s. Therefore, the cointegration analysis using these sampling methods gives $|\frac{\alpha_1}{\alpha_2}| < 1$.

With the aid of Figure 3-A(d), we can better understand the reason why the sampling method of $lag = 9$ can produce the ratio $|\frac{\alpha_1}{\alpha_2}| > 1(1.224)$. That is because, these points in time are only 1 one time unit interval ahead the points in time of $\eta_{2,t}$'s. That is, these $\eta_{2,t}$'s have not been fully absorbed by market 1. Therefore, the cointegration analysis often shows that market 1 moves towards market 2, giving the ratio $|\frac{\alpha_1}{\alpha_2}| > 1$.

It is worth while to note that when $m = 5$, the sampling methods of $lag = 6$ to $lag = 9$ generates $|\frac{\alpha_1}{\alpha_2}| > 1$. As explained before, at these points in times, theses $\eta_{2,t}$ have not been fully absorbed by market 1. Therefore, $|\alpha_1| > |\alpha_2|$. Furthermore, when $m = 10$, market 1 keeps adjusting its price towards to the price in market 2 and therefore $|\frac{\alpha_1}{\alpha_2}| > 1$.

According to the Hasbrouck's (1995) definition of price discovery, market 1 in our simulations contributes more to the price discovery than market 2 does. That is, market 1 incorporates most of the innovations $\eta_{1,t} + \eta_{2,t}$ that drive the asset price movement. Our simulations show that, relying on the ratio $|\frac{\alpha_1}{\alpha_2}|$ from the cointegration analysis to interpret price discovery may be subject to a set of more restrictive assumptions as the ratio $|\frac{\alpha_1}{\alpha_2}|$ is sensitive to the speed of information absorption, the relative size of innovations, and the sampling method.

From the Monte Carlo simulations, we can conclude that using data of different frequencies may lead to different adjustment coefficients in cointegration analysis. The underlying reasons are (1) different markets may be exposed to different kinds of innovations, which may arrive at different points in time; (2) different markets may incorporate innovations at different speeds; and (3) the adjustment coefficients may be affected by different sampling methods.

Our Monte Carlo simulations show that $|\frac{\alpha_1}{\alpha_2}|$ will be *greater* than one in value when market 1 takes *many lags* ($m = 18$) to absorb market 2's innovation under the condition that, relative to market 1's innovation, market 2's innovation is of much *lower* frequencies. These simulations also indicate that $|\frac{\alpha_1}{\alpha_2}|$ will be *greater* than one in value even when market 1 takes only *one* lag ($m = 1$) to absorb market 2's innovation under the condition that,

Table A-3: Monte Carlo simulation for $|\frac{\alpha_1}{\alpha_2}|$ based on model (A-4) with different sampling methods

m=**2**	lag=**0**	lag=**1**	lag=**2**	lag=**3**	lag=**4**	lag=**5**	lag=**6**	lag=**7**	lag=**8**	lag=**9**
25th quantile	0.727	0.208	0.222	0.237	0.219	0.282	0.212	0.213	0.124	0.654
50th quantile	1.719	0.588	0.571	0.584	0.620	0.626	0.610	0.631	0.540	1.224
75th quantile	3.317	1.252	1.404	1.247	1.681	1.418	1.393	1.555	1.527	3.405
m=**5**	lag=**0**	lag=**1**	lag=**2**	lag=**3**	lag=**4**	lag=**5**	lag=**6**	lag=**7**	lag=**8**	lag=**9**
25th quantile	0.807	0.239	0.179	0.211	0.181	0.177	0.440	0.486	0.439	0.465
50th quantile	1.551	0.538	0.464	0.672	0.417	0.546	1.100	1.424	1.078	1.088
75th quantile	3.290	1.161	1.233	1.793	1.531	1.545	2.613	3.837	2.408	2.480
m=**10**	lag=**0**	lag=**1**	lag=**2**	lag=**3**	lag=**4**	lag=**5**	lag=**6**	lag=**7**	lag=**8**	lag=**9**
25th quantile	0.901	0.547	0.477	0.516	0.420	0.602	0.690	0.484	0.466	0.451
50th quantile	2.170	1.290	1.192	1.030	1.039	1.222	1.371	1.175	1.002	1.072
75th quantile	5.137	4.153	2.621	2.437	3.075	2.675	2.715	3.720	2.086	2.592

relative to market 1's innovation, market 2's innovation is *substantially greater* in size, and of *lower* frequencies. Our Monte Carlo simulations also show that under the condition that, relative to market 1's innovation, market 2's innovation is of much *lower* frequencies, if the sampling method has no lag or does not miss any market 2's innovations in the sample, we will observe $|\frac{\alpha_1}{\alpha_2}| > 1$. But using some sampling methods that have lags or miss market 2's innovations in the sample, we may observe $|\frac{\alpha_1}{\alpha_2}| < 1$. Therefore, when the two markets have their own innovations and absorb the other market innovations at different speeds, $|\frac{\alpha_1}{\alpha_2}| < 1$ could be a result of omissions of observations with some sampling methods. Under this circumstance, it is critical to examine $|\frac{\alpha_1}{\alpha_2}|$ across the intraday of different frequencies.