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US Cross-Listing and Domestic High-Frequency Trading: Evidence from Canadian Stocks

ABSTRACT

We find that US cross-listing of Canadian stocks enhances domestic high-frequency trading (HFT) activity in the form of both opportunistic trading and market-making. First, US cross-listing boosts HFT low-latency cross-border arbitrage. This highly correlated HFT arbitrage activity across markets enhances stock price efficiency by correcting mispricing. Second, US cross-listing leads to an increase in news trading activity by high-frequency traders around US public macro-news releases. Finally, cross-listing increases a stock's reliance on high-frequency market makers to provide liquidity. Yet, we find no evidence of higher fragility in liquidity supply after cross-listing.

JEL classifications: G12, G14, G15, G23

KEYWORDS: US cross-listing, high-frequency trading, cross-market arbitrage, US news announcements, liquidity, equity markets

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1. Introduction

As of July 1st, 2021, 514 non-US stocks were listed on the NYSE, including 120 Canadian stocks.[1] Non-US firms that cross-list in the US benefit from greater stock liquidity, lower cost of capital, higher market valuation, lower information asymmetry risk, and greater stock price efficiency (e.g., Easley and O'Hara, 2004; Chemmanur and Fulghieri, 2006, and Dodd and Gilbert, 2016). As such, cross-listing in the US has important implications for firms and their investors. In this paper, we examine one aspect of cross-listing that has not yet been studied, which is the impact of US cross-listing on the stock's domestic high-frequency trading (HFT) activity.

High-frequency traders (HFTs) are proprietary traders that use ultra-fast computer algorithms and low-latency technology and services to exploit short-lived profit opportunities generated by the trading process.[2] Their strategies include market-making, cross-venue latency arbitrage, directional speculation, and aggressive undercutting of orders (Boehmer, Li, and Saar, 2018; Foley, Dyhrberg, and Svec, 2022). The success of these strategies relies on HFTs' speed advantage in accessing and processing signals (Baron, Brogaard, Hagströmer, and Kirilenko, 2019). Ease of trading, low trading costs, and fragmented trading environments are essential to HFTs, which explains why HFTs focus on liquid assets (Brogaard, Hendershott, and Riordan, 2014). US cross-listing creates profitable opportunities for high frequency (HF) traders in the form of improved liquidity and reduced trading costs, and fragmentation in liquidity between the US and home markets (e.g., Foerster and Karolyi, 1998; Moulton and Wei, 2009).[3] We, therefore, expect non-US stocks to become more attractive to HFTs after US cross-listing.

[1]Data source: https://www.nyse.com/listings/international-listings (accessed 1 July 2021).
[2]Biais and Foucault (2014), SEC (2014), O'Hara (2015), and Menkveld (2016) provide excellent surveys of the literature on algorithmic and high-frequency trading.
[3]Conversely, US cross-listing reduces trading inefficiencies and mispricing of cross-listed stocks due to increased disclosure, information production, and monitoring. This, to some extent, reduces the financial rewards for HFTs.

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We test this hypothesis by examining domestic HFT activity for a sample of 112 Canadian stocks that had a cross-listed status on the NYSE between 2005 and 2017.[4,5] Within this sample, we focus on 62 cross-listing events that took place between 2005 and 2017 to examine the changes in HFT after US cross-listing. We compare the HFT activity of cross-listed Canadian stocks with that of matched non-cross-listed Canadian stocks. We use three proxies for HFT activity: the algorithmic trading metric of Hendershott, Jones, and Menkveld (2011) as implemented by Boehmer, Fong, and Wu (2020); the quotation intensity metric of Conrad, Wahal, and Xiang (2015), and the average trade size, used, among others, by Weller (2018).

Our findings support the argument that cross-listing in the US increases domestic HFT activity. We document that Canadian cross-listed stocks have significantly higher HFT activity than non-cross-listed stocks. Importantly, when we examine the changes in HFT activity around the cross-listing event, we observe a significant increase in domestic HFT activity after the cross-listing event vs. matched non-cross-listed stocks.

We explore three potential channels (or latency-sensitive strategies) through which cross-listing-induced HFT activity may manifest itself: (1) increased cross-market low-latency arbitrage; (2) enhanced news trading around public news originated in the US; and (3) greater activity of high-frequency market makers (HF-MMs) to provide liquidity.

Theory predicts (e.g., Kozhan and Tham, 2012; Foucault, Kozhan, and Tham, 2017), and empirical studies corroborate (e.g., Chaboud, Chiquoine, Hjalmarsson, and Vega, 2014; Shkilko and Sokolov, 2020) that HFTs exploit low-latency arbitrage opportunities across related assets in fragmented environments. We hypothesize that US cross-listing creates a new channel for low-latency cross-market arbitrage that HFTs can exploit. We test this hypothesis by looking at the

[4]Unlike other non-US stocks, Canadian stocks trade as ordinary shares in the US (Eun and Sabherwal, 2003).
[5]Our sample 112 cross-listed stocks include stocks that are already cross-listed at the beginning of the period (January 2005) as well as stocks that become cross-listed during our sample period (2005-2017).

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contemporaneous relation between US-Canadian mispricing and HFT activity using a structural vector autoregressive model. We document that an increase in HFT activity in the US market (US HFT) causes a significant contemporaneous increase in HFT activity in the Canadian market and vice versa. Moreover, an increase in US HFT activity leads to a significant decrease in the US-Canadian mispricing. Our results confirm that US cross-listing engenders low-latency arbitrage between Canada and the US, and this activity enhances price efficiency.

Theory also predicts (e.g., Foucault, Hombert, and Roşu, 2016) and empirics confirm (e.g., Benos and Sagade, 2016) that HFTs engage in directional or speculative trading, demanding liquidity in the same direction as subsequent price movements. Among the many sources of public information that drive HFTs' speculative trading, the literature shows that HFTs trade aggressively on macroeconomic news releases (Brogaard, Hendershott, and Riordan, 2014). We propose that US cross-listing increases a stock's price sensitivity to public news from the US, giving local opportunistic HFTs more events to trade on.[6] Accordingly, we predict an increase in domestic HFT activity around US public news after a US cross-listing event. To test this hypothesis, we examine changes in domestic HFT activity around pre-scheduled Federal Open Market Committee (FOMC) announcements. Supporting our hypothesis, we document a significant increase in domestic HFT activity around FOMC announcements vs. days with no FOMC announcements for cross-listed stocks but not for non-cross-listed stocks.

Finally, HFTs are also active in market-making, with some HFT firms mainly acting as liquidity providers (Hagströmer and Nordén, 2013; Brogaard, Hagströmer, Nordén, and Riordan, 2015). HF-MMs benefit from fragmented trading environments in managing their inventories (e.g., Menkveld, 2013; Lescourret and Moinas, 2018), exploiting transient decreases in liquidity

[6]Supporting this proposition, Dodd and Frijns (2018) show that non-US stocks become more dependent on the US as a source of information after US cross-listing, while Frijns, Indriawan, and Tourani-Rad (2015) find that the relative contribution of the US market to the price formation of Canadian cross-listed stocks changes around US macro news.

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(e.g., Foucault, Kadan, and Kandel, 2013; Foucault and Moinas, 2018), managing the risk of being adversely selected (e.g., van Kervel, 2015), or finding a counterparty faster (e.g., Degryse, de Winne, Gresse, and Payne, 2018). As cross-listing increases the overall fragmentation of the stock's trading environment, we expect non-US stocks to become more attractive to HF-MMs after US cross-listing. To test this hypothesis, we use the introduction of an excessive message traffic fee in Canada in April 2012. This fee works as a *de facto* tax on HF-MMs (Malinova, Park, and Riordan, 2018) and serves as an exogenous shock to HFT activity independent of the cross-listing event. We find that domestic HFT activity decreases following the fee introduction, and this decrease is larger for cross-listed stocks than for matched non-cross-listed stocks. The decrease in HFT after the fee introduction is accompanied by a deterioration in market liquidity, especially for cross-listed stocks. Thus, taxing HF-MMs has a greater impact on US cross-listed stocks, not only in terms of HFT activity but also in terms of market quality. Our findings align with the hypothesis that, after cross-listing, the stock's liquidity supply becomes more reliant on HF-MMs.

There is a general agreement in the literature that HF-MMs have a positive effect on market liquidity (Hendershott et al., 2011; Carrion, 2013; Brogaard and Garriott, 2019). However, their presumed low risk-bearing capacity (Roşu, 2019), the absence of any affirmative obligation to "lean against the winds" during turbulent times (Anand and Venkataraman, 2016), and the proliferation of episodes of a sudden evaporation of liquidity (Kirilenko, Kyle, Samadi, and Tuzun, 2017), have raised concerns that HFTs are making markets more fragile. Yet, we find no evidence that the increased HFT activity after US cross-listing increases market fragility. In fact, we document that the second moment of the distribution of stock liquidity metrics increases (decreases) after the fee introduction (cross-listing event) for Canadian cross-listed vs. non-cross-listed stocks.

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To our knowledge, this is the first study to examine the consequences of international cross-listings for HFT activity. Our study contributes to the novel but fast-growing literature on the determinants of HFT activity by documenting that US cross-listing is a significant driver of domestic opportunistic and market-making HFT activity. Knowledge of how trading in a company's shares is affected by cross-listing is highly relevant for firms. We show that US cross-listing makes cross-listed stocks more attractive to HFTs and more reliant on high-frequency market makers to supply stock liquidity. Although we find no evidence that boosted HFT activity after cross-listing harms market quality, corporate managers should be aware that US cross-listing may entail risks that are not yet well understood.[7]

We organize the rest of the paper as follows. We develop our hypotheses in Section 2. In Section 3, we define our HFT proxies. We introduce the data and provide sample details in Section 4. We present our empirical findings in Section 5 and conclude in Section 6.

2. Hypotheses development

2.1. US cross-listing and HFT Activity

Non-US firms that cross-list in the US are subject to US laws and regulations. US cross-listing involves registration and compliance with the US Securities and Exchange Commission's (SEC) listing requirements that include mandatory information disclosure (Coffee, 2002; Leuz, 2003). This leads to firms cross-listed in the US having higher disclosure levels than non-cross-listed firms (Khanna, Palepu, and Srinivasan, 2004). Cross-listed firms benefit from greater visibility, analyst coverage, and monitoring by institutional investors (e.g., Baker, Nofsinger, and Weaver, 2002; Lang, Lins, and Miller, 2003; Ferreira and Matos, 2008), which should

[7]For example, Malceniece, Malcenieks, and Putniņš (2019) show that HFT activity increases commonality in returns and liquidity, a finding that connects HFT activity with systematic risk (Acharya and Pedersen, 2005).

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reduce adverse selection costs (Brennan and Subrahmanyam, 1995). In line with this, Fernandes and Ferreira (2008) and Dodd and Gilbert (2016) report improvements in price efficiency and lower information asymmetries in the home market after a US cross-listing.

While an improved information environment could reduce potential profits of certain HFT strategies, US cross-listing also creates conditions that make stocks more attractive to HFTs. In particular, the cross-listing literature shows that cross-listing in the US enhances liquidity and reduces trading costs. For Canadian companies, Foerster and Karolyi (1993) report an increase of 62% (26%) in total (domestic) trading volume after cross-listing, while You, Parhizgari, and Srivastava (2012) report a decrease in trading volume after delisting. Foerster and Karolyi (1998) find a reduction in transaction costs (quoted and effective spreads) in the Canadian market after US cross-listing, which they attribute to intensified competition among market makers. When domestic and US trading hours diverge due to time zone differences, domestic trading of US-listed stocks concentrates during the overlapping trading period (e.g., Werner and Kleidon, 1996; Howe and Ragan, 2002), traders split orders across markets (e.g., Menkveld, 2008), and spreads and depth improve after cross-listing (e.g., Moulton and Wei, 2009).

HFTs hold short-lived open positions, have zero inventory overnight, and have small profit margins (SEC, 2010; Menkveld, 2013; Carrion, 2013). As such, high turnover and low trading costs are required to generate sizable profits, which explains why HFTs concentrate their activity on liquid stocks (e.g., Brogaard et al., 2014). Trading of liquid stocks incurs lower market-making costs, as it is easier to manage inventory (Aït-Sahalia and Saglam, 2017) and the risk of being adversely selected (Hoffmann, 2014).

In sum, US cross-listing offers Canadian stocks greater liquidity in the home market, which should attract HFTs. Therefore, our first hypothesis is as follows:

H1: US cross-listing leads to an increase in domestic HFT activity.

2.2. US cross-listing and cross-market arbitrage

Fragmented trading environments create opportunities for HFTs to exploit price inefficiencies across venues. US cross-listing opens an additional trading venue for HFTs to exploit potential misalignments between prices in the domestic and US markets via cross-market arbitrage. Suarez (2005), Alsayed and McGroarty (2012), and Ghadhab and Hellara (2015) document price discrepancies and arbitrage opportunities in cross-listed stocks. Gagnon and Karolyi (2010) show that deviations from price parity are economically small but volatile and can reach large extremes. They report that price parity deviations relate positively to proxies for holding costs that can limit arbitrage.

HFTs engage in low-latency arbitrage, which consists of exploiting extremely short-lived deviations from parity for prices of identical or related securities across venues, mostly through market orders.[8] The current highly fragmented trading landscape in the US facilitates latency arbitrage (e.g., O'Hara and Ye, 2011). Budish, Cramton, and Shim (2015) estimate an average of US$75 million per year at stake in latency arbitrage between the S&P500 ETF and the S&P500 E-mini futures contract. Wah (2016) estimates a potential profit resulting from latency arbitrage in S&P500 stocks of US$3.03 billion in 2014. Due to their ultra-fast algorithms, high-speed connectivity, and direct data feed access, HFTs are well-suited to exploit fleeting arbitrage opportunities (Biais and Foucault, 2014). Chaboud et al. (2014), Baron et al. (2019), and Boehmer et al. (2018), among others, provide empirical evidence that HFTs engage in cross-market latency arbitrage.

[8] Aquilina, Budish, and O'Neil (2020), Budish, Cramton, and Shim (2015), Foucault et al. (2017), Shkilko and Sokolov (2020), and Shkilko, Van Ness, and Van Ness (2008), among others, provide examples of low-latency arbitrage.

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We hypothesize that the predicted higher domestic HFT activity after US cross-listing (hypothesis H1) is, at least partly, driven by an increase in cross-market latency arbitrage. If this hypothesis holds, we should observe a positive contemporaneous correlation between HFT activity in the US and Canada. Additionally, enhanced latency arbitrage activity by HFTs should result in a reduction in the stock's mispricing between the Canadian and the US markets. Our next set of hypotheses is as follows:

H2a: HFT activity in the US and Canadian equity markets for Canadian cross-listed stocks has a positive contemporaneous correlation.

H2b: For Canadian stocks cross-listed in the US, HFT activity reduces the mispricing between US and Canadian equity markets.

2.3. US cross-listing and US public news announcements

Literature has documented that HFTs improve price efficiency at relatively high frequencies by trading on low-latency events such as order flow signals (Carrion, 2013; Hirschey, 2020). Brogaard et al. (2014) find that HFTs facilitate faster price discovery by trading aggressively in the direction of permanent price changes and provide liquidity against transient price pressures. Brogaard, Hendershott, and Riordan (2019) show that HFTs contribute to price discovery through both their liquidity demanding (market) orders and, most notably, their liquidity supplying (limit) orders. More recently, Chordia and Miao (2020) and Bhattacharya, Chakrabarty, and Wang (2020) extend the earlier evidence to low-frequency events by showing that HFTs facilitate the efficient assimilation of firm-specific fundamental information contained in earnings news releases. Other studies find that HFT activity increases around macroeconomic news events (Scholtus, van Dijk, and Frijns, 2014; Chordia, Green, and Kottimukkalur, 2018). Brogaard et al. (2014) find that HFTs facilitate faster price discovery by trading aggressively in the direction of permanent price changes and provide liquidity against transient price pressures. This is in line with Van Kervel and Menkveld (2019), who find that HFTs trade in the same direction with informed institutional orders, particularly if such orders are split into a series of small trades, which may take a few hours to complete.

Since the US is a world-leading economy, a large trading partner for many developed countries, and has the world's largest equity market, investors worldwide closely follow US news releases. Rapach, Strauss, and Zhou (2013) show that lagged US stock returns predict returns in non-US industrialized countries, while lagged foreign stock returns have limited predictive power for US stock returns. Wongswan (2006) finds that macroeconomic shocks that originate in the US quickly spread to capital markets of developing economies, affecting both volatility and trading volume. Singh, Nejadmalayeri, and Lucey (2013) find that Canada and Japan are particularly responsive to US macroeconomic news.

Finally, recent studies suggest that a US cross-listing could increase the sensitivity of stock price in the domestic market to US public news, giving HFTs more low-frequency events to trade on. Using data on US cross-listed stocks from 36 countries, Dodd and Frijns (2018) show that cross-listed stocks become more dependent on the US market as a source of information after US cross-listing. Similarly, Frijns, Indriawan, and Tourani-Rad (2015) examine the price discovery process of Canadian cross-listed stocks around US-released macroeconomic events. They find that the relative contribution of the US market to price discovery increases around the release of US macroeconomic news, which indicates that US news releases significantly affect the trading of Canadian stocks cross-listed in the US.

Building on these studies, we hypothesize that the increase in HFT activity after US cross-listing (hypothesis H1) can partly be explained by HFTs trading on low-frequency public news originating in the US. Specifically, our hypothesis is:

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H3: Domestic HFT activity around US public news announcements increases after US cross-listing.

2.4. US cross-listing and high-frequency market-making

Hypotheses H2 and H3 deal with opportunistic HFT, which usually involves aggressive trading that demands liquidity. Our last hypotheses relate to market-making strategies by HFTs. HF-MMs are endogenous liquidity providers, meaning they supply liquidity by posting non-marketable limit orders even though they have no obligation to do so (Anand and Venkataraman, 2016).[9] Academic studies generally agree that algorithmic traders (e.g., Hendershott et al., 2011; Boehmer et al., 2020) and HFTs specifically (e.g., Brogaard et al., 2015; Chakrabarty, Pankaj, Shkilko, and Sokolov, 2020) contribute to more liquid markets. Competition between HF-MMs also reduces the trading costs of non-HFTs (Brogaard and Garriott, 2019) and short-term volatility (Boehmer, Li, and Saar, 2018).

Counterbalancing these positive effects is the concern that HF-MMs are potentially making markets more fragile. The Flash Crash of May 6, 2010, and other episodes of a sudden evaporation of liquidity raise questions about the stability and reliability of the liquidity supplied by HFTs, especially in times of high volatility.[10] The empirical evidence in this regard is mixed. Hasbrouck and Saar (2013) find no evidence of reduced liquidity supply by HFTs during high volatility periods. Kirilenko et al. (2017) conclude that even though HF-MMs did not behave differently on the day of the Flash Crash relative to the preceding days, they did not contribute to preventing it. Brogaard et al. (2018) find that HFTs provide liquidity during extreme price

[9]For example, Hagströmer and Nordén (2013) examine 30 Swedish large caps traded on the NASDAQ-OMX Stockholm. They find that HF-MMs as a group represent 62.8% to 71.5% of all HFT trading volume and more than 80% of HFT limit order submissions are on the passive side in most of their trades.
[10]See the joint CFTC-SEC report on the Flash Crash https://www.cftc.gov/sites/default/files/idc/groups/public/@aboutcftc/documents/file/jacreport_021811.pdf

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movements by absorbing large order imbalances in single stocks. However, when several stocks experience extreme price movements simultaneously, HFTs become net liquidity takers. In related research, Benos, Brugler, and Hjalmarsoon (2017) and Boehmer et al. (2018) document commonality in trading strategies across HFT firms. Correlated trading behavior suggests that independent HFT firms often respond as a unified group to signals or market events, such as news releases or changes in expected profits, which fuels the fears that the HFT industry could destabilize markets. Anand and Venkataraman (2016) find that HF-MMs at the Toronto Stock Exchange scale back in unison when profit opportunities are small or market-making risk is high.

HFT and market fragmentation are symbiotic phenomena (Menkveld, 2016). Existing literature suggests that in a fragmented environment, HF-MMs can reduce their inventory management costs (Lescourret and Moinas, 2018), exploit more opportunities of making abnormal profits (Foucault and Moinas, 2018), lessen the risk of being adversely selected (van Kervel, 2015), and reduce search costs (Degryse et al., 2018). As US cross-listing increases the level of fragmentation of the stock's trading environment, Canadian stocks become more attractive to HF-MMs after cross-listing.

Building on these arguments, we hypothesize that US cross-listing will increase the reliance on (the contribution of) HF-MMs in the stock's domestic liquidity supply. While cross-listing-induced HFT activity can have positive effects on the *level* of domestic market liquidity, it might also increase the *dispersion* (fragility) in liquidity, causing lower stability. We, therefore, hypothesize that:

H4a: US cross-listing increases the relative weight of HF-MMs in liquidity supply.

H4b: Liquidity supply becomes more fragile (has higher dispersion) after US cross-listing.

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3. Measures of HFT activity

We consider three proxies for HFT activity motivated by the literature: the message-traffic-based algorithmic trading proxy of Hendershott et al. (2011), the quotation intensity metric of Conrad, Wahal, and Xiang (2015), and the average trade size (e.g., Weller, 2018). We compute these HFT proxies daily.

Our first HFT proxy is a function of electronic message traffic. International evidence shows that HFTs are the main contributors to message traffic in developed markets (e.g., Brogaard et al., 2015; Brogaard et al., 2019; Chakrabarty et al., 2020). Using message traffic normalized by trading volume, Hendershott et al. (2011) (hereafter, HJM) conclude that algorithmic trading improves liquidity and enhances price informativeness.[11] In their study, message traffic includes all order submissions, cancellations, and trade reports on the NYSE. While we do not have access to order-level data, we have access to quote updates for each market's consolidated best bid and offer (BBO). Therefore, we measure a subset of all order-related messages. Boehmer, Fong, and Wu (2020) find that the correlation between the order-level HJM metric and our BBO approximation is high and that "using just trades and changes in the best quotes should not impose serious problems" (p.13). In addition, HJM show that scaling message traffic by the number of trades rather than volume does not alter their findings.

We compute HJM's normalized message traffic metric (AT) as follows:

$$AT = -\frac{\$Vol/100}{MT}, \tag{1}$$

where $\$Vol$ is the dollar trading volume, and MT is total message traffic defined as the total number of all BBO updates and trades. Because we normalize the measure by trading activity,

[11] HJM's metric has been used by, e.g., Weller (2018), Degryse, Karagiannis, Tombeur, and Wuyts (2018), Boehmer, Fong, and Wu (2020), and Cox and Woods (2021), and is closely related to the order-to-trade and cancellation-to-trade ratios that have been used by, e.g., Hagströmer and Norden (2013), and Boehmer, Li, and Saar (2018).

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the changes in *AT* in Equation (1) are driven, for the most part, by limit order submissions or cancellations rather than executions. Therefore, *AT* is well suited to capture variation in HFT liquidity supply.[12] Higher values of *AT* indicate more HFT activity.

Our second HFT activity proxy is quotation intensity (a.k.a. quote flickering or high-frequency quoting). Flickering quotes that result from submitting and quickly canceling or revising orders are common and frequent events in modern markets (Hasbrouck and Saar, 2009; 2013) and are often associated with HFT (SEC, 2010). Baruch and Glosten (2013) propose a model where flickering quotes result from limit order traders managing their exposure by rapidly canceling their quotes and replacing them with randomly chosen ones. Similarly, Hasbrouck (2018) shows that quote flickering may arise from the strategies and interactions (such as successive undercutting) of HF-MMs competing for liquidity supply. Hasbrouck and Saar (2009) associate quote flickering with trading strategies whereby technologically sophisticated traders chase prices or search for hidden or latent liquidity. Finally, in the theoretical models of Hoffmann (2014) and Jovanovic and Menkveld (2016), fast traders update their quotes quickly and actively to manage their risk of being picked off.

Following Conrad et al. (2015), we compute quotation intensity (*QI*) as the number of best quote updates, which includes any changes in the BBO quote or size normalized by the number of trades.[13] A higher *QI* indicates more HFT activity.

Our third HFT proxy is the average trade size (*ATS*).[14] HFTs trade small quantities to maintain close-to-zero inventory positions (Menkveld, 2013). Angel, Harris, and Spatt (2011) report a significant decrease in ATS over time, which they attribute to the rise of algorithmic

[12]Our findings persist if we normalize *MT* by the number of trades instead of volume or if we simply use the raw message traffic numbers.
[13]This proxy has also been used by Chakrabarty, Moulton, and Pascual (2017); Brennan, Huh, and Subrahmanyam (2018), and Chakrabarty and Pascual (2021).
[14]Trade size has been previously used as an HFT activity proxy by Chung and Lee (2016), Aitken, Cumming, and Zhan (2017), and Weller (2018), among others.

trading. O'Hara, Yao, and Ye (2014) show that HFTs extensively use odd lot trades (i.e., trades for less than 100 shares). We compute *ATS* as the ratio of trading volume (in 100 shares) to the number of trades.

4. Data

To examine the impact of US cross-listing on HFT activity, we focus on a sample of Canadian stocks with their primary listing on the Toronto Stock Exchange (TSX) that are cross-listed (or become cross-listed) on the New York Stock Exchange (NYSE) during the period January 2005 to December 2017. We obtain the company name and industry of each Canadian cross-listed stock and the date of cross-listing from the NYSE website. Since we examine HFT activity in the Canadian market, we exclude direct foreign IPOs, i.e., Canadian stocks that do not trade in the Canadian market. We also exclude stocks that are not covered in Refintiv Datastream, our source for firm-level variables, such as market value and market-to-book ratio. Finally, we check for the availability of intraday data for the cross-listed stocks in the Refinitiv Tick History database.

Our final sample includes 112 Canadian stocks cross-listed on the NYSE, including 50 stocks already cross-listed at the beginning of our sample period and 62 stocks with cross-listing events during our sample period. Table I reports the sample distribution of cross-listed stocks and cross-listing events by year.[15] The largest number of cross-listed stocks is in 2017 (91) and 2013 (87). The largest number of cross-listing events took place in 2017 (12) and 2012 (9).

[Table I]

[15]The number of cross-listed stocks does not always equal to the number of cross-listed stocks in the previous year plus the number of cross-listing events due to delisting of Canadian stocks from the NYSE.

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For each cross-listed stock and year, we identify a matching non-cross-listed Canadian stock. We employ annually estimated propensity scores (Bacidore and Sofianos, 2002; Cumming, Hou, and Wu, 2017) to find the closest match based on the average daily price level, trading volume (the number of shares traded), and bid-ask spread.[16] Similar to the cross-listed stocks, we require coverage of matched non-cross-listed stocks in Datastream and Tick History.

We obtain intraday data from Refinitiv Tick History for cross-listed and matched non-cross-listed stocks. These data contain the consolidated best bid and offer (BBO) quotes and depths for the US and Canadian markets and the trades completed in each market. Trade data include the trade price and size. Both trades and quotes are time-stamped to the nearest millisecond.

In Figure 1, we plot the HFT time trends and compare the HFT activity of cross-listed stocks with non-cross-listed stocks. All three proxies suggest that HFT activity in the Canadian market has increased over time both for cross-listed and non-cross-listed stocks. The *AT* measure (Figure 1a) becomes less negative over time, and *QIT* (Figure 1b) increases over time, although not monotonically, with a significant increase up to 2013 and a subsequent decline. *ATS* (Figure 1c) shows a decreasing trend. Between cross-listed and non-cross-listed stocks, the former has higher levels of HFT activity (i.e., higher *AT* and *QIT*, and lower *ATS*).

[Figure 1]

Next, we examine cross-sectional differences in HFT activity between cross-listed and non-cross-listed stocks using the full sample of 112 Canadian stocks. In univariate analysis (reported in Appendix A.1), we find that cross-listed stocks have significantly higher levels of HFT activity than non-cross-listed stocks for all HFT proxies, consistent with the relative trends displayed in Figure 1. We also estimate multivariate Fama-MacBeth regressions

[16]The number of non-cross-listed stocks comparable with cross-listed Canadian stocks is limited given that most major Canadian companies are cross-listed in the US. If we do not find a unique match for a cross-listed stock based on our criteria, we match the same non-cross-listed stock with more than one cross-listed stock in the same year. In either case, the match is determined by propensity scores.

controlling for firm size, market-to-book ratio, stock liquidity, transaction costs, price level, and volatility. The estimation results (reported in Appendix A.2) indicate significantly higher levels of HFT activity for cross-listed relative to non-cross-listed stocks for all HFT proxies. The cross-sectional results provide initial support for our first hypothesis that cross-listing is associated with a higher domestic HFT activity.

5. Results

5.1. HFT activity before and after the cross-listing event

In this section, we provide a direct test for hypothesis H1 by examining the differences in HFT activity of cross-listed before and after the cross-listing event relative to non-cross-listed stocks. In this analysis, we use the subsample of 62 stocks that cross-listed during our sample period and their matched non-cross-listed stocks. We consider 6-month windows before and after each cross-listing date ("event") as the pre- and post-event periods.[17]

In Table II, we report average statistics for our HFT proxies, including pre- and post-event mean values, differences in means, and *t*-statistics for those differences. For cross-listed stocks, all three proxies show a significant increase in HFT activity after the cross-listing date (increases in *AT* and *QIT*, and a decrease in *ATS*). The difference-in-difference statistics show significantly larger changes in all HFT proxies for cross-listed stocks than non-cross-listed stocks.[18] These results support hypothesis H1.

[17]We find similar results using 9-month windows before and after the cross-listing date. These results are available upon request.

[18]We also plot the HFT proxies six months before and after the cross-listing date (reported in Appendix C). We observe that, compared to their non-cross-listed (NCL) counterparts, cross-listed (CL) stocks faced higher HFT activity following the cross-listing in the US, i.e., AT and QIT are higher, while ATS is smaller for CL relative to NCL.

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[Table II]

Next, we estimate the following multivariate regression models. Equation (2) is estimated for cross-listed stocks only, while Equation (3) is estimated for cross-listed and matched non-cross-listed stocks.

$$HFT_{i,t} = \alpha + \beta_{Post}Post_{i,t} + \beta_{MV}MV_{i,t} + \beta_{MTB}MTB_{i,t} + \beta_{VOL}VOL_{i,t} + \beta_{RSPR}RSPR_{i,t} + \beta_{P}\,(1/P_{i,t}) + \beta_{RV}RV_{i,t} + e_{i,t}, \tag{2}$$

$$HFT_{i,t} = \alpha + \beta_{CL\_Post}CL\_Post_{i,t} + \beta_{CL}CL_{i} + \beta_{Post}Post_{i,t} + \beta_{MV}MV_{i,t} + \beta_{MTB}MTB_{i,t} + \beta_{VOL}VOL_{i,t} + \beta_{RSPR}RSPR_{i,t} + \beta_{P}\,(1/P_{i,t}) + \beta_{RV}RV_{i,t} + e_{i,t}, \tag{3}$$

where $HFT_{i,t}$ is one of the HFT proxies for stock *i* on day *t.* The main explanatory variable in Equation (2) is $Post_{i,t}$, an indicator variable that takes the value 1 for post-event observations and 0 otherwise. The main explanatory variable in Equation (3) is $CL\_Post_{i,t}$, which is the product of CL_i, an indicator variable that takes the value 1 for cross-listed stocks and 0 for matched stocks, and $Post_{i,t}$. We control for firm characteristics using the log of the market value of equity ($MV_{i,t}$), and the ratio of market to book value of equity ($MTB_{i,t}$).[19] We also control for stock characteristics such as trading volume (in shares) ($VOL_{i,t}$), relative quoted bid-ask spread ($RSPR_{i,t}$) which is a direct (inverse) metric of trading costs (liquidity), the inverse of the daily average stock price ($1/P_{i,t}$), and realized volatility ($RV_{i,t}$), computed as the sum of the squared quote midpoint 5-minute returns. We include year-fixed effects to control for time trends in HFT activity. Continuous variables are winsorized at 1% at each tail of the distribution. HFT proxies are normalized by subtracting the mean and dividing by the standard

[19]In unreported robustness test, we also include financial analysts' coverage, and institutional ownership to control for the changes in firm characteristics around the cross-listing event. Our results on the impact of cross-listing on HFT are robust to the inclusion of these additional variables.

deviation. We estimate the model by OLS with standard errors clustered by stock and date. We report the estimation results in Table III.

[Table III]

The first three columns of Table III report the estimation results of Equation (2) for 62 cross-listed stocks. The *Post* variable that indicates the change after the cross-listing event is significant at the 1% level for all HFT proxies confirming a significant increase in HFT activity (increase in *AT* and *QIT* and decrease in *ATS*) in the home market after the US cross-listing. The last three columns of Table III report the estimation results of Equation (3) for 62 cross-listed stocks and the matched non-cross-listed stocks. We find positive and significant coefficients for the *CL_Post* dummy for *AT* and *QIT* and a negative and significant coefficient for *ATS*, all indicating a significant increase in HFT activity for cross-listed stocks after the cross-listing event relative to non-cross-listed stocks. *CL* and *Post* are insignificant in all three models, indicating no significant differences in HFT activity between cross-listed and matched stocks before the cross-listing event and no differences in HFT activity for the non-cross-listing stocks between the pre- and post-event periods, respectively. For the control variables, we find that stocks with larger market capitalization, higher realized volatility, and smaller quoted spread have higher levels of HFT activity in all models. Overall, these results provide direct support for our H1, as US cross-listing enhances HFT activity in the domestic market.

5.2. Channels of cross-listing-induced HFT activity

We have shown that cross-listing leads to an increase in domestic HFT activity. In this section, we examine three specific channels (or trading strategies) to explain the increase in HFT activity after cross-listing: (1) cross-market arbitrage activity (hypothesis H2a, H2b); (2) news

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trading around US public news announcements (hypothesis H3); and (3) high-frequency market making (hypotheses H4a, H4b).

5.2.1. Cross-market arbitrage

According to hypothesis H2a, an increased cross-market arbitrage activity should manifest in an increased positive relation between HFT activity in the Canadian and US markets. According to hypothesis H2b, cross-listing-induced low-latency arbitrage between the US and Canadian markets should reduce the occurrence of mispricing between the two markets. To test these two hypotheses, we model the contemporaneous and dynamic relationship between mispricing and HFT activity.

We define mispricing as the sum of the squared log differences between quote midpoints in the Canadian and US markets. We compute the mispricing as follows. For each stock-day, we match 1-second quote midpoints in the two markets, expressing the US quotes in Canadian dollars using the 1-second CAD/USD exchange rate from Tick History. For each second, we first take the log difference in quotes between the two markets and then square this difference. Finally, we aggregate the squared differences for the day. Since mispricing and HFT affect each other contemporaneously and both variables can exhibit some degree of persistence, we implement a Structural Vector Autoregressive (SVAR) model to capture their contemporaneous and dynamic relation,

$$\Pi_0 Y_t = c + \sum_{l=1}^{L} \Pi_l Y_{t-l} + \varepsilon_t \,, \tag{4}$$

where $Y_t = (Misp_t, HFT_t^{CAN}, HFT_t^{US})'$ is a (3×1) vector containing the mispricing ($Misp_t$) and the HFT proxy for Canada and the US, Π_l is a (3×3) matrix with autoregressive coefficients for lag l, c is a (3×1) vector with intercept terms, and ε_t is a vector of error terms. The matrix Π_0

contains the structural parameters, where all diagonal elements are set to unity, and the off-diagonal elements, which capture the contemporaneous interactions between the variables, are free parameters

$$\Pi_0 = \begin{pmatrix} 1 & a_{12} & a_{13} \\ a_{21} & 1 & a_{23} \\ a_{31} & a_{32} & 1 \end{pmatrix}.$$

Since Π_0 is asymmetric, the parameters in Π_0 cannot be obtained by OLS. Instead, we use the identification-through-heteroskedasticity approach of Rigobon (2003).

We start by obtaining the reduced form of the SVAR in Equation (4),

$$\begin{aligned} Y_t &= \Pi_0^{-1} c + \sum_{l=1}^{L} \Pi_0^{-1} \Pi_l Y_{t-l} + \Pi_0^{-1} \varepsilon_t, \\ Y_t &= \tilde{c} + \sum_{l=1}^{L} \tilde{\Pi}_l Y_{t-l} + \tilde{\varepsilon}_t \end{aligned} \tag{5}$$

We estimate the VAR in Equation (5) by OLS and use the estimated residuals, $\tilde{\varepsilon}_t$, as the basis for the heteroskedasticity identification scheme. Specifically, we split the residuals into subsamples, such that the covariance matrices under these subsamples are not proportional to each other. Once the different heteroskedastic regimes have been identified, we increase the number of available moment conditions to identify the parameters in Π_0 (Appendix B elaborates on the identification procedure).

Using our sample of 112 Canadian cross-listed stocks, we estimate Π_0 for each HFT proxy and report the results in Table IV. The dependent variables are in the top-most row and the explanatory variables are in the left-most column.

[Table IV]

For all three HFT proxies, we find that an increase in US HFT activity (HFT^{US}) leads to a significant decrease in mispricing, as indicated by the significant negative coefficients of

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HFT^{US} for the AT and QIT models (Panels A and B) and the significant positive coefficient for the ATS model (Panels C). Consistent with hypothesis H2b, US HFT activity contributes to keeping prices of Canadian cross-listed stocks in the two markets close to each other. Consistent with hypothesis H2a, we find that an increase in HFT^{US} causes a significant contemporaneous increase in Canadian HFT activity (HFT^{CAN}) and vice versa. Causal positive effects from HFT^{US} to HFT^{CAN} and from HFT^{CAN} to HFT^{US} hold for all three HFT proxies and are significant at the 1% level. Our findings, therefore, show that HFT activity in both markets affects each other and provide evidence that cross-market low-latency arbitrage is a significant channel of cross-listing-induced HFT activity. Our findings, therefore, show that HFT activity in both markets affects each other and provide evidence that cross-market low-latency arbitrage is a significant channel of cross-listing-induced HFT activity. Our findings are in line with Chen et al. (2017), who provide direct evidence that Canadian HFTs are highly active in a fragmented trading environment domestically.[20]

5.2.2. US public news announcements

According to hypothesis H3, cross-listing-induced HFT is partly explained by trading around US public news releases, which is a consequence of the enhanced sensitivity of the stock's price to public news originating in the US after the US cross-listing event. To test this hypothesis, we focus on the widely followed pre-scheduled US FOMC announcements. More specifically, we use the sample of 112 cross-listed and their corresponding matched stocks to examine whether HFT activity increases around FOMC releases and whether the increase in HFT activity around

[20] Chen et al. (2017) investigate the relaunch of a Canadian exchange TSX Alpha, which involves several modifications including a randomized speed bump and an exemption from the Order Protection Rule. They find that a millisecond delay can enable costly informational leakage across venues, suggesting that HFTs are highly active in a fragmented trading environment.

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FOMC announcements is higher for cross-listed stocks than for non-cross-listed stocks. We collect the date and time of the FOMC announcements from Bloomberg. For the announcement period, we focus on the 30 minutes before and after the news release.[21] For the non-announcement period, we consider two days before and after each FOMC release date and take the same 60-minute window as for the announcement day.

We report univariate results in Table V. For all three HFT proxies, HFT activity of cross-listed stocks is significantly higher during announcement than non-announcement periods. In contrast and in line with our expectations, there is no significant difference in HFT activity for non-cross-listed stocks between the announcement and non-announcement periods. We also find that HFT activity for cross-listed stocks is significantly higher than for non-cross-listed stocks during both non-announcement and announcement periods. In the last columns of Table V, we report the difference-in-difference estimates. Significant and positive differences for *AT* and *QIT*, and significant and negative difference for *ATS* suggest that cross-listed stocks experience a significant increase in HFT activity relative to non-cross-listed stocks around FOMC announcement times.

[Table V]

We complement the univariate statistics with a multivariate regression analysis. We estimate the following pooled regression model:

$$HFT_{i,t} = \alpha + \beta_{CL\_USnews} CLpost\_USnews_{i,t} + \beta_{CL} CLpost_i + \beta_{USnews} USnews_t + \beta_{MV} MV_{i,t} + \beta_{VOL} VOL_{i,t} + \beta_{RSPR} RSPR_{i,t} + \beta_P \left(1/P_{i,t}\right) + \beta_{RV} RV_{i,t} + e_{i,t}, \quad (6)$$

where $HFT_{i,t}$ is one of our HFT proxies estimated for stock *i* on day *t*. The main explanatory variable is the interaction term $CLpost\_USnews_{i,t}$, which is the product of $CLpost_i$, an

[21]Prior to 2013, the release time of these announcements vary between 12:30pm and 2:15pm (ET). Since 2013, the release occurs at 2:00pm (ET).

indicator variable that takes the value 1 for cross-listed stocks after the cross-listing event and 0 for matched stocks, and $USnews_t$, an indicator variable that takes the value 1 for the FOMC announcement periods and 0 for non-announcement periods. The coefficient for $CLpost\_USnews_{i,t}$ indicates the incremental change in HFT activity of cross-listed stocks during the announcement period, beyond the changes in HFT experienced by all stocks (cross-listed and matched). The coefficient on $CLpost_i$ captures potential differences in HFT activity between cross-listed and matched stocks, whereas the coefficient on $USnews_t$ indicates changes in HFT activity during event periods experienced by both cross-listed and matched stocks. We include the same control variables as in Equations (2) and (3) and year fixed effects to control for time trends in HFT activity. We winsorize all continuous variables at 1% at each tail of the distribution and normalize the HFT activity proxies. We estimate the model using OLS with standard errors clustered by stock and date and report the estimation results in Table VI.

[Table VI]

We report positive and significant coefficients for $CLpost\_USnews_{i,t}$ for AT and QIT proxies. This result indicates that HFT activity for cross-listed stocks tends to increase relative to non-cross-listed stocks around the US public news announcements, controlling for other factors that may affect HFT activity. Overall, our findings show that Canadian HFT activity around US public news releases increases significantly more for the cross-listed sample. Cross-listing offers HFTs additional profitable opportunities to trade cross-listed stocks in their home market during public news releases. This evidence provides support to our hypothesis H3.

5.2.3. High-frequency market-making

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Hypotheses H4a and H4b postulate that US cross-listing boosts the contribution of HF-MMs to the cross-listed stock's liquidity supply (H4a), potentially increasing the average liquidity supply but also its fragility (H4b). To test these hypotheses, we use the introduction of a message traffic fee in Canada in April 2012 as an instrument. The Investment Industry Regulatory Organization of Canada imposed this message fee to cope with the increasing information technology costs for real-time market surveillance, based on the notion that those who generate the most costs should cover most of the cost-recovery fees. As such, the introduction of excessive message fee is an exogenous shock to HFTs. Korajczyk and Murphy (2019) document that daily HFT message traffic decreased by about 20% following the change, while Malinova et al. (2018) find that the message fee predominantly affected HF-MMs. Thus, it is a suitable regulatory change to test H4a and H4b. Malinova et al. (2018) also find that because of this *de facto* tax on HF-MMs, trading costs for both retail (quoted and effective spreads) and institutional investors (implementation shortfall) increased. They, however, do not consider the cross-listing angle.

To test hypothesis H4a and to evaluate the differences in HFT activity between cross-listed and non-cross-listed stocks around the message fee introduction, we estimate the following pooled regression model:

$$HFT_{i,t} = \alpha + \beta_{CL\_Fee} CL\_Fee_{i,t} + \beta_{CL} CL_i + \beta_{Fee} Fee_{i,t} + \beta_{MV} MV_{i,t} + \beta_{MTB} MTB_{i,t} + \beta_{VOL} VOL_{i,t} + + \beta_{RSPR} RSPR_{i,t} + \beta_P (1/P_{i,t}) + \beta_{RV} RV_{i,t} + e_{i,t}, \quad (7)$$

Where *Fee* is an indicator variable that takes the value 1 for the period after the introduction of the message fee and 0 otherwise. CL is an indicator variable that takes the value 1 for cross-listed stocks and 0 for matched stocks. The main explanatory variable is the interaction term *CL_Fee,* the product of *CL* and *Fee* variables; the coefficient on *CL_Fee* indicates the incremental impact of the message fee on HFT activity of cross-listed stocks. We use the same control variables as in the preceding models. As a pre-event period, we take three months before April 1, 2012, and as a post-event period, we take the three months after May 1, 2012. We drop April 2012 because even though the message fee was in force since April 2012, HFTs were charged from May 2012 onwards (Korajcyzk and Murphy, 2019; Malinova et al., 2018). We report our findings in Table VII (Panel A).

[Table VII]

According to hypothesis H4a, we expect cross-listed stocks to experience a greater reduction in HFT activity than non-cross-listed stocks after the message fee implementation. Our estimation results confirm this expectation. Only the stocks that were cross-listed in the US by the time the message traffic fee was introduced experience a significant reduction in HFT activity after the regulatory change, as measured by two out of three of our HFT proxies: *AT* decreases ($CL\_Fee + Fee < 0$) and *ATS* increases ($CL\_Fee + Fee > 0$). In general, our findings are consistent with hypothesis H4a and provide additional support to the causal link between cross-listing and HFT activity (H1).

In Panel B of Table VII, we report the estimation results on the impact of the message traffic fee implementation on the level of stock liquidity. We measure stock liquidity using four variables: (1) the relative quoted spread in basis points, *RSPR*, (2) the quoted depth at the National Best Bid and Offer in logs, *DEPTH*, (3) trading activity measured by the logarithm of the volume in shares, *VOL*, and (4) message traffic, *MSSG*, also in logs. We re-estimate Equation (7) but change the dependent variable to one of the above liquidity metrics, winsorized and normalized as in previous tests.

Consistent with Malinova et al. (2018), we observe that the message fee (*Fee*) has a negative effect on liquidity both in terms of higher immediacy costs (a wider *RSPR*) and lower *DEPTH*. Trading activity is also lower after the message fee implementation, suggesting lower gains from trading. Consistent with hypothesis H4a, the negative impact on liquidity is more severe for cross-listed stocks, as shown by the significant *CL_Fee* coefficient, positive for *RSPR*, and negative for *DEPTH* and *VOL*. The message fee also reduces *MSSG* for cross-listed stocks more than for non-cross-listed stocks. Overall, our findings support hypothesis H4a, that after cross-listing in the US, HF-MM contribution to liquidity supply increases. As a result, their liquidity supply becomes more sensitive to any regulatory restriction imposed on HFTs.

Finally, we address the question raised in hypothesis H4b: does liquidity supply for cross-listed stocks become more fragile after cross-listing? To proxy fragility, we use the second moment of the distribution of stock liquidity. We first examine whether the introduction of the excessive message fee decreases the dispersion of liquidity. We measure dispersion in stock liquidity using four variables: (1) the standard deviation of the quoted relative bid-ask spread (*SD_RSPR*), (2) the standard deviation of the quoted depth at the best quotes (*SD_DEPTH*), (3) the semi-deviation of the quoted relative bid-ask spread with zero weight to negative deviations from the mean of *RSPR* (*SMD_RSPR*), and (4) the semi-deviation of the quoted depth at the best quotes with zero weight to negative deviations from the mean of *DEPTH* (*SMD_DEPTH*). These semi-deviations are expected to reveal any change in worse-case scenarios as a result of the fee on excessive message traffic. We estimate Equation (7) again, this time using the fragility metrics as dependent variables. Results are reported in Panel A of Table VIII.

[Table VIII]

We observe that, after the introduction of the excessive message fee, *SD_RSPR* increases for all Canadian stocks (positive and significant at the 1% level *Fee* variable) and, more notably for cross-listed stocks (positive and significant at the 1% level *CL_Fee* variable), suggesting that HF-MMs stabilize trading costs, at least, during normal times. The semi-deviation of *RSPR* (*SMD_RSPR*) shows a similar positive increase for all stocks and additionally for cross-listed stocks, indicating that the augmented instability of the quoted spread is not driven by negative

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fluctuations from the mean. For the depth dimension of liquidity, *SD_DEPTH* decreases after the message traffic fee implementation for all stocks and more so for cross-listed stocks, suggesting higher stability in quoted depth once HF-MMs were penalized. However, the *SMD_DEPTH* regression shows that this finding is mostly driven by positive fluctuations from the depth mean.

For robustness, we also test hypothesis H4b around cross-listing events. For that, we use the subsample of 62 Canadian stocks that cross-list during our sample period and their matched stocks. We estimate Equation (3) using our fragility metrics as the dependent variables and report findings in Panel B of Table X.[22] Canadian stocks experience significant declines in both *SD_RSPR* and *SD_DEPTH* after cross-listing, supporting our message-fee experiment conclusions. Therefore, our results show that enhanced high-frequency market making activity after cross-listing brings about higher stability in liquidity supply.

Overall, our analysis shows that US cross-listing of Canadian firms increases the dependence of Canadian stocks on HF-MMs to supply liquidity (H4a not rejected). This increase in high-frequency market making activity does not result in a more fragile liquidity supply (H4b rejected). HF-MMs behavior under stress could differ from the one we observe, as the literature suggests. Therefore, corporate managers and investors should be aware that a higher reliance on HF-MMs after cross-listing to supply liquidity may expose their firms to risks and costs that are not yet researched.

6. Conclusion

[22]Since we match each cross-listed stock with a non-cross-listed stock annually, we cannot compute the semi-deviations in this case. Therefore, we only report our findings with the standard deviations of liquidity metrics.

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This study contributes to understanding the consequences of US cross-listings when HFTs populate equity markets. Using a sample of Canadian stocks cross-listed on the NYSE, we provide robust evidence that domestic HFT activity of Canadian stocks increases significantly after cross-listing in the US.

Our empirical analysis suggests that US cross-listing increases both opportunistic trading and market-making by HFTs. First, cross-listing opens a venue for cross-market low-latency arbitrage that HFTs can exploit. We document a significant bi-directional contemporaneous causality in HFT activity between the Canadian and US equity markets. We also show that HFT activity on cross-listed stocks significantly reduces mispricing between the US and Canadian markets.

Second, US cross-listing provides additional profit opportunities that HFTs can exploit through their relative speed advantage around US public news announcements. We document a significant increase in HFT activity of cross-listed relative to non-cross-listed stocks around the US FOMC news announcements.

Third, US cross-listing enhances high-frequency market making by increasing the fragmentation of the stock's trading environment. As a result, the HF-MMs' contribution to liquidity supply increases after a US cross-listing event. We report that after the introduction of an excessive message fee in Canada in April 2012, market liquidity deteriorates more for cross-listed than non-cross-listed stocks. In the context of the regulatory restrictions on HFT activity, we find that this shock to high-frequency market making activity does not increase the fragility of the liquidity supply.

Our findings have important implications for market regulators to understand the determinants and consequences of HFT and for stock exchanges when considering low latency platforms to compete for order flow in fragmented markets. Our results also have implications

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for non-US companies cross-listed in the US or are considering that possibility. Malceniece, Malcenieks, and Putniņš (2019) show that HFT activity increases co-movements in returns and liquidity across stocks. Greater co-movement in returns means reduced benefits of cross-sectional diversification and, hence, higher systematic risk. Similarly, greater commonality in liquidity means higher expected returns as investors require a premium on stocks that become illiquid when the overall market becomes illiquid (Acharya and Pedersen, 2005). Malceniece et al. (2019) show that the correlated strategies of both opportunistic HFTs and MF-MMs increase the systematic risk of investors. The knowledge that cross-listing boosts HFT activity in their stocks in the home market should therefore be a matter of concern for firms, as it could lead to an increase in the firm's cost of capital and, therefore, impact real investments. Although we do not find that the incremental HFT activity after cross-listing harms market liquidity or increases market fragility, corporate managers should be aware that US cross-listing may expose their firms to risks that are not yet well understood.

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Figure 1
HFT activity of cross-listed and matched non-cross-listed stocks over time

This figure presents the average daily values of our HFT proxies for 112 cross-listed (CL) Canadian stocks and their matched non-cross-listed Canadian stocks (NCL) for the period 2005-2017. AT is the message-to-trade ratio (Figure 1a), QIT is the quote-intensity-to-trade ratio (Figure 1b), and ATS is the average trade size (Figure 1c). All HFT proxies are winsorized at 1%.

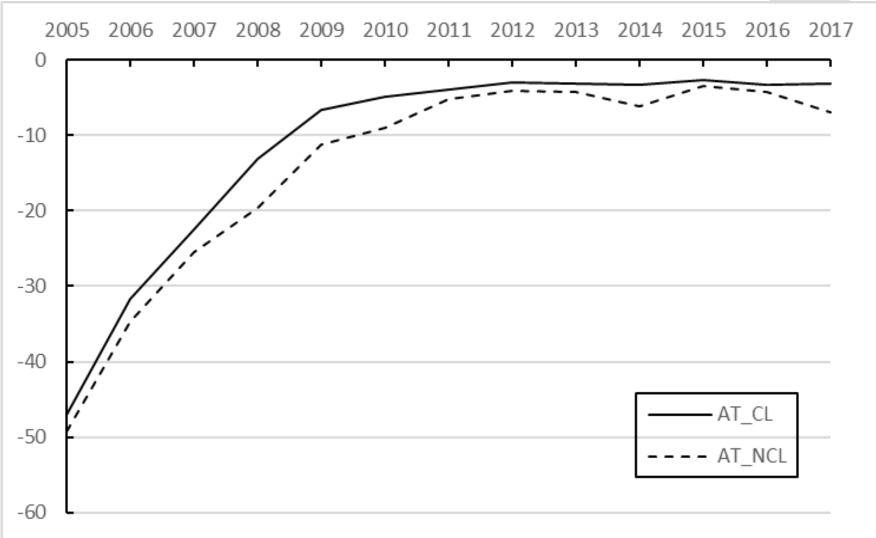

Figure 1a. AT

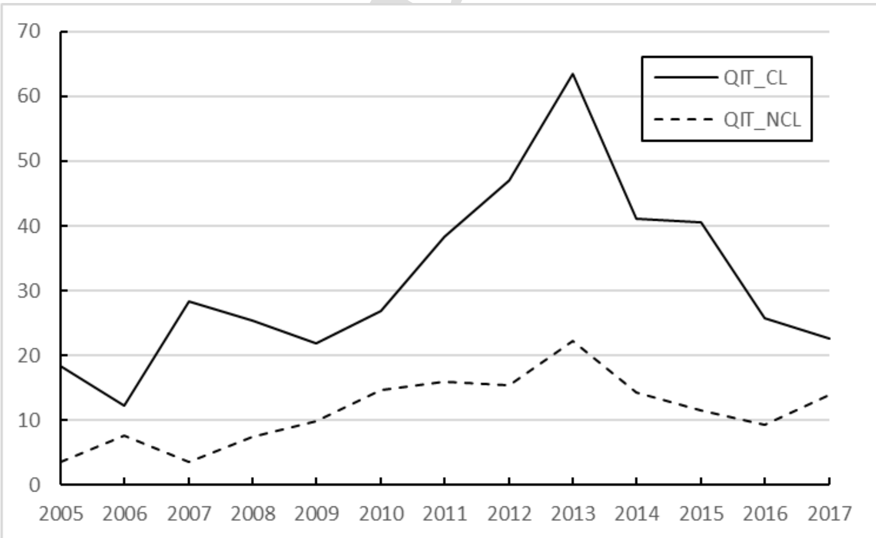

Figure 1b. QIT

Figure 1 continued

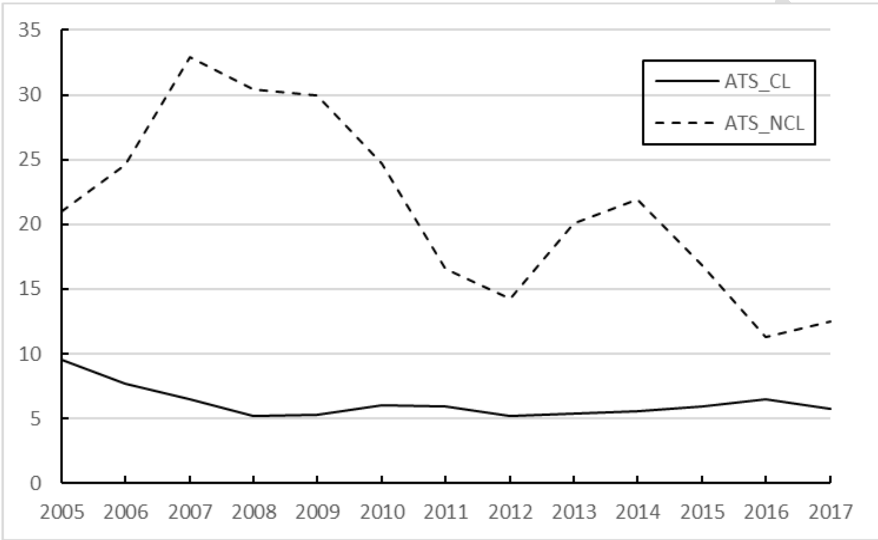

Figure 1c. ATS

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Table I
Cross-listed Canadian stocks: Sample distribution by year

This table reports the number of Canadian stocks cross-listed on the NYSE and the number of cross-listing events by year during the sample period 2005 to 2017.

Year	Number of cross-listed stocks	Number of cross-listing events
2005	59	5
2006	64	7
2007	65	4
2008	66	1
2009	72	2
2010	76	4
2011	85	4
2012	86	9
2013	87	3
2014	85	3
2015	82	3
2016	81	5
2017	91	12
Total number of unique stocks	112	62

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Table II
Changes in HFT activity around the cross-listing event: Univariate analysis

This table reports mean values of HFT proxies six months before and after the cross-listing date (Before and After, respectively) for 62 cross-listed stocks and their matched non-cross-listed stocks, and the differences in means with *t*-statistics in parentheses. *AT* is the message-to-trade ratio from Hendershott et al. (2011), *QIT* is the quote-intensity-to-trade ratio, and *ATS* is the average trade size. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level, respectively.

	Cross-listed stocks			Matched stocks			Difference (Cross-listed - Matched)		
	Before	After	Difference (After - Before)	Before	After	Difference (After - Before)	Before	After	Difference (After - Before)
AT	-14.07	-8.99	5.09*** (2.96)	-13.95	-11.58	2.37** (2.21)	-0.13 (-0.05)	2.59 (1.10)	2.72* (1.91)
QIT	9.48	13.37	3.89** (2.49)	12.70	11.04	-1.66 (-0.84)	-3.22 (-1.20)	2.33 (0.82)	5.55* (1.66)
ATS	6.21	3.53	-2.68*** (-3.07)	9.54	9.60	0.06 (0.05)	-3.32 (-1.41)	-6.07** (-2.33)	-2.74* (-1.74)

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Table III
Multivariate analysis of HFT around cross-listing events

This table reports the estimation results of Equation (2) for the sample of 62 cross-listed stocks (first three columns) and Equation (3) for the sample of 62 cross-listed stocks and their matched non-cross-listed stocks (last three columns). The event window is six months before and after the cross-listing date. The dependent variables are three HFT proxies computed daily. *AT* is the message-to-trade ratio from Hendershott et al. (2011), *QIT* is the quote-intensity-to-trade ratio, and *ATS* is the average trade size. *Post* is an indicator variable that takes the value 1 for post-cross-listing-event observations and 0 otherwise. *CL* is an indicator variable that equals 1 for cross-listed stocks and 0 for matched non-cross-listed stocks. *CL_Post* is the interaction variable between *CL* and *Post*. Control variables include the log of market capitalization (*MV*), the ratio of market to book value (*MTB*), trading volume (in shares) (*VOL*), the relative quoted bid-ask spread (*RSPR*), the inverse of the daily average stock price (*1/P*), and realized volatility (*RV*). All continuous variables are winsorized at 1% at each end of the distribution; HFT proxies are normalized per stock. Standard errors are clustered by stock and date; *t*-statistics are reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Cross-listed stocks			Cross-listed and matched stocks		
	AT	QIT	ATS	AT	QIT	ATS
CL_Post	-	-	-	0.30**	0.20*	-0.38***
				(2.54)	(1.67)	(-3.94)
CL	-	-	-	-0.04	-0.01	0.03
				(-0.59)	(-0.14)	(0.39)
Post	0.42***	0.29***	-0.42***	0.13	0.08	-0.02
	(6.24)	(3.44)	(-6.31)	(1.29)	(0.86)	(-0.31)
MV	0.20***	0.17***	-0.17***	0.15***	0.17***	-0.24***
	(5.94)	(5.30)	(-4.63)	(4.57)	(7.31)	(-7.11)
MTB	-0.07**	-0.03	0.03	-0.02	0.01	-0.03
	(-2.13)	(-1.60)	(0.74)	(-1.01)	(0.48)	(-0.90)
VOL	-0.34***	-0.20***	0.34***	-0.28***	-0.19***	0.36***
	(-8.26)	(-6.21)	(7.58)	(-9.29)	(-8.08)	(10.48)
RSPR	-0.42***	-0.11	0.48***	-0.26***	-0.04	0.32***
	(-3.80)	(-1.01)	(3.45)	(-3.34)	(-0.76)	(3.69)
1/P	0.55**	0.24***	-0.22*	0.31***	0.11*	-0.31***
	(2.46)	(2.73)	(-1.87)	(3.52)	(1.95)	(-3.38)
RV	0.14***	0.02	-0.14***	0.16***	0.04*	-0.10***
	(4.52)	(0.91)	(-3.76)	(6.61)	(1.86)	(-3.76)
Constant	2.46***	0.85**	-2.60***	2.18***	0.78***	-2.17***
	(4.80)	(2.28)	(-4.70)	(6.20)	(3.07)	(-5.60)
Year fixed effects	YES	YES	YES	YES	YES	YES
Observations	15,928	15,928	15,928	27,712	27,712	27,712
R-squared	0.18	0.10	0.20	0.13	0.09	0.22

Table IV
Cross-market HFT activity and mispricing

This table reports the estimation results of the VAR in Equation (4) for the sample of 112 cross-listed stocks over the period 2005-2017, using the identification through heteroskedasticity approach of Rigobon (2003). The table reports coefficient estimates for the contemporaneous interactions between mispricing ($Misp_t$) and HFT activity in Canadian (HFT^{CAN}) and the US (HFT^{US}) markets. Mispricing is the sum of the squared log differences between prices in Canadian and US markets, where quote midpoints are collected at 1-second frequency. We consider three HFT proxies: *AT* is the message-to-trade ratio from Hendershott et al. (2011) (Panel A), *QIT* is the quote-intensity-to-trade ratio (Panel B), and *ATS* is the average trade size (Panel C). The column variable is the dependent variable, while the row variable is the explanatory variable. Robust *t*-statistics are reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Dependent variables		
	$Misp_t$	HFT^{CAN}	HFT^{US}
Panel A: *AT*			
$Misp_t$		-0.002	-0.002
		(-1.36)	(-1.31)
HFT^{CAN}	-0.036		0.144***
	(-0.75)		(4.04)
HFT^{US}	-0.398***	0.221***	
	(-2.89)	(2.98)	
Panel B: *QIT*			
$Misp_t$		-0.005	0.000
		(-1.57)	(-0.04)
HFT^{CAN}	-0.137*		0.199***
	(-1.87)		(5.72)
HFT^{US}	-0.131*	0.214***	
	(-1.81)	(5.11)	
Panel C: *ATS*			
$Misp_t$		0.000	0.000
		(0.41)	(0.08)
HFT^{CAN}	-0.030		0.063***
	(-0.36)		(3.25)
HFT^{US}	0.163**	0.089**	
	(1.99)	(2.10)	

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Table V
HFT activity around US public news announcements: Univariate analysis

This table reports mean values of HFT proxies in Canada around the Federal Open Market Committee (FOMC) announcements for 112 cross-listed Canadian stocks and matched non-cross-listed stocks. For the announcement period, we use the 30-minute interval before and after each FOMC announcement (Ann.). For the non-announcement period, we use the same time interval for the two days before and after the announcement day (Non-ann.). The table also reports the differences in means with *t*-statistics in parentheses. *AT* is the message-to-trade ratio from Hendershott et al. (2011); *QIT* is the quote-intensity-to-trade ratio, and *ATS* is the average trade size. ***, **, and * indicate statistical significance at the 1%, 5% and 10 % level, respectively.

	Cross-listed stocks			Matched stocks			Difference (Cross-listed - Matched)		
	Non-ann.	Ann.	Difference (Ann. - Non-ann.)	Non-ann.	Ann.	Difference (Ann. - Non-ann.)	Non-ann.	Ann.	Difference (Ann. - Non-ann.)
AT	-9.90	-8.54	1.36*** (6.22)	-12.66	-12.14	0.52 (1.40)	2.76*** (8.19)	3.60*** (9.16)	0.84** (2.23)
QIT	18.13	20.42	2.29** (2.22)	9.77	9.6	-0.17 (-0.31)	8.36*** (10.43)	10.82*** (14.10)	2.46** (2.10)
ATS	3.13	2.92	-0.21** (-2.26)	8.28	8.46	0.18 (0.89)	-5.15*** (26.28)	-5.54*** (24.42)	-0.39* (-1.69)

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Table VI
HFT activity around US public news announcements: Multivariate analysis

This table reports the estimation results of the pooled regression model in Equation (6) for the sample of 112 cross-listed stocks and their matched non-cross-listed stocks. As US news, we use the Federal Open Market Committee (FOMC) announcements. For the announcement period, we use the 30-minute interval before and after each US news announcement. For the non-announcement period, we take the same time interval for the two days before and the two days after the announcement day. *AT* is the message-to-trade ratio from Hendershott et al. (2011), *QIT* is the quote-intensity-to-trade ratio, and *ATS* is the average trade size. The main explanatory variable is *CL_USnews*, the interaction between the cross-listing indicator variable (*CLpost*) that equals 1 for cross-listed stocks after the cross-listing event and 0 for matched non-cross-listed stocks, and the post-event indicator variable (*USnews*). Control variables include the log of market capitalization (*MV*), the ratio of market value to book value (*MTB*), trading volume (in shares) (*VOL*), the relative quoted bid-ask spread (*RSPR*), the inverse of the daily average stock price (*1/P*), and realized volatility (*RV*). All continuous variables are winsorized at 1% at each end of the distribution; HFT proxies are also normalized per stock. Standard errors are clustered by stock and date; *t*-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10 % level, respectively.

	AT	QIT	ATS
CLpost_USnews	0.10***	0.14***	0.00
	(3.35)	(3.39)	(0.13)
CLpost	0.01	-0.02	-0.00
	(0.40)	(-1.21)	(-0.16)
USnews	0.05*	0.17***	0.04**
	(1.95)	(5.89)	(2.11)
MV	0.09***	0.06***	-0.06***
	(11.25)	(9.05)	(-8.62)
MTB	-0.03***	-0.01***	0.00
	(-5.92)	(-2.81)	(1.17)
VOL	-0.19***	-0.11***	0.16***
	(-17.38)	(-14.00)	(16.57)
RSPR	-0.36***	-0.08**	0.38***
	(-9.26)	(-2.43)	(10.46)
1/P	0.40***	0.16***	-0.34***
	(10.51)	(5.42)	(-10.75)
RV	0.11***	0.03***	-0.05***
	(10.33)	(2.77)	(-5.53)
Constant	1.78***	0.96***	-1.59***
	(13.18)	(9.30)	(-13.12)
Year fixed effects	YES	YES	YES
Observations	53,389	53,389	53,389
R-squared	0.04	0.03	0.03

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Table VII
High-frequency market-making: Fee on excessive message traffic

This table reports the estimation results of the pooled regression model in Equation (7) for HFT activity (Panel A) and market liquidity (Panel B) of cross-listed stocks vs. non-cross-listed stocks. The sample includes 86 Canadian stocks cross-listed in the US by the time of the event (April 1, 2012) and the matched non-cross-listed Canadian stocks. The pre-event window is the three months before the event day, the post-event window is the three months beginning May 1, 2012. In Panel A, the dependent variables are three HFT proxies: *AT* is the message-to-trade ratio, *QIT* is the quote-intensity-to-trade ratio, and *ATS* is the average trade size. In Panel B, the dependent variables are proxies for stock liquidity: the relative bid-ask spread (*RSPR*), the logarithm of depth at the National Best Bid and Offer (*DEPTH*), the ratio of market value to book value (*MTB*), the logarithm of the trading volume in shares (*VOL*), and the logarithm of the message traffic (*MSSG*). The main explanatory variable is *CL_Fee*, the interaction between the cross-listing indicator variable (*CL*) that equals 1 for cross-listed stocks and 0 for matched non-cross-listed stocks and the post-fee indicator variable (*Fee*). Control variables include the log of the market value of equity (*MV*), trading volume (in shares) (*VOL*), the relative quoted bid-ask spread (*RSPR*), the inverse of the daily average stock price (*1/P*), and realized volatility (*RV*). All variables are winsorized at 1% at each end of the distribution, and HFT proxies are normalized per stock. Robust *t*-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10 % level, respectively.

Panel A: HFT Activity			
	AT	QIT	ATS
CL_Fee	-0.23***	-0.05*	0.09***
	(-8.96)	(-1.77)	(3.95)
CL	0.23***	0.03	-0.07***
	(11.10)	(1.45)	(-3.71)
Fee	0.13***	0.03	-0.07***
	(6.73)	(1.60)	(-4.09)
MV	0.08***	-0.12***	0.00
	(2.76)	(-3.06)	(0.09)
MTB	0.13***	0.14***	0.08***
	(5.84)	(4.35)	(3.62)
VOL	-0.58***	-0.33***	0.68***
	(-58.38)	(-36.55)	(68.49)
RSPR	-0.18***	0.00	0.19***
	(-14.04)	(0.12)	(20.25)
1/P	0.35***	-0.08***	0.09***
	(18.16)	(-3.43)	(4.90)
RV	0.50***	0.23***	-0.76***
	(4.75)	(3.14)	(-5.30)
Constant	-0.15***	-0.03*	0.09***
	(-9.19)	(-1.94)	(5.50)
Observations	17,892	17,892	17,892
R-squared	0.33	0.11	0.43

Table VII (Continued)

Panel B: Market Quality				
	RSPR	DEPTH	VOL	MSSG
CL_Fee	0.17***	-0.22***	-0.02	-0.19***
	(7.02)	(-7.86)	(-0.69)	(-6.37)
Fee	0.38***	-0.18***	-0.06**	0.15***
	(18.43)	(-7.74)	(-2.46)	(6.15)
CL	-0.06***	0.09***	0.04**	0.12***
	(-4.00)	(4.62)	(2.03)	(6.02)
MV	-0.21***	0.13***	0.12***	0.07**
	(-6.32)	(4.23)	(3.80)	(2.15)
MTB	-0.07***	0.02	0.05*	0.13***
	(-2.62)	(0.65)	(1.70)	(4.97)
VOL	-0.21***	0.33***	-	-
	(-22.91)	(38.06)		
RSPR	-	-	-0.30***	-0.28***
			(-29.03)	(-20.47)
1/P	0.13***	0.02	0.30***	0.20***
	(6.38)	(0.99)	(15.69)	(9.76)
RV	0.79***	-0.66***	1.17***	1.10***
	(5.33)	(-3.48)	(5.03)	(5.19)
Constant	-0.24***	0.13***	-0.05**	-0.15***
	(-16.16)	(7.16)	(-2.31)	(-7.25)
Observations	17,892	17,892	17,892	17,892
R-squared	0.37	0.18	0.10	0.10

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Table VIII
Fragility in liquidity supply

Panel A reports the estimates of the impact of the increased HFT activity after US cross-listing on the stability of liquidity supply (fragility) using the introduction of an excessive message fee as exogenous shock. The sample includes 86 Canadian stocks cross-listed in the US by the time of the message fee introduction (April 1, 2012) and the matched non-cross-listed Canadian stocks. The pre-event window is January 1, 2012 to March 31, 2012, and the post-event window is May 1, 2012 to July 31, 2012. We estimate a pooled regression model with robust standard errors. Dependent variables are our proxies for the fragility in liquidity supply including the daily standard deviation of the one-minute intraday time series of the relative bid-ask spread (*Std_RSPR)* and quoted depth (*Std_DEPTH)*, as well as the semi-deviation of the relative bid-ask spread (*SMD_RSPR*) and quoted depth (*SMD_DEPTH*). The main explanatory variable is *CL_Fee*, the interaction between the cross-listing indicator variable (*CL*) that equals 1 for cross-listed stocks and 0 for matched non-cross-listed stocks, and the post-fee indicator variable (*Fee*). Control variables include the log of the market value of equity (*MV*), the ratio of market value to book value (*MTB*), trading volume (in shares) (*VOL*), the relative quoted bid-ask spread (*RSPR*), the inverse of the daily average stock price (*1/P*), and realized volatility (*RV*). Panel B reports the estimates of the impact of the cross-listing events on the liquidity fragility. The sample consists of 62 Canadian cross-listed stocks and their matched non-cross-listed stocks. *Post* the post-cross-listing event indicator variable. The event window covers six months centered on the cross-listing date. The dependent variables and controls are the same as in Panel A. All variables are winsorized at 1% at each end of the distribution, and the fragility proxies are normalized per stock. Robust *t*-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10 % level, respectively.

	Panel A: Fee on excessive message traffic				Panel B: Cross-listing event	
	Std_RSPR	Std_DEPTH	SMD_RSPR	SMD_DEPTH	Std_RSPR	Std_DEPTH
CL_Fee	0.29***	-0.15***	0.33***	-0.01	-	-
	(10.22)	(-4.99)	(9.39)	(-0.19)		
Fee	0.36***	-0.10***	0.20***	-0.18***	-	-
	(15.18)	(-4.15)	(6.83)	(-5.78)		
CL_Post	-	-	-	-	-0.14***	-0.14***
					(-6.53)	(-6.15)
Post	-	-	-	-	-0.17***	0.18***
					(-11.47)	(10.53)
CL	-0.11***	0.07***	-0.13***	0.02	0.07***	0.06***
	(-6.23)	(3.13)	(-6.00)	(0.59)	(4.42)	(4.06)
MV	0.00	-0.03	0.00	-0.12***	-0.27***	0.07***
	(0.00)	(-0.84)	(0.07)	(-2.60)	(-25.03)	(6.16)
MTB	-0.16***	-0.09***	-0.10***	-0.03	0.00	0.00
	(-6.41)	(-4.61)	(-3.87)	(-0.90)	(0.06)	(-0.01)
VOL	-0.20***	0.25***	-0.23***	-0.22***	-0.11***	0.25***
	(-18.95)	(29.70)	(-17.52)	(-16.26)	(-14.96)	(39.57)
RSPR	-0.06***	-0.20***	0.09***	-0.04	0.08***	-0.10***
	(-2.94)	(-8.88)	(3.40)	(-1.47)	(7.31)	(-9.76)
1/P	1.06***	-0.24***	1.02***	0.38***	0.00***	0.00*
	(5.29)	(-3.93)	(7.40)	(4.75)	(5.28)	(1.74)
RV	-0.25***	0.07***	-0.17***	0.06***	0.22***	-0.28***
	(-13.86)	(3.85)	(-9.36)	(2.66)	(5.53)	(-9.45)
Constant	0.29***	-0.15***	0.33***	-0.01	-0.14***	-0.14***
	(10.22)	(-4.99)	(9.39)	(-0.19)	(-6.53)	(-6.15)
Year FEs	NO	NO	NO	NO	YES	YES
Obs.	17,892	17,892	10,962	10,962	29,637	29,637
Adj. R2	0.17	0.09	0.18	0.06	0.19	0.11

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Appendix A.1. HFT of cross-listed and matched stocks: Summary statistics

This table reports the mean and median values of our HFT proxies for the sample of 112 cross-listed Canadian stocks and the matched non-cross-listed Canadian stocks. *AT* is the message-to-trade ratio from Hendershott et al. (2011), *QIT* is the quote-intensity-to-trade ratio, and *ATS* is the average trade size. The last column reports the differences in mean and median values (cross-listed minus matched). In parentheses are the *t*-statistics, and in brackets are the Wilcoxon signed-rank test p-values for the differences in means and medians, respectively. *** indicates statistical significance at the 1% level.

HFT proxy		Cross-listed stocks	Matched stocks	Difference (Cross-listed - Matched)	
AT					
	Mean	-11.43	-14.13	2.71***	(5.64)
	Median	-3.90	-6.91	3.01***	[0.00]
QIT					
	Mean	37.33	12.64	24.69***	(6.05)
	Median	28.40	14.02	14.37***	[0.00]
ATS					
	Mean	6.45	22.40	-15.96***	(-7.51)
	Median	5.99	22.17	-16.18***	[0.00]

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Appendix A.2. HFT of cross-listed and matched stocks: Fama-MacBeth regressions

This table reports cross-sectional average coefficient estimates and the corresponding Fama-Macbeth *t*-statistics (in parenthesis) for a series of Pooled OLS regressions per year (from 2005 to 2017). Dependent variables are HFT proxies estimated daily. *AT* is the message-to-trade ratio from Hendershott et al. (2011), *QIT* is the quote-intensity-to-trade ratio, and *ATS* is the average trade size. The sample includes 112 cross-listed stocks and the matched non-cross-listed stocks. The main explanatory variable is the cross-listing indicator variable (*CL*) that equals 1 for cross-listed stocks and 0 for matched non-cross-listed stocks. Control variables include the log of the market value of equity (*MV*), the ratio of market value to book value (*MTB*), trading volume (in shares) (*VOL*), the relative quoted bid-ask spread (*RSPR*), the inverse of the daily average stock price (*1/P*), and realized volatility (*RV*), computed as the sum of the squared quote midpoint 5-minute returns. Figures in parentheses are Newey-West corrected *t*-statistics. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	AT	QIT	ATS
CL	5.49***	6.52***	-3.47***
	(3.14)	(17.51)	(-4.08)
MV	-2.90***	3.69***	-5.48***
	(-2.86)	(5.12)	(-4.33)
MTB	-0.23***	0.35*	0.52***
	(-3.59)	(1.70)	(7.37)
VOL	-5.78	-9.78***	9.13***
	(-1.57)	(-18.30)	(6.49)
RSPR	-0.45***	-0.14*	0.33***
	(-2.60)	(-1.75)	(9.15)
1/P	4.02**	-1.48*	13.66***
	(1.99)	(-1.77)	(21.68)
RV	1.52**	1.83***	-0.66**
	(1.97)	(11.48)	(-2.26)
Constant	27.66*	50.18***	-25.89***
	(1.66)	(15.38)	(-10.19)
Obs.	29,704	29,704	29,704
Adj. R-squared	0.23	0.31	0.72

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Appendix B: Identification through Heteroskedasticity

This appendix details the identification through heteroskedasticity (ITH) approach employed in Section 5.2.1 (see Rigobon (2003) for the theoretical underpinnings of this approach). We use the ITH methodology to estimate the contemporaneous relations among variables in a structural VAR (SVAR). From Equation (6), we are interested in estimating the structural parameters in matrix Π_0. However, we cannot estimate the SVAR directly using OLS, but estimate its reduced form and then recover the parameters in matrix Π_0.

We obtain the parameters in Π_0 as follows. First, we estimate the reduced-form VAR model using OLS (Equation (7)), where the optimal lag is determined using the Schwartz Information Criterion. Using the reduced-form residuals, $\tilde{\varepsilon}_t$, we define the heteroskedastic regimes by computing rolling window variances of twenty observations each, as in Ehrmann, Fratzscher, and Rigobon (2011). A new regime is identified when the variance of a variable in *Y* exceeds its average variance over the sample period plus one standard deviation, while at the same time, the variances of the other variables in *Y* do not exceed their average variance plus one standard deviation. Doing so, we identify five regimes: one regime where the *Y* variables do not exhibit elevated conditional volatility levels; three regimes where only one variable in *Y* exhibits elevated conditional volatility while the other two remain low; and one regime where at least one variable exhibits elevated conditional volatility. Once the regimes are identified, we estimate the variance-covariance matrices, $\tilde{\Omega}_r$, of the reduced-form residuals in variance regime r ($r = 1,2,\dots,5$). Given that Ω_r are the variance-covariance matrices of the SVAR model that we are interested in, and assuming the following moment conditions hold, then we can identify Π_0 by solving the following equation:

$$\Pi_0, \tilde{\Omega}_r \Pi_0{}' = \Omega_r. \quad \text{(A.2.1)}$$

We then identify the parameters in Π_0 and Ω_r using generalized method of moments, minimizing the objective function $min\, g'g$, where $g = \Pi_0 \tilde{\Omega}_r \Pi_0{}' - \Omega_r$. Identification is achieved as long the covariance matrices constitute a system of equations that is linearly independent. The basic idea of the ITH approach is to increase the number of available moments or equations and obtain matrix Π_0 that satisfies Equation (A.1) across different regimes. When the variance of the shocks to the system changes across regimes but the parameters in Π_0 remain constant, the system can be identified. Hence, the shift in variances provides an extra source of variation needed for identification in the presence of endogeneity, such that Π_0 can be identified.

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Appendix C. HFT activity around the cross-listing date

The figures present the average daily values of our HFT proxies for 62 Canadian cross-listed (CL) stocks and matched non-cross-listed stocks (NCL) 6 months before and after the cross-listing date. AT is the message-to-trade ratio (Figure R.1a), QIT is the quote-intensity-to-trade ratio (Figure R.1b), and ATS is the average trade size (Figure R.1c). All HFT proxies are winsorized at 1% at each end of the distribution per stock.

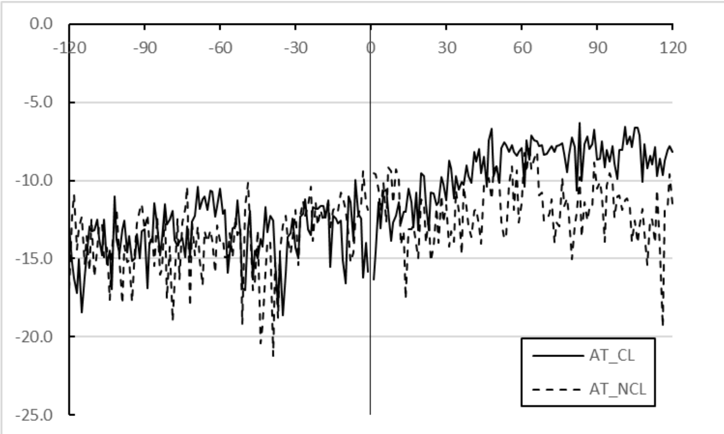

Figure C.1. AT

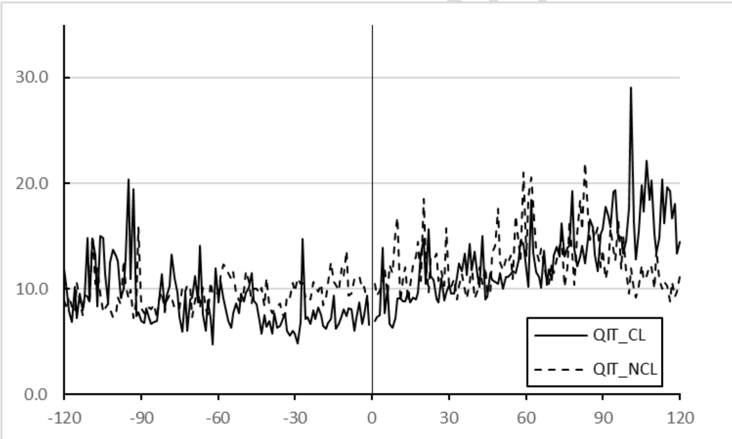

Figure C.2. QIT

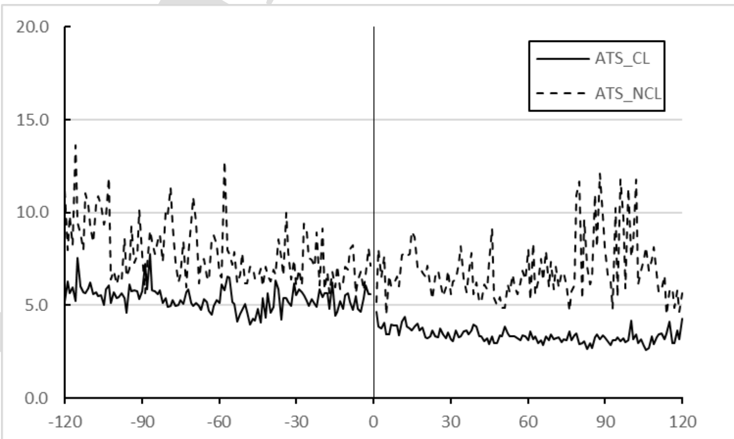

Figure C.3. ATS

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- We examine the impact of cross-listing on the domestic high-frequency trading (HFT) activity.
- US cross-listing enhances both opportunistic and HF market-making in the Canadian market.
- US cross-listing boots low-latency cross-border arbitrage.
- US cross-listing increases news trading by HFTs in the Canadian market around US public macro-news releases.
- Following cross-listing in the US, Canadian firms increase their reliance on high-frequency market makers to provide liquidity.

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US Cross-Listing and Domestic High-Frequency Trading: Evidence from Canadian Stocks

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ABSTRACT

We find that US cross-listing of Canadian stocks enhances domestic high-frequency trading (HFT) activity in the form of both opportunistic trading and market-making. First, US cross-listing boosts HFT low-latency cross-border arbitrage. This highly correlated HFT arbitrage activity across markets enhances stock price efficiency by correcting mispricing. Second, US cross-listing leads to an increase in news trading activity by high-frequency traders around US public macro-news releases. Finally, cross-listing increases a stock's reliance on high-frequency market makers to provide liquidity. Yet, we find no evidence of higher fragility in liquidity supply after cross-listing.

JEL classifications: G12, G14, G15, G23

KEYWORDS: US cross-listing, high-frequency trading, cross-market arbitrage, US news announcements, liquidity, equity markets

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