APPENDIX A

Design Report
for the CSA Pilot Study on Rebate Prohibition
(revised to address public comments)*

Katya Malinova Andreas Park Andriy Shkilko

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Katya Malinova – DeGroote School of Business, McMaster University, malinovk@mcmaster.ca

Andreas Park – Rotman School of Management, University of Toronto, Institute of Management and Innovation@UTM, andreas.park@rotman.utoronto.ca (corresponding author)

Andriy Shkilko – Lazaridis School of Business and Economics, Wilfrid Laurier University, ashkilko@wlu.ca

I. Executive Summary

The CSA has proposed a pilot study to better understand the effects of the prohibition of rebate payments by Canadian marketplaces (the Pilot). The United States Securities and Exchange Commission (SEC) has announced its intention to conduct a pilot study examining a similar set of issues (the SEC Pilot).

Rebates are often paid to market participants to attract their orders to a particular platform. The CSA has commissioned the authors of this report to develop the methodology for the Pilot, analyze the results, and complete a final research report detailing the findings. In this document, we propose a design and discuss the framework for the analysis. In particular, we cover the following issues: timing, sample construction, empirical measures, statistical tools, and anticipated challenges. We also address feedback received during public consultations.

An important feature of the Pilot is design simplicity. A complex design that aims to address too many questions may confound the analysis to the detriment of drawing policy-relevant conclusions. Consequently, key conditions for the Pilot to be successful are as follows:

- for a group of securities selected using objective and transparent criteria (hereafter, *treated securities*), marketplaces are prohibited from paying fee rebates[1] to dealers, including offering discounts on liquidity removal fees if such discounts are linked to the dealers' liquidity-providing activities. For all remaining securities, the rules remain unchanged;
- the prohibition applies to all marketplaces trading equity securities;
- with respect to interlisted securities, the timing of the Pilot and the set of the Pilot securities are coordinated with the SEC to the extent possible;
- the Pilot is introduced in two stages, if possible, to mitigate the effects of unexpected market-wide events that may coincide with the Pilot start date;
- in the analysis stage, a set of market quality and order routing metrics is computed using detailed audit-trail-level data;
- a set of standard techniques is applied to examine this data; and
- the codes used in the analysis are publicly available through GitHub, and comments are encouraged.

The sample will be selected from corporate equity securities and Exchange Traded Products (ETPs). The corporate equity securities will be split into highly liquid and medium liquid. Each treated security will be matched with a control security that has similar characteristics, e.g., firm size, share price, and trading volume. The control securities will not be treated. The sample selection will be governed exclusively by statistical considerations. We expect the sample to consist of:

- 50-60 highly liquid and 20-30 medium liquid, interlisted securities, with an equal number of interlisted matches,
- 60-80 highly liquid and 80-100 medium liquid, non-interlisted securities, with an equal number of non-interlisted matches, and

[1] This will include the prohibition of rebate payments for intentional crosses.

- 20-30 ETPs, with an equal number of matches selected from among ETPs that follow distinctly different security baskets.

The precise numbers of securities will be determined on the date the sample is finalized prior to the start of the Pilot.

In the analysis stage, we will use standard market quality metrics (e.g., quoted spreads and depths, effective and realized spreads, implementation shortfall, volatility, trade and order autocorrelation, time to execution for competitively priced limit orders, etc.). We will examine these metrics before and after rebate prohibition for the market overall and for several types of market participants separately (e.g., market makers, dealers, retail investors, institutional participants, participants using high frequency strategies, etc.). The final report will present the results taking care to preserve anonymity of the participants.

II. Details

A. Background

In its 2014 Request for Comments on Proposed Amendments to NI 23-101 Trading Rules,[2] the CSA points out that concerns had been raised about the maker-taker model's ability to "distort transparency of the quoted spread, introduce inappropriate incentives and excessive intermediation, and create conflicts of interest" and proposes conducting a pilot study to formally examine these issues. The CSA specifically states that any pilot should "examine the impact of prohibiting the payment of rebates by marketplaces."

In proposing the Pilot design, we seek to better understand how the prohibition of rebates may affect dealers' routing practices, the level of intermediation, and standard measures of market quality. The analysis will be carried out for the market overall and for various groups of market participants separately. We anticipate that this analysis will facilitate future policy decisions with respect to rebates and allow these decisions to be made in the most fair and transparent manner, reflecting the interests and views of all stakeholders.

In what follows, we provide a detailed description of the data, variables, and methods that will allow us to address the issues raised by the CSA. For the results to be meaningful and policy-relevant, it is important to have sufficiently large and well-structured treatment and control samples. Where possible, a staggered introduction of treatment would help minimize the likelihood of an exogenous event confounding the results. Furthermore, we will seek close coordination with the SEC, since trading in Canada may be affected by the implementation of the SEC Pilot.

B. Merits of a Canadian Pilot

Although the U.S. and the Canadian equity markets are similar, there are several key differences that may affect dealer routing decisions. Examples include the practice of retail order internalization in the U.S. and broker-preferencing in Canada. Therefore, while we expect rebate prohibition to have a similar impact on market-wide measures of market quality in both countries,

[2] http://www.osc.gov.on.ca/en/SecuritiesLaw_csa_20140515_23-101_rfc-pro-amd.htm.

changes in routing practices and the extent to which different groups of market participants are affected may differ. Consequently, a Canadian Pilot, in combination with sufficiently granular data, will substantially improve our understanding of the existing fee system and will be necessary for a well-informed Canadian regulatory policy.

C. Required Data

The Pilot aims to examine discretionary routing practices and the impact of fees on different groups of market participants. Using detailed data, we will define a trader ID as the combination of the dealer ID, user ID, and account type (specialist, client, inventory, etc.). Once defined, we will use trader IDs following the classification of market participants proposed by Devani, Tayal, Anderson, Zhou, Gomez, and Taylor (2014).

III. Pilot Securities and Sample Construction

A. Background

There are about 3,800 securities listed on Canadian stock exchanges, some of which are interlisted on foreign exchanges. Trading characteristics differ significantly across securities and in constructing the sample we must ensure that such differences do not confound the results.

First, many securities trade almost exclusively in rebate-free environments. Examples include CSE-listed securities, as well as TSX- and TSXV-listed securities priced under $1 that trade on the TSX, TSXV, and MatchNow. Such securities will not be included in the sample.

Second, we expect that our analysis will provide the most statistically reliable results for the highly liquid securities. However, we recognize that there is significant interest in examining the impact of a rebate prohibition on securities with medium activity levels. Therefore, we will analyze a sample of such securities, but we caution that the resulting market quality measures may be statistically noisy. We will also examine the effect of a rebate prohibition on ETPs. We will not examine very illiquid securities, as such an analysis will not yield statistically meaningful insights. We will split the corporate equities into two subsamples: U.S.-interlisted equities and non-interlisted equities. In our analysis, we will present the results separately for the two subsamples.

B. Sample Selection and Matching Criteria for Corporate Securities

The two subsamples of corporate equities will be further split into highly liquid and medium liquid securities. IIROC defines a security to be "highly liquid" if it trades on average at least 100 times per day and with an average trading value of at least $1,000,000 per trading day over the past month.[3] Highly liquid securities account for more than 90 percent of TSX market capitalization and as such are reasonably representative of the wealth invested in publicly-listed Canadian corporate equities. We will define a security as "medium liquid" if it trades on average at least 50 times a day and with an average daily trading value of at least $50,000 over the past month.

[3] http://www.iiroc.ca/industry/rulebook/Pages/Hightly-liquid-Stocks.aspx

To select the treatment and control groups, we will use a procedure that finds stocks similar to each other based on a set of predefined characteristics and then randomly selects a stock to treat from each pair. We will use the following matching characteristics captured prior to the Pilot start date: listing status (single market vs. interlisted), liquidity status (highly liquid vs. medium liquid), firm size (market capitalization), price, and dollar trading volume, with the last three characteristics averaged over the month preceding the selection date. The list of Pilot securities will be appended to the orders implementing the Pilot.

We will follow the approach known as *the nearest-neighbour matching*. Specifically, for each possible pair of securities, i and j, we will compute the pairwise scaled matching error as follows:

$$matcherror_{ij} = \sum_{k=1}^{M} \left(\frac{C_k^i - C_k^j}{C_k^i + C_k^j} \right)^2, \tag{1}$$

where C_k is one of the above-mentioned matching characteristics, e.g., firm size, price, and trading volume. We will then sequentially select pairs with the lowest matching errors until all stocks are allocated a pair. Finally, we will randomly assign one stock in each pair for treatment and retain the other stock as a control.

C. Sample Selection and Matching Criteria for ETPs

The comments on the original pilot design were mixed, although largely in support of including ETPs in the study. This said, respondents were concerned that the necessary partition of ETPs into a no-rebate and a control sample could create "winners and losers." As an example, consider two fictional ETPs that have the same underlying basket of securities: ATSX and ZTSX. The similarity of the underlying basket makes it tempting to assign these ETPs as matches, with one in the no-rebate group and the other in the control group. Such an assignment may, however, result in investors favouring one product over the other. If the current system of rebates is beneficial to liquidity, the control product will benefit. If the current system is not beneficial, the treated product will benefit.

To address respondents' concerns and avoid influencing investor preferences for similar ETPs, we will use the underlying index as one of the criteria to assign ETPs into the treatment and control groups. More specifically, both ATSX and ZTSX in the example above will be assigned into either a treatment or a control group. Their matches will be selected from ETPs with different underlying baskets. Further, we expect to match ETPs with the same underlying security type: equity ETPs to equity ETPs, fixed income to fixed income, etc. The rest of the matching procedure will resemble that described earlier for the corporate securities. In particular,

- we will separate ETPs into categories based on the underlying security type;
- within these categories, we will identify ETP groups that have the same underlying basket;
- we will match these groups with the ETP groups that have the same security type but a different underlying basket. Matching will be done by traded volume and price; and
- once matches are identified, we will randomly assign one of the matched groups to be treated and the other as a control.

We do not anticipate active ETPs to be included in the Pilot.

IV. Empirical Measures and Statistical Analysis

A. Empirical Measures

Quoted Liquidity. The quoted spread will be computed as the difference between the Canada-wide best ask and bid prices (the CBBO). We will compute this metric in two ways: (i) across all markets and (ii) for the markets with protected quotes. The quoted spread at time *t* for security *i* is defined as:

$$qs_{it} = ask_{it} - bid_{it}. \tag{2}$$

We will drop instances of locked markets, when the bid and the ask are equal, and instances of crossed markets, when the bid is greater than the ask.

Spreads usually vary by stock price. As such, it is common practice to compute the proportional spread as:

$$qsp_{it} = \frac{qs_{it}}{m_{it}}, \tag{3}$$

where m_{it} is the CBBO midquote defined as:

$$m_{it} = \frac{ask_{it} + bid_{it}}{2}. \tag{4}$$

To aggregate the spread metrics to the daily level, we will compute the *time-weighted* quoted spread on day *d* as follows:

$$twqsp_{id} = \frac{1}{\sum_t \Delta_{t,t+1}} \times \sum_t \Delta_{t,t+1} \; qsp_{it}, \tag{5}$$

where $\Delta_{t,t+1}$ is the number of time units during which the quote is active. For instance, if a quote is active from 14:35:00.002 to 14:35:08.004, then $\Delta_{t,t+1}$ = 8,002 milliseconds (ms).

Some of the stocks in our sample will likely be constrained by the minimum tick size of one cent. To account for this possibility, we will compute the fraction of the day that a stock is quoted with a one cent spread.

We will compute *quoted depth* as the sum of the number of shares posted on both sides of the CBBO. We will compute *quoted dollar depth* as the sum of the dollar value of shares posted on both sides of the CBBO. We will time-weight both depth metrics.

In addition, we will examine the breadth of liquidity provision and diversification of passive liquidity by counting the number of market participants that provide liquidity and the level of competition among them based on presence at the best quotes and the frequency as well as degree of price improvement.

Price Efficiency. The finance literature has developed a number of metrics that capture the speed with which (and the extent to which) prices incorporate new information. Generally speaking, the faster the price discovery process, the more informationally efficient the prices.

Autocorrelation of Returns. Similarly to Hendershott and Jones (2005), we will compute the autocorrelation of midquote returns for 30-second, 1-minute, and 5-minute intervals. A lower absolute value of autocorrelation is associated with greater market efficiency as prices better resemble a random walk.

Variance Ratios. If prices are efficient and follow a random walk, the variance of midquotes is linear in the time horizon. Campbell, Lo, and MacKinlay (1997) define the scaled ratio of variances over k time horizons as: $|(\sigma_{tk}/k\sigma_t) - 1|$ and suggest that the closer this ratio is to 0, the more efficient the market. We will follow the existing literature and compute the variance ratios for two intervals: 30-seconds to 1-minute and 1-minute to 5-minutes.

Intra-Day Volatility. We will compute two volatility metrics: range-based and variance-based. The range-based metric is the daily average of the high-low price range computed over ten-minute intervals, scaled by the interval's midquote defined in equation 4 above. Aggregated over many securities, this metric is usually strongly correlated with overall market volatility as measured by the CBOE Volatility Index (VIX).[4] The variance-based metric is the standard deviation of the one-minute midquote returns for the day.

Activity Levels. To measure market activity, we will compute several trading volume metrics such as volume at the open and close, volume during the continuous market, volume in intentional crosses, and dark volume.

We will further compute a set of order-related metrics, such as the number of orders and their value, the proportion of canceled and executed orders, the proportion of executed order value, the number of orders that match or improve the CBBO, and the proportion of orders one and two cents away from the best quotes, as well as one percent and five percent of the midquote away from the best quotes. We will pay particular attention to changes in order routing practices to examine the effects of incentive changes related to rebate prohibition.

[4] The VIX is a calculation designed to produce a measure of constant, 30-day expected volatility of the U.S. stock market, derived from real-time, midquote prices of S&P 500 Index call and put options.

We note that there are no agreed upon economic measures that determine whether a change in market activity levels is beneficial or harmful. Therefore, volume and order submission figures must be interpreted with caution.

Effective Spreads. Effective spreads measure the costs that market participants incur when they trade. It is conventional to base the computation of effective spreads on the midquote of the prevailing CBBO. For security i, the proportional effective spread for a trade at time t is:

$$esp_{it} = 2 \times q_{it} \times \frac{p_{it} - m_{it}}{m_{it}}, \tag{6}$$

where p_{it} is the transaction price, m_{it} is the midquote of the CBBO prevailing at the time of the trade, and q_{it} is an indicator variable that equals 1 if the trade is buyer-initiated and −1 if the trade is seller-initiated. The factor 2 is used to make the estimate comparable to the quoted spread by capturing the cost of a round-trip transaction. We will also examine a variation of the effective spread, entitled *investable spread*, which is the dollar cost of trading of a standard size order.

To obtain a daily effective spread estimate, it is common to volume-weight transaction-specific estimates, i.e., for trades of volumes v_{it}, the effective spread on day d is the sum of the trades' effective spreads weighted by the trades' shares of total daily volume:

$$vwesp_{id} = \frac{1}{\sum_t v_{it}} \times \sum_t v_{it} esp_{it}. \tag{7}$$

The purpose of the Pilot is to gain a better understanding of the effects of the prohibition of rebate payments by Canadian marketplaces, and we will therefore compute the "cum fee" effective spread (often referred to in the industry as the "economic" spread):[5]

$$cum\ fee\ esp_{it} = esp_{it} + 2 \times taker\ \ fee_{it}/m_{it}. \tag{8}$$

Price Impact and Realized Spread. It is common practice to decompose the effective spread into the *price impact* and the *realized spread*. The price impact measures by how much the trade moves the price and is formally defined as:

$$primp_{it} = 2 \times q_{it} \times \frac{m_{i,t+\tau} - m_{it}}{m_{it}}, \tag{9}$$

where $m_{i,t+\tau}$ is the CBBO midquote τ time units after the trade. The idea behind this measure is that trades reveal information about the fundamental value of the underlying security and the market

[5] This measure will be computed per transaction. We caution that it will be difficult to determine precisely which fees apply; dark, lit, and post-only orders may all command different fees, market-makers may receive bulk-discounts, etc. We will apply a uniform rule by employing only the "most common" fee that applies on the specific venue.

needs time to incorporate this information into prices. The time horizon τ usually varies between five milliseconds for frequently traded stocks and five minutes for less frequently traded ones.

The price impact is directly related to the realized spread, which is defined as:

$$rsp_{it} = esp_{it} - primp_{it} \tag{10}$$

and is interpreted as the revenue that liquidity providers receive net of the adverse selection costs captured by the price impact. Analogously to the cum fee effective spreads, we will account for the rebates that liquidity providers are eligible to receive and will compute the cum rebate realized spreads as follows:

$$cum\,fee\,rsp_{it} = rsp_{it} + 2 \times maker\ \ rebate/m_{it}. \tag{11}$$

Implementation Shortfall. Buy-side institutions often trade amounts that are larger than the depth available at the best prices and therefore commonly slice large “parent” orders into smaller “child” orders. The child orders may move market prices away from the price prevalent at the beginning of the large trade and as such increase the total cost of the parent order. Buy-side traders therefore worry about the total cost of their parent orders, which is usually measured by the implementation shortfall (IS).

While we likely cannot identify buy-side trades directly, we will proxy for parent orders by identifying instances where a single trader executes several trades in the same direction on a given day and trades only in that direction. The total cost associated with such a string of trades will be measured by the implementation shortfall defined as:

$$IS_{it} = q_{it} \times (\$vol_{it} - p_{i0} \times vol_{it}) \tag{12}$$

where q_{it} is +1 for a string of buys and −1 for a string of sales that begins at time t in stock i, $\$vol_{it}$ is the total dollar volume for the string, p_{i0} is the prevailing midquote at the time of the first trade in the string, and vol_{it} is the total share volume for the string.

A positive shortfall indicates that prices move in the same direction as the parent order. In our reporting, the aggregate shortfall will be computed in basis points of the aggregate dollar volume traded. We will consider two types of trade strings: (i) those that originate from marketable orders only and (ii) those that originate from marketable and non-marketable orders.

Passive Order Execution Quality. We will examine the impact of the Pilot on orders of a variety of different types, paying particular attention to liquidity-providing orders. For retail orders and for large trade strings, we will compute the resting time of non-marketable orders. We will specifically focus on orders with prices that suggest that the submitter is interested in a timely execution. As such, we will consider orders that are submitted at prices that match or improve the CBBO.

For large trade strings, we will also report the average fraction of volume that is traded with marketable orders. A change in this measure captures the possibility that institutional investors may change their strategies and choose to "cross the spread" more/less often.

We will also examine the ratio of traded to submitted orders; this ratio captures how many orders an institution needs to submit to fill a position. We will consider only the orders submitted at prices matching or improving the CBBO. We will also compute this ratio for share volume. Finally, we will examine the opportunity costs of passive, as well as marketable, orders that are not filled by comparing prices at the time of submission to prices obtained through post-cancellation execution of similar directional volume by the same trader ID.

B. Statistical Analysis

The basis of our statistical approach is a conventional difference-in-differences analysis of a panel dataset (securities×days). Analyses of this kind usually rely on two approaches to examine the treatment effect (i.e., the effect of rebate prohibition). We discuss these approaches below using the bid-ask spread as an example.

In the first approach, the dependent variable ΔDV_{it} is the value of the bid-ask spread for the treated security i at time t less the value for the matched security. Using this dependent variable, we will estimate the following regression:

$$\Delta DV_{it} = \alpha \cdot pilot_t + controls_t + \delta_i + \varepsilon_{it}, \qquad (13)$$

where $Pilot_t$ is an indicator variable set to 1 on the Pilot start date, $controls_t$ are time series controls such as the VIX, and $\underline{\delta_i}$ are security-pair fixed effects. The coefficient of interest α captures the effect of the Pilot on treated securities.[6]

In the second approach, the dependent variable DV_{it} is the value of the bid-ask spread for each security from the treatment and control groups. Using this dependent variable, we will estimate the following regression:

$$\Delta DV_{it} = \alpha_1 \cdot pilot_t + \alpha_2 \cdot pilot_t \times treated_i + \alpha_3 \cdot treated_i + controls_t + \delta_i + \varepsilon_{it}, \quad (14)$$

where $Pilot_t$ is the indicator variable set to 1 on the Pilot start date, $treated_i$ is 1 if the security is from the treatment group and 0 otherwise, $controls_t$ are time series controls such as the VIX, and $\underline{\delta_i}$ are security fixed effects. The coefficient of interest is α_2; it estimates the incremental effect of the Pilot on the treated securities. For instance, with quoted spread as the dependent variable, a positive α_2 will indicate that the spreads for the treatment group increased relative to the control group.

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[6] This regression methodology is similar to that in Hendershott and Moulton (2011) and Malinova and Park (2015).

We will conduct inference in all regressions using double-clustered Cameron, Gelbach, and Miller (2011) standard errors, which are robust to cross-sectional correlation and idiosyncratic time-series persistence.[7]

Each approach will use two controls for the market-wide effects that are known to affect trader behaviour and market quality. First, we will use the VIX to control for the level of market-wide volatility. We acknowledge that Canada has its own volatility index, but note that this index may be directly affected by trading in the sample securities, while VIX is less likely to be similarly affected. Second, we will use the cumulative return for the S&P GSCI commodity index. Comerton-Forde, Malinova, and Park (2018) show that this index is highly correlated with the Canadian TSX Composite index, but is unlikely to be significantly affected by trading in Canada and therefore serves as a proxy for Canadian market-wide returns.

V. Anticipated Challenges

We caution that several possible scenarios may affect our ability to deliver meaningful conclusions. First, individual firms in the sample may experience events during the Pilot that render them unusable for the subsequent statistical analyses (e.g., mergers, bankruptcies, or delistings). We will mitigate the impact of such events by building the sample as close as possible to the start of the Pilot, while providing market participants with sufficient time to prepare for the Pilot's implementation. This said, if one of the above-mentioned events occurs after the sample is finalized, we may omit the affected security and its match from further analyses.

Second, all securities may be affected by major market-wide confounding events. Examples are a failure of a major financial institution, a market crash, or a political event. While a staggered introduction, the use of control groups, and a sufficiently long Pilot period alleviate some of the concerns regarding such events, the CSA will reserve the right to extend the Pilot or to delay the start of the Pilot should it be necessary.

Third, the marketplaces may develop workarounds for rebate prohibitions that undermine the Pilot, e.g., differentiated fees, bulk discounts, new order types, new venues or order books, etc. The orders implementing the Pilot aim to prevent such workarounds so as to preserve the scientific integrity of the Pilot.

VI. Timing

We propose that the Pilot for the interlisted stocks match the duration of the SEC Pilot. We also propose that the Pilot proceed in two stages, with treatment introduction for the non-interlisted stocks and ETPs separated from the treatment introduction for the interlisted stocks by two to three months.

As described above, the staggered introduction may alleviate concerns that arise if the Pilot start date is close to an unexpected market-wide event. For example, in July 2011, the SEC adopted a

[7] Cameron, Gelbach, and Miller (2011) and Thompson (2011) developed the double-clustering approach simultaneously. See also Petersen (2009) for a detailed discussion of (double-)clustering techniques.

new rule that restricted some aspects of direct market access (DMA). Several research teams endeavored to analyze this event. Unfortunately, about two weeks after the DMA rule adoption, the U.S. credit rating was downgraded, creating a substantial amount of noise in the data. No research team was able to produce meaningful conclusions because the noise completely confounded the results (Chakrabarty, Jain, Shkilko, and Sokolov, 2019). We caution that a similarly unpredictable event may confound the results if all stocks are introduced into the Pilot at once.

Our conversations with market participants suggest that they share this concern and we received feedback that the difference between the two-stage and all-at-once alternatives is immaterial in terms of technical implementation.

VII. Monitoring, Communication, and Transparency

We believe that transparency is integral to conducting pilot studies and commit to providing timely and comprehensive updates to the CSA for disclosure to market participants. We will continuously monitor the empirical measures described in section IV, share the ongoing statistical analysis with the CSA, and discuss any adverse trends that may be indicative of a decrease in market quality.

In the interest of transparency, we will make all codes publicly available via GitHub (the online code depository). GitHub includes a comment function and feedback on code improvement is welcome. Where possible, we will also provide the data (e.g., the non-proprietary data that will be used for the matching process). We believe that this level of transparency will bring added trust in the integrity of our analysis. However, we will not publish the matched securities to prevent possible gaming.

We have received excellent feedback from the CSA, the members of the OSC Market Structure Advisory Committee, the Canadian Security Traders Association, participants at the Rotman Capital Markets Institute Panel Discussion, and respondents to the Request for Comments. This report reflects this feedback.

Appendix I: A Sample Matching Procedure

This appendix provides an example of the matching procedure used to assign Canadian stocks interlisted in the U.S. into the treatment and control groups.

Trading volume, price, and market capitalization figures are the latest available from the Canadian Financial Markets Research Centre (CFMRC).[8] Trading volume is the average daily dollar volume, price is the closing price, and market capitalization is the product of the price and the number of shares outstanding. We use Canadian dollars for variables that require a price component.

We arrive at the matched sample using the following procedure:

1. We begin with a sample of 181 Canadian securities that are also interlisted on the NYSE, NYSE Arca, NYSE MKT, Nasdaq GM, and Nasdaq CM.

2. Among these, we identify 18 securities that trade at prices below $1 and refer to them as low-priced (LP). Price volatility in such securities is rather high, and as mentioned previously, LPs will not be included in the Pilot. We however discuss them here for the sake of completeness.

3. Among the remaining securities, we identify 107 that are on IIROC's "highly liquid" list. We refer to these as HL stocks and the remaining 56 securities are nHL (not highly liquid). We match HL stocks to HL stocks and nHL stocks to nHL stocks.

4. For each possible pair of *i* and *j* securities, we estimate a match error as follows:
$$matcherror_{ij} = \sum_{k=1}^{3} \left(\frac{C_k^i - C_k^j}{C_k^i + C_k^j} \right)^2 ,$$
where C_k are natural logs of trading volume, price, and market capitalization as defined above.

5. From the matrix of match errors that spans all stock-pairs, we then select stock-pairs with the lowest errors, for a total of 53 HL pairs, 28 nHL pairs, and 9 LP pairs.

6. Finally, to assign stocks into the treated and control groups, for each pair we generate a random number between 0 and 1. If this number is below 0.5, we assign the first stock in the pair to be treated and vice versa.

Figure 1 provides an illustration of match quality. The horizontal and vertical axes represent logarithms of market capitalization, dollar volume, and stock price for pairs of securities, with a random assignment of one member in the pair to the treatment and the other to the control group. A good match obtains if the points are on or close to the 45-degree line. A formal *t*-test shows no evidence that the treatment and control samples are different for any of the matching criteria.

[8] http://clouddc.chass.utoronto.ca/ds/cfmrc. In rare cases when CFMRC does not have a valid record for a security, we obtain the missing data from https://www.tmxmoney.com/en/index.html.

References

Battalio, Robert, Shane Corwin, and Robert Jennings, 2016, Can brokers have it all? On the relation between make-take fees and limit order execution quality, *Journal of Finance* 71, 2193–2238.

Battalio, Robert, Brian Hatch, Mehmet Sağlam, 2019, The cost of routing orders to high frequency traders, Working paper.

Brogaard, Jonathan, Terrence Hendershott, and Ryan Riordan, 2014, High-frequency trading and price discovery, *Review of Financial Studies* 27, 2267-2306.

Brogaard, Jonathan, Terrence Hendershott, and Ryan Riordan, 2019, Price discovery without trading: Evidence from limit orders, *Journal of Finance*, forthcoming.

Cameron, A. Colin, Jonah B. Gelbach, and Douglas L. Miller, 2011, Robust inference with multi-way clustering, *Journal of Business Economics and Statistics* 29, 238-249.

Campbell, John Y., Andrew W. Lo, and A. Craig MacKinlay, 1997, *The Econometrics of Financial Markets* (Princeton University Press).

Chakrabarty, Bidisha, Pankaj Jain, Andriy Shkilko, and Konstantin Sokolov, 2019, Unfiltered Market Access and Liquidity: Evidence from the SEC Rule 15c3-5, *Management Science*, forthcoming.

Cimon, David, 2019, Broker Routing Decisions in Limit Order Markets, Working paper.

Comerton-Forde, Carole, Katya Malinova, and Andreas Park, 2018, Regulating dark trading: Order flow segmentation and market quality, *Journal of Financial Economics* 130, 347-366.

Devani, Baiju, Ad Tayal, Lisa Anderson, Dawei Zhou, Juan Gomez, and Graham W. Taylor, 2014, Identifying trading groups – methodology and results, Discussion paper, IIROC Working Paper.

Hendershott, Terrence, and Charles M. Jones, 2005, Island goes dark: Transparency, fragmentation, and regulation, *Review of Financial Studies* 18, 743–793.

Hendershott, Terrence, and Pam Moulton, 2011, Automation, speed, and stock market quality: The NYSE's hybrid, *Journal of Financial Markets* 14, 568–604.

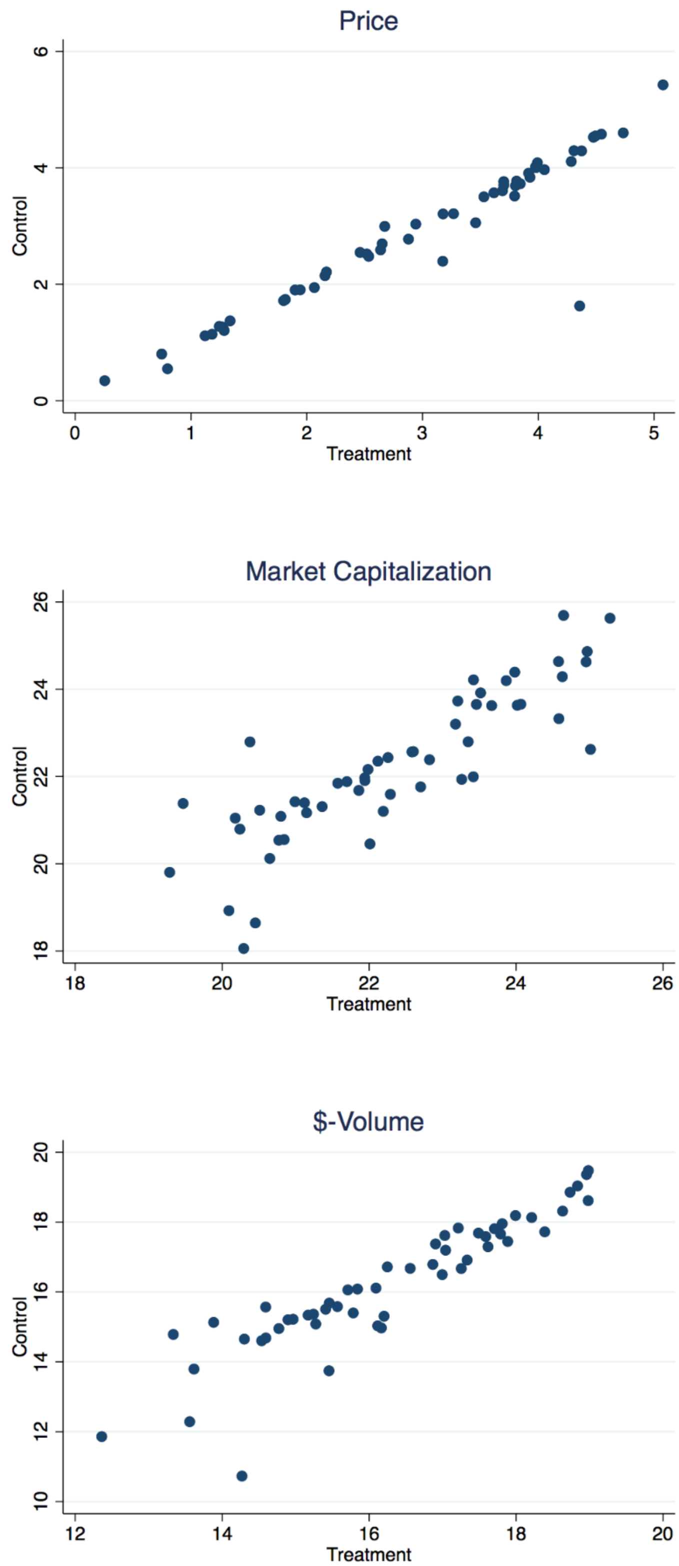
Korajczyk, Robert, and Dermot Murphy, 2018, High-frequency market making to large institutional trades, *Review of Financial Studies* 32, 1034-1067.

Malinova, Katya, and Andreas Park, 2015, Subsidizing liquidity: The impact of make/take fees on market quality, *Journal of Finance* 70, 509–536.

Menkveld, Albert, 2013, High frequency trading and the new market makers, *Journal of Financial Markets* 16, 712-740.

Petersen, Mitchell A., 2009, Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches, *Review of Financial Studies* 22, 435–480.

Thompson, Samuel B., 2011, Simple formulas for standard errors that cluster by both firm and time, *Journal of Financial Economics* 99, 1–10.



Price
Control
Treatment
0
2
4
6
0
1
2
3
4
5
Market Capitalization
Control
Treatment
18
20
22
24
26
18
20
22
24
26
$-Volume
Control
Treatment
10
12
14
16
18
20
12
14
16
18
20

Figure 1