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Matching and the Estimated Impact of Interlisting

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Abstract

We show that tests for differences in trade execution costs using standard nearest neighbor matching estimation techniques typically have comparable empirical power but less bias than more "sophisticated" alternatives. However, estimation techniques that place more weight on distant firms (e.g. kernel-based matching) have better testing power and produce tighter confidence intervals when there are few matched pairs. For stocks listed on the Toronto Stock Exchange, we employ these techniques to estimate the impact of US interlisting on percentage bid-ask spreads, institutional and market maker participation rates, and market maker profits.

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1 Introduction

Despite the widespread use of the matched sample estimation approach in finance, very little is known about the sensitivity of results to the matching technique used. This paper aims to fill in this vacuum by illustrating how the bias and variance of matching estimates influence the empirical power of tests for differences in transaction costs, as commonly studied in market microstructure. To provide a vehicle for the analysis, we estimate the effect of being interlisted on the Toronto Stock Exchange (TSE) and a US exchange on the percentage bid-ask spread in Toronto and examine whether this coincides with changes in market maker participation or with changes in institutional order flow.

The matched sample approach compares the trading properties of each interlisted stock with an otherwise similar non-interlisted stock. This approach is one way to overcome the problem that, in general, it is not possible to observe what the trading properties of interlisted stocks would be if they were not listed on a US exchange. Similar matched sample estimation approaches are frequently used in the finance literature. In market microstructure, matched samples are often used to compare execution costs on different exchanges or across different groups of stocks. For example, execution costs on the NYSE and the Nasdaq have been compared by constructing matched samples of NYSE-listed firms and "comparable" Nasdaq-listed firms.[1] Matched sample techniques are also used in a vast variety of other research areas of finance, such as: forced CEO succession (Farrell and Whidbee (2000)), media visibility of firms on NYSE and Nasdaq (Baker et al. (1998)), stock return comovements (Karoyli and Stulz (1996)), and countless other applications.

[1]For example, Huang and Stoll (1996) construct matched samples of NYSE- and Nasdaq- listed firms using a nearest-neighbor approach that first grouped firms by Standard Industrial Classification (SIC) codes and then minimized the difference between four criteria (long-term debt level, book value, share price, number of shares outstanding). Bessembinder and Kaufman (1997) extend Huang and Stoll's study to consider small and medium capitalization firms. Later, Bessembinder (1999) conducts a similar analysis using size matched firms to examine whether new order-handling rules introduced on the Nasdaq in 1997 impacted the previously reported differences in trade execution costs on the two exchanges. Venkataraman (2001) also uses the matched sample approach to compare trade execution costs on the Paris Bourse and the NYSE.

Despite the existence of more sophisticated matching estimation techniques[2] (e.g. those commonly used to measure treatment effects in medical research and in labor economics), most finance applications use the standard nearest neighbor matching estimation approach. With this in mind, our goal is to use Monte Carlo simulation to investigate whether the size-power properties of tests for differences in trade execution costs (between interlisted and non-interlisted stocks) can be improved by using different weighting schemes for nearest-neighbor estimation techniques or by using kernel-based matching estimation techniques. Essentially, these alternative estimators weight closest neighbors by more, but still place some weight on more distant neighbors. The potential benefit is that these estimators are less sensitive to a mis-match along un-measured dimensions, but the cost is that they introduce an added mis-match along measured dimensions.

We find evidence that the commonly used nearest neighbor matching approach (based on a one-to-one matching of firms) typically performs the best in market microstructure applications, despite its apparent simplicity. This is important, because many researchers unnecessarily apologize for using the nearest neighbor approach without being fully aware of its statistical properties. In comparison with the alternative estimators considered, the nearest neighbor approach has less bias and thus less probability of type I error (rejecting the null hypothesis when the null hypothesis is true). When the number of matched pairs is small, however, additional test power and narrower confidence intervals may be obtained by using a matching estimation technique that places additional weight on more distant firms (e.g. kernel-based matching estimates).

Based on the lessons gained from our simulation results, we measure the effect on the percentage bid-ask spread in Toronto of a TSE-listed stock being interlisted on a US exchange. Theory suggests that becoming interlisted on a US exchange could have two possible effects on transaction costs. On the one hand, Mendelson (1987) describes a scenario in which an additional trading venue could cause the market to become 'fragmented', reducing liquidity and increasing the bid-ask spread. On the other hand, Hamilton (1979) provides a model in

[2]Some of these techniques include: regression-adjusted matching, local linear matching, subclassification, and propensity score matching.

which the additional trading venue would increase competition among market makers and lead to lower transaction costs.

The potential negative effects of market fragmentation will be offset if the addition of an American trading venue allows new US investors to enter the market that were previously unable to. Becoming listed on a US exchange increases US media coverage of the firm and reduces investment barriers, either real or perceived, for potential US investors. Empirical studies by Booth and Johnston (1984), Jorion and Schwartz (1986), Mittoo (1992), Foerster and Karolyi (1993) and Karolyi (1998) find evidence of segmentation between Canadian and US equity markets.[3] Doukas and Switzer (2000) find evidence that this segmentation has persisted despite institutional changes which should have enhanced capital market integration between the two markets. Ahn, et al. (1998) show that despite an economically significant reduction in the spread on the TSE from decimalization, orders for interlisted stocks did not migrate from US markets to the TSE.

Our results suggest that listing on the NYSE or Nasdaq decreases percentage bid-ask spreads in Toronto and increases the share of Toronto-based order flow from non-client (institutional) accounts. Responsible registered trader participation appears to fall for NYSE-interlisted stocks but rise for Nasdaq-interlisted stocks. Our results also suggest that responsible registered trader (TSE market maker) profits are not affected by US listing status. These results are generally robust to different matching estimation techniques and thus provide useful information to firms deciding whether the significant costs of becoming interlisted are sufficiently compensated for by lower transaction costs and/or increased trade volume from institutions and foreign investors.

The remainder of the paper is organized as follows. Section 2 outlines the estimation approach. Section 3 provides a brief description of the relevant institutional details. Section 4 describes the data and the selection criteria used. Section 5 presents the Monte Carlo simu-

[3]Not surprisingly, there is also considerable evidence of market segmentation between other countries and US markets (e.g., Werner and Kleidon (1996) find evidence for UK and US equity markets). For other studies of international dual-listing, see Noronha, et al. (1996), Domowitz et al. (1998), and Smith and Sofianos (1997).

lation results. Section 6 presents the estimation results. Section 7 concludes.

2 Estimation Approach

Two possible approaches to estimating the effect of being interlisted on a US exchange are:

1. **"Transitional window" approach** restricts attention to the subset of TSE-listed firms that became interlisted on a US exchange over the sample period. An estimate of the impact of becoming interlisted is then constructed by comparing the trading properties of these firms over a period prior to the date at which they became interlisted with the trading properties of these firms over a period after the date at which they became interlisted.

2. **"Matched sample" approach** involves pairing each interlisted firm with a non-interlisted firm that, otherwise, has similar properties. An estimate of the effect of being interlisted is obtained by comparing the trading properties of these pairs of stocks.

The transitional window approach was used by Foerster and Karolyi (1998) to examine a sample of 52 TSE securities that became interlisted on US exchanges between January 1981 and December 1990. Using a 60 day window surrounding interlisting, they find that, after controlling for price level, trade size and trading volume effects, overall posted and effective spreads on the TSE decrease after interlisting.

The transitional window approach was also used by Noronha, et al. (1996) to examine 91 NYSE- and AMEX-listed stocks that became interlisted on the London Stock Exchange and 68 NYSE- and AMEX-listed stocks that became interlisted on Tokyo Stock Exchange between 1983 and 1989. They find that, in spite of increased competition from other market makers, spreads do not decrease on the US exchange following interlisting. They argue that interlisting increases the level of informed trading and thus any negative pressures on the spread from increased competition are offset by an increase in the adverse selection component of the spread.

In a different context, the transitional window approach is used by Barclay (1997), Christie and Huang (1994), and Bessembinder (1998) to examine the change in market liquidity of stocks that move from the Nasdaq to AMEX and NYSE; and by Clyde, et al. (1997) to examine the change in spreads of stocks that voluntarily move from the AMEX to the Nasdaq.

The transitional window approach has at least two significant problems:

- The sample of securities that become interlisted in any given year is small. Unfortunately, the sample size cannot be increased by simply increasing the length of the time horizon considered without introducing serious sources of bias. In particular, the rapid pace of innovation in financial institutions means that the trading properties of a group of securities in the past are probably not directly comparable to the trading properties of a similar group of securities today.

- It is difficult to determine the optimal length of the time window used for comparison. On the one hand, a relatively short time window may not be long enough to identify the long-term impact of becoming interlisted. It takes time for a stable pattern of order flow to emerge after a listing change. There are lots of contaminating effects, reflecting transitional aspects that may not characterize outcomes in the long run (rebalancing of portfolios for institutional reasons, information release associated with interlisting, etc.). On the other hand, a longer time window may introduce another source of bias if newly interlisted firms tend to be growing rapidly. The average firm size prior to becoming interlisted may be significantly different from the average firm size after becoming interlisted. It is well established that trading properties are closely related to firm size.

Because of these limitations of the transitional window approach, this paper uses several variants of the matched sample approach. The matched sample approach allows us to consider a much larger sample of securities and provides a snapshot of the long-term impact of becoming interlisted. Specifically, the transitional window approach used by Foerster and Karolyi (1998) limits their study to five NYSE-interlisted stocks, seven AMEX-interlisted stocks and 40 Nasdaq-interlisted stocks. In contrast, our matched sample approach allows us to examine

60 NYSE-interlisted stocks, 19 AMEX-interlisted stocks, and 55 Nasdaq-interlisted stocks.

2.1 Matching Estimates

Heckman et al. (1997,1998) use the method of matching to evaluate the success of a job training programme. Their evaluation technique compares the mean post-programme earnings of programme participants with the mean earnings of "comparable" non-participants. We use a similar technique to compare the trading properties (e.g. percentage bid-ask spread) of firms interlisted on a US exchange with the trading properties of "comparable" non-interlisted firms. Differences in the trading properties of the two groups are attributed to being interlisted.

As much as possible, we adopt the notation in Heckman et al. (1997,1998). The sample of securities listed on the TSE can be divided into four main groups: NYSE-interlisted stocks (identified by subscript $nyse$), AMEX-interlisted stocks (identified by subscript $amex$), Nasdaq-interlisted stocks (identified by subscript $nasd$), and securities that are not interlisted on a US exchange (identified by subscript 0). Let Y_E denote the trading property outcome that would occur if the security has listing attribute $E \in \{nyse, amex, nasd, 0\}$. Let $D_E = 1$ if the firm has listing attribute E; $D_E = 0$ otherwise. The trading property outcome observed for a firm is $Y = D_{nyse}Y_{nyse} + D_{amex}Y_{amex} + D_{nasd}Y_{nasd} + D_0Y_0$. The effect of being interlisted on US exchange $L \in \{nyse, amex, nasd\}$ is denoted Δ_L, where $\Delta_L = Y_L - Y_0$.

Each firm has observed characteristics $\mathbf{X}$, which can be partitioned into two not-necessarily mutually exclusive sets of variables, $(\mathbf{T}, \mathbf{Z})$, where the $\mathbf{T}$ variables determine the trading property outcome and the $\mathbf{Z}$ variables determine whether or not the firm decides to become interlisted. In practice, firm characteristics often impact both the listing decision and the firm's trading properties. For example, the amount of business a firm conducts outside of Canada obviously could impact its decision about whether to become interlisted but it may also impact its percentage bid-ask spread if this business creates uncertainty and additional informational asymmetries. The trading property associated with listing property E can then be written as a function of observables ($\mathbf{T}$) and unobservables U_E, where

$$Y_E = g_E(\mathbf{T}) + U_E \tag{1}$$

where $E(U_E) = 0$ and g_E is assumed to be a nonstochastic function. Unobservables include firm characteristics such as the firm's management style that directly impact trading properties, such as percentage bid-ask spreads (through adverse selection costs), but that are difficult, or impossible, to quantify.

The mean effect of being interlisted on a US exchange $L \in \{nyse, amex, nasd\}$ on the trading property for a firm with characteristics $\mathbf{X} \in \mathbf{S}$, where $\mathbf{S}$ is a given set, is given by:

$$E(\Delta_L|\mathbf{X}, D_L = 1) = g_L(\mathbf{X}) - g_0(\mathbf{X}) + E(U_L - U_0|\mathbf{X}, D_L = 1). \tag{2}$$

The focus of this paper is to estimate the *average* effect of being interlisted on US exchange $L \in \{nyse, amex, nasd\}$, which is given by:

$$M_L(\mathbf{S}) = \frac{\int_{\mathbf{S}} E(\Delta_L|\mathbf{X}, D_L = 1) dF(\mathbf{X}|D_L = 1)}{\int_{\mathbf{S}} dF(\mathbf{X}|D_L = 1)} \tag{3}$$

where $\mathbf{S}$ is a subset of the support of $\mathbf{X}$ given $D_L = 1$. In practice, the choice of $\mathbf{S}$ can be non-trivial if there does not exist a sufficient number of firms with characteristic $\mathbf{X}$ such that either $D_L = 1$ or $D_L = 0$. For example, if the matching characteristic is market capitalization, there are no other firms listed on the TSE that come close to having the same market capitalization as Northern Telecom Ltd. during the period under study. In the same vein, perhaps small firms should also be excluded from $\mathbf{S}$ since they may be either unable to meet US listing requirements or unable to justify/afford paying US listing fees. This is discussed further in section 4.

Let $\mathbf{I}_E$ denote the set of indices for firms with listing attribute E. We distinguish between the P trading properties of interest by using the subscript $p \in \{1, \ldots, P\}$. To estimate the effect of being interlisted on US exchange L for each firm $i \in \mathbf{I}_L$, trading property Y_{Li}^p is compared to an average of the outcomes Y_{0j}^p for matched firms $j \in \mathbf{I}_0$ in the sample of non-interlisted firms. Matches are constructed on the basis of observed characteristics $\mathbf{X}$. Typically, a non-interlisted firm receives a higher weight in constructing a match when its observed characteristics are "closer" to those of an interlisted firm $i \in \mathbf{I}_L$, using a specific distance measure. The estimated change in a trading property for each firm i in the sample of firms interlisted on US exchange L is

$$Y_{Li}^p - \sum_{j \in \mathbf{I}_0} W_L(i,j) Y_{0j}^p \tag{4}$$

where $W_L(i,j)$ is a positive valued weight function, defined such that $\sum_{j \in \mathbf{I}_0} W_L(i,j) = 1 \; \forall i \in \mathbf{I}_L$, and N_L and N_0 are the number of firms in $\mathbf{I}_L$ and $\mathbf{I}_0$, respectively. The weighting function assigns weights to the trading properties of each non-interlisted firm based on distances in the space of observed characteristics, $\mathbf{X}$. Different matching estimates can be constructed by using different weighting functions and/or different distance measures.

In general, an estimate of the average effect of being interlisted on US exchange L on trading property p is given by

$$\hat{M}(L,p,\mathbf{S}) = \frac{1}{N_L} \sum_{i \in \mathbf{I}_L} \left(Y_{Li}^p - \sum_{j \in \mathbf{I}_0} W_L(i,j) Y_{0j}^p \right). \tag{5}$$

We consider three alternative matching estimators that can be constructed based on (5). A neighborhood $C(\mathbf{X}_i)$ is defined for firm $i \in \mathbf{I}_L$. Neighbors for firm i are non-interlisted firms $j \in \mathbf{I}_0$ for which $\mathbf{X}_j \in C(\mathbf{X}_i)$. The firms matched to i are those firms in set $\mathbf{A}_i$ where

$$\mathbf{A}_i = \{ j \in \mathbf{I}_0 | \mathbf{X}_j \in C(\mathbf{X}_i) \}.$$

The alternative estimators are defined as follows:

Nearest neighbor (1-NN) matching estimator: For each $i \in \mathbf{I}_L$, select the match

$$C(\mathbf{X}_i) = \min_j ||\mathbf{X}_i - \mathbf{X}_j||, \;\; j \in \mathbf{I}_0$$

where $||\cdot||$ is a norm. For the univariate case, the distance measure we select is $(x_i - x_j)/(x_i + x_j)$. $\mathbf{A}_i$ is a singleton set except for ties that are broken by a random draw. The weighting scheme for the nearest-neighbor estimator assigns all the weight to the single match: $W_L(i,j)$ equals 1 if $j \in \mathbf{A}_i$ and equals 0 otherwise.[4]

[4]We also considered a variant of the nearest-neighbor matching estimator (known as caliper matching), where

k-NN matching estimator with uniform weights: Now, $\mathbf{A}_i$ is a set of k closest firms to firm i according to the distance measured employed. The weights are $W_L(i,j)$ equals $1/k$ if $j \in \mathbf{A}_i$ and equals 0 otherwise. We focus on the case where $k = 2$.

k-NN matching estimator with triangular weights: Now, rank the k closest firms to firm i, where $r = 1$ is the closest, $r = 2$ is the next closest, etc. Then, the weights are $W_L(i,j) = 2(k - r + 1)/(k(k+1))$ if $j \in \mathbf{A}_i$ and equals 0 otherwise.

Kernel-based matching estimators: As k increases, k-NN matching estimators become effectively Nadaraya-Watson kernel-based matching estimators. Univariate kernel-based matching estimates based on characteristic $x \in \mathbf{X}$ are constructed as follows. Kernel matching sets $\mathbf{A}_i = \mathbf{I}_0$ and defines

$$W_L(i,j) = \frac{K_{ij}}{\sum_{k \in \mathbf{I}_0} K_{ik}},$$

where $K_{ik} = K((x_i - x_k)/h)$ is a kernel function and h is a bandwidth parameter. We use a kernel based on the standard normal density function,

$$K_{ik} = \frac{1}{h} K\left(\frac{x_i - x_k}{h}\right) = \frac{1}{h}\left[\frac{1}{\sqrt{2\pi}} \exp\left\{-\frac{1}{2}\left(\frac{x_i - x_k}{h}\right)^2\right\}\right].$$

To investigate the sensitivity of predictions to the bandwidth parameter, we first consider two bandwidth parameters: $h_1 = 1.059 s N_0^{-1/5}$ and $h_2 = 1.059 s N_0^{-1/3}$; where

$$s = \sqrt{\frac{1}{N_0}\sum_{j \in \mathbf{I}_0} x_j^2 - \left(\frac{1}{N_0}\sum_{j \in \mathbf{I}_0} x_j\right)^2}.$$

Intuitively, the bandwidth parameter controls the amount of smoothing across firms: A larger value causes the matching estimate to place more weight on firms that are further away, in terms of the matching characteristic. The choice of h_1 is motivated by the desire to minimize the approximate mean-integrated squared error (AMISE). This essentially equates the trade-off between the bias and the variance of the kernel estimate (see Pagan and Ullah (p. 24,

matches are made to interlisted firm i only if there exists a non-interlisted firm j such that

$$||\mathbf{X}_i - \mathbf{X}_j|| < \varepsilon, \quad j \in \mathbf{I}_0$$

where ε is a pre-specified tolerance. Otherwise, no match is undertaken, and firm i is omitted. This procedure is designed to circumvent the problem of a substantial gap between i and j. In practice, caliper matching produces similar results to that of eliminating the largest interlisted firms, which we consider later.

1999)). The choice of h_2 is motivated by the observation that when constructing bootstrap confidence intervals, the criterion should be to minimize the potential bias of the estimate since the variance will be "dealt with" through the bootstrap repetitions. It turns out that the bias is minimized by a bandwidth parameter that is proportional to $n^{-1/3}$, instead of the usual $n^{-1/5}$ (see Davison and Hinkley (p. 228, 1997)).

Because of the significant heterogeneity in firm market capitalization, we also consider a variable window-width kernel estimator where $K_{ik} = K((x_i - x_k)/h_i^{min})$ and h_i^{min} is distance of firm i from its closest nearest neighbor.

3 Institutional Details

The TSE faces intense competition from US exchanges. In 1998, 58.7% of the total value of trading volume on the TSE was comprised of trading in securities that were also listed on a US exchange. At the end of 1998, 220 Canadian firms were interlisted and 25% of trading in these stocks occurs in US markets.[5]

The TSE, Nasdaq, NYSE, and AMEX have concurrent regular trading hours between 9:30AM and 4:00PM. The TSE operates as a transparent electronic limit order market, with a responsible registered trader (RRT) assigned to each security.[6] TSE member firms can *internalize* order flow: after receiving an order, the member firm's "upstairs traders" can either trade the order with a member firm account or with another customer order prior to sending it to the consolidated limit order book.

The NYSE and AMEX have similar market structures: an auction market with floor trading and specialist intermediation. Unlike the RRT, the specialist has exclusive knowledge of the limit order book. Most NYSE stocks and some AMEX stocks are also traded on the US regional exchanges with market orders executed against the best posted quote in the consoli-

[5]Source: TSE 1998 Annual Report.

[6]The RRT's main responsibilities are: (i) to contribute to market liquidity; (ii) to moderate price volatility; (iii) to maintain a continuous two-sided market; and (iv) to fill odd lot orders and orders eligible for a Minimum Guaranteed Fill (MGF).

dated limit order book. Often, smaller retail orders are sent to the US regional exchanges in return for a payment for order flow. In partial response to this competition, the NYSE specialist often posts a wide spread but then attempts to obtain price improvement for incoming orders. Nasdaq operates as a dealer market with several competing dealers posting quotes. Prices of larger trades may be negotiated on a one-on-one basis with each dealer. Preferencing arrangements and competition from Electronic Communication Networks (ECNs) play a particularly important role on the Nasdaq.

US exchanges trade shares of Canadian firms in US dollars, but as ordinary securities (not as American Depository Receipts (ADRs)). Thus, from a legal perspective, a firm's shares traded on US and Canadian exchanges are equivalent. There are, however, important logistical considerations, including: foreign exchange transaction costs and risks; different settlement procedures; and brokerage firms may not be members of all exchanges. While US dollar trading accounts are relatively common in Canada, very few US retail investors would have the same easy access to Canadian markets. During the period under consideration, there were important restrictions on Canadian retail trade interlisted stocks on Nasdaq (which was considered an OTC market by Canadian regulators). These restrictions meant that Canadian retail trade in Nasdaq-interlisted stocks must be sent to a Canadian market unless the price was strictly better on Nasdaq.

As discussed in Aggarwal and Angel (1998), the listing requirements and the market structures of each of the US exchanges tends to attract different firm types. A dealer market, such as the Nasdaq, provides strong incentives for broker-dealers to promote a stock which tends to be attractive for newer, technology firms with possibly little, or no profit record. In contrast, NYSE rules explicitly prevent the specialist from generating order flow and require prospective firms to have a history of profits prior to listing. As a result, the NYSE tends to attract larger, more established firms. The AMEX tends to attract smaller firms that may not meet the more stringent NYSE listing requirements or firms that have multiple classes of shareholders (something discouraged on the NYSE). In the subsequent analysis, it is important to remember that apparent differences between the effect of interlisting on these exchanges may be a result of differences in the type of firm that tends to interlist on the exchange, not a direct result of differences in market structure.

4 Data

From the 1998 TSE Equity History database, we obtain records of executed trades (board[7] and odd lot) and inside quote revisions for all TSE-listed securities.[8] A benefit to using data from 1998 is that it provides us with a sufficient sample of non-interlisted stocks with which to match the largest interlisted stocks. During the past few years, many of these previously non-interlisted stocks have subsequently become interlisted on a US exchange (e.g. Bank of Nova Scotia).[9] We restrict attention to a sample of 451 actively traded common stocks of Canadian-based companies with market capitalizations greater than C$100 million on Dec. 31, 1997.[10]

The final sample is composed of 317 non-interlisted firms, 55 Nasdaq-interlisted firms, 19 AMEX-interlisted firms, and 60 NYSE-interlisted firms. Figure 1 presents a scatter plot of the distribution of firms by market capitalization and average daily trading dollar volume. Notice that of the largest fifteen firms included in the sample, 11 are NYSE-interlisted and one is AMEX-interlisted. It will be especially challenging to find suitable matches for these firms on the basis of market capitalization. Figure 2 shows that these distributional problems are reduced for the smaller firms in the sample. While it is tempting to focus solely on the smaller firms, it is important to emphasize that similar distributional problems exist in most other previous applications of matched samples and therefore it is important to investigate the impact of including the "outliers".

[7] Typically, orders in units of 100 shares.

[8] Refer to Davies (2003) for additional details about this database.

[9] This is somewhat reassuring since it implies that there would be little benefit to using a propensity score adjustment for the propensity to list on a US exchange. Specifically, it suggests that all major Canadian companies have high propensities to list on a US exchange – actual listing decisions have been driven by historical factors.

[10] Our sample excludes securities that were under suspension, securities that were added or eliminated from the TSE stock list at any time during 1998, and securities that had a monthly trading dollar volume less than C$100,000 during any month in the sample period. For convenience, we also exclude any security that changed its symbol during 1998.

For each firm, the percentage bid-ask spread is calculated as $2 * (ask - bid)/(ask + bid)$ and the average is based on the latest bid and ask price posted at five minute intervals during regular trading hours.[11]

For the subperiod from January to July 1998, the TSE Equity History Database provides information about whether executed trades involved orders submitted for a client, a non-client, or a registered trader (RT) account. Non-client account orders can be further classified as either an inventory account or a non-inventory account order. Inventory account orders are orders involving the member firm's liability account managed by the member firm's upstairs traders. These trades may originate either as upstairs trades that are executed as "put-throughs" or as trades against the public limit order book. We use this trade record information to examine the effect of being interlisted on the trading behavior of different market participants.

The estimation results presented are obtained using market capitalization as the matching characteristic.[12] In general, larger firms are more actively traded, have narrower bid-ask spreads, are held by more institutional investors, and are more widely followed (and thus have lower associated adverse selection costs). Thus, for most purposes, market capitalization provides the most obvious characteristic over which to match firms. The addition of other matching characteristics (e.g. share price, market beta) may or may not improve these results

[11]Other measures, such as an effective bid-ask spread, are difficult to construct using the available database. The TSE Equity History Database records all quote and trade timestamps at six second intervals: as a result, it is difficult to order sequentially all trades and quotes in periods with high trade volumes. Because price improvement is much less common on the TSE, there should be little or no difference between the effective spread and the observed spread.

[12]Doukas and Switzer (2000) find evidence of mild segmentation between Canadian and US markets, resulting in significant positive abnormal returns from an announcement by a Canadian-based firm of its intention to become interlisted on a US exchange. Specifically, they find that firms have a cumulative abnormal return of 2.17% during the period -1 day to $+1$ day around the announcement date. To the extent that becoming interlisted impacts the market capitalization of interlisted firms, our results may be biased from using market capitalization as the matching characteristics. The bias is likely to be *very* small since the listing effect is small relative to the large number of other factors influencing firm size and relative to the differences in market capitalization among firms in the sample.

- in order to focus on the estimation method, rather than the data inputs, we do not explore this here.[13]

5 Monte Carlo Simulation Results

The size-power properties of tests based on the various matching estimation approaches are determined using Monte Carlo simulation. A similar approach has been used in the abnormal performance literature.[14] Kahle and Walkling (1996) simulate a typical financial experiment to explore how the ability to detect abnormal performance varies between tests using matched samples based on firm size only and tests using matched samples based on firm size and industry classification. They show that tests based on industry-matched samples are more powerful than pure size matches and that the actual database source of the industry classifications matters. These results are revisited in Lie (2001) who shows that the methods used can produce severely biased test statistics. Unlike Kahle and Walkling (1996) and Lie (2001), we focus on the matching estimation approach (i.e. nearest neighbor versus kernel-based estimation) rather than the inputs (i.e. firm characteristics) used in the matching.

We proceed as follows. For each of 10,000 Monte Carlo replications:

1. We randomly select without replacement N stocks out of the total sample of 451 firms (no distinction is made for listing status).[15] The percentage bid-ask of each of these N

[13]In results not reported here, we use an approach similar to that used by Huang and Stoll (1996) that includes additional firm characteristics. Specifically, for each firm $j \in I_L$ that is interlisted on exchange L, we select non-interlisted firm $i \in I_0$ that solves:

$$\text{argmin}_{i \in I_0} \sum_{k=1}^{3} \left(\frac{2(x_{Lj}^k - x_{Oi}^k)}{x_{Lj}^k + x_{Oi}^k} \right)^2 \tag{6}$$

where x_{Oi}^k is firm characteristic k for a non-interlisted firm i and x_{Lj}^k is firm characteristic k for interlisted firm j. We match over the following three firm characteristics (obtained from Datastream): (i) the number of shares outstanding; (ii) the share price; and (iii) the stock's beta. We also consider the possibility of restricting matches to within the same TSE-provided industry code (industrial, mining, and oil). While different in magnitude, these results lie within the confidence intervals found using market capitalization as the only matching characteristic.

[14]See also Barber and Lyon (1996).

[15]We also conducted Monte Carlo simulations in which the firms were randomly selected *with replacement*. The

stocks is artificially changed by θ: $\hat{Y}_i = Y_i + \theta$,

2. Each of the N stocks are "matched" with a "hypothetical" firm created using a weighting of the remaining $451 - N$ firms. The weighting scheme used depends on the matching estimation technique.

3. Based on a comparison of the N stocks with induced differences and their hypothetical matched pairs, we then construct a two-sided nonparametric Wilcoxon signed rank test of size α of the difference in bid-ask spreads between the two groups.

Figure 3 illustrates the power of 1-NN, 2-NN (equal weights) and 3-NN (triangular weights) matching techniques for different levels of induced changes in the percentage bid-ask spread, θ. The k-NN matching techniques are compared with a random selection approach that randomly matches two firms independently of their market capitalization (or any other firm characteristic). In some sense, the "random" selection approach provides a lower bound for the power of the matching estimates. In comparison with this lower bound, using market capitalization as a matching characteristic generates a significant improvement in power.

All three k-NN matching techniques produce similar results. Notice, however, as k increases (i.e. as nearest neighbor estimates are constructed over additional closest firms), the power curve is biased away from zero and shifted to the right. The intuition for the bias in the power curve is as follows. Recall that bid-ask spreads (Y) are a function of market capitalization (X) and unobservables (U),

$$Y_i = g(X_i) + U_i.$$

Then in our simulation, the estimated difference between the two samples for a firm with market capitalization $\tilde{X}$ is

$$\hat{\Delta}(\tilde{X}) = g(\tilde{X}) + \theta - \sum_i W_i g(X_i) + \tilde{U} - \sum_i W_i U_i \tag{7}$$

A bias is introduced because $\sum_i W_i g(X_i) \neq g(\sum_i W_i X_i)$ except for the 1-NN matching estimates. Increasing the number of firms given positive weights ($W_i > 0$) and/or increasing the

problem with this approach is that the nearest neighbor of a firm is often itself - this increases the power of the 1-NN estimation method relative to the other approaches.

dispersion of weights in the matching estimate (either by increasing k in nearest neighbor estimates or by increasing h in kernel estimates) increases this bias. In the case of k-NN estimates, the bias is made worse because the X_i values are not equispaced and do not follow a uniform distribution.

While increasing the number of firms given positive matching weights increases the bias, it also helps reduce the variance associated with unobservable firm characteristics, since $\text{plim}_{n\to\infty} n^{-1/2}(\tilde{U} - \sum_{i=1}^{n} W_i U_i) = b$, where b is a constant. Clearly, there is a trade-off between bias and variance. The optimal matching technique then depends on: (i) the number of matched pairs; and (ii) how small is the difference we are attempting to measure. This is further illustrated by figures 4 and 5.

Figure 4 illustrates the power of the kernel-based matching estimate for bandwidth parameters h_1, h_2, and h_i^{min} (variable bandwidth) for different levels of induced changes in the percentage bid-ask spread, θ. The figure also illustrates the 1-NN results for comparison purposes. The theoretical bandwidth parameters are much too large - this is caused by the extremely large differences in market capitalization of the largest few firms. As a result, the power curves of the kernel estimates are biased to the right, much in the same way as increasing k did for the k-NN estimates. In fact, for small positive induced differences, there is a region in which the simplistic random match approach actually performs better than the kernel-based matching estimate with bandwidth parameters h_1 and h_2. The variable bandwidth kernel estimates appear to perform much better than fixed bandwidth kernel estimates - the variable bandwidth approach may therefore be appropriate when there is significant heterogeneity across firms (as is the case in most market microstructure applications).

Figure 5 considers how the power of tests based on nearest neighbor estimates change with the number of matched pairs N. The results are based on 20,000 Monte Carlo replications in which the induced difference is $+0.5s(Y)$ for 50% of the replications and $-0.5s(Y)$ for 50% of the replications, where $s(Y)$ is the standard deviation of the percentage bid-ask spreads of the stocks in the sample. As expected, the power of all of the tests decreases with the number of matched pairs. Interestingly, the highest level of power is obtained using the $h_2 =$

$1.059sN_0^{-1/3}$ kernel-based matching estimate, while the worst level of power is obtained by using the $h_1 = 1.059sN_0^{-1/5}$ kernel based matching estimate. This highlights how important the choice of bandwidth parameter can be.

In this example, four of the five alternative estimates provide *higher* power than the standard nearest neighbor matching estimate. This suggests that if the expected difference is large and the number of matched pairs is small, then minimizing the variance is relatively more important than the estimation bias and we should use a matching estimate that places more weight on more distant firms.

In figure 6, we illustrate an analogous power graph for a smaller induced difference of $0.2s(Y)$ for 50% of the replications and $-0.2s(Y)$ 50% of the replications. Clearly, all of the matching estimation techniques have much less power than the previous case. Again, the highest level of power is obtained using the h_2 kernel-based matching estimate. The worst power is obtained using the nearest-neighbor (1-NN) based approach.

6 Results on the impact of interlisting

With these insights into the power properties of our matching estimates, we proceed to estimate the actual effect of interlisting using the real data. The matching estimate of the impact of interlisting on exchange L for firms with market capitalization of $\tilde{X}$ is:

$$\hat{\Delta}_L(\tilde{X}) = g_L(\tilde{X}) - \sum_{i \in I_0} W_i g_0(X_i) + \tilde{U} - \sum_{i \in I_0} W_i U_i \tag{8}$$

This is analogous to equation (7) for our simulation results. Our Monte Carlo results tell us that the estimation bias is such that our test power will be higher for negative differences in bid-ask spreads and lower for positive differences in bid-ask spreads. Our Monte Carlo results also suggest that, because of the relatively small sample of AMEX-interlisted firms, additional “smoothing” may be lead to more powerful tests of the impact of interlisting on AMEX.

6.1 Nonparametric Tests

Table 1 presents the Wilcoxon signed rank tests for NYSE-, AMEX- and Nasdaq-interlisted stocks. There is significant evidence that interlisting on the NYSE causes a decrease in percentage bid-ask spreads for trading on the TSE.[16] The results for AMEX- and Nasdaq-interlisted stocks depend on the estimation technique used. For Nasdaq-interlisted stocks, there is a significant negative difference (at the 5% significance level) for all cases except for the 1-NN matching estimates. For AMEX-interlisted stocks, there is a significant negative difference for only the kernel-based matching estimates with bandwidth parameters h_1 and h_2. As demonstrated in our Monte Carlo analysis, this reflects the additional power (and higher potential type 1 error) of tests using kernel-based estimates to detect negative differences in bid-ask spreads.

We now proceed to investigate whether interlisting results in changes in the share of order flow from institutional investors. Non-client account orders provide a useful proxy for the level of institutional trade in a security. It is difficult to predict whether interlisting will have a positive or negative effect on the share of orders for non-client accounts. On the one hand, the share of order flow involving non-client accounts may be higher for interlisted stocks if they are more attractive to institutional investors. Interlisted stocks may be more attractive to institutions for a variety of reasons: (i) firms interlisted on a US exchange may be subject to more stringent disclosure and accounting rules; (ii) firms interlisted on a US exchange generally have a greater following by financial analysts and the media; (iii) stocks interlisted on a US exchange may be easier to unload quickly in large quantities if unexpected news arises.

On the other hand, the share of order flow involving non-client accounts may be lower for interlisted stocks if institutional order flow tends to migrate to the US exchange. While retail order flow is largely constrained to trade on the domestic exchange, institutions have greater discretion as to which exchange they send their orders to. Under certain circumstances, they

[16] This is despite recent evidence that NYSE specialists participate less actively in Canadian-based firms interlisted on the NYSE (Bacidore and Sofianos (2002)).

may prefer to send their orders to the US exchange if they think that by doing so they will receive better execution (i.e. better current prices) and/or will incur lower informational costs (i.e. better future prices).

Table 2 reports that listing on the NYSE or Nasdaq results in a significant increase in the percentage of order flow involving non-client orders. Thus, decreases in the percentage bid-ask spread coincide with increases in institutional order flow. The effect is not significant for AMEX-interlisted firms.

We now examine whether the existence of alternative trading facilities and competing US market makers influences the RRT participation and RRT trading revenues. To construct an estimate of RRT gross trading revenues, we assume that:

1. The RRT begins the sample period with a position of zero in all stocks of responsibility;
2. The RRT closes out his accumulated position at the end of the sample period at the last recorded transaction price.

Let K_i^t denote the number of trades for security i involving the RRT during trading day $t \in [1, T]$. Let $n_i(t,k)$ denote the number of shares of security i sold (negative values indicate purchases) at trade number $k \in [1, K_i^t]$ on trading day t, and let $P_i(t,k)$ denote the corresponding transaction price. Average daily RRT gross trading revenues in security i over the sample period are estimated as:

$$\pi_i = \frac{1}{T}\left\{\left(\sum_{t=1}^{T}\sum_{k=1}^{K_i^t} P_i(t,k)n_i(t,k)\right) - P_i(T, K_i^T)\sum_{t=1}^{T}\sum_{k=1}^{K_i^t} n_i(t,k)\right\}. \tag{9}$$

Table 3 reports the estimates of the impact on RRT participation and RRT gross trading revenues from being interlisted on a US exchange. The results suggest that there is no significant impact on RRT trading revenues from interlisting on any of the US exchanges.

The effect of interlisting on RRT participation is less clear. There is weak evidence that interlisting on Nasdaq and the NYSE has opposite effects on RRT participation levels: RRT participation levels decrease for NYSE-interlisted stocks, RRT participation levels increase for Nasdaq-interlisted stocks. Thus, the competitive response of Toronto-based market makers to the multiple dealer trading environment for Nasdaq stocks appears to be stronger than that of the specialist trading environment of the NYSE. Overall, there does not appear to be a direct relationship between changes in TSE market maker participation and changes in bid-ask spreads.

6.2 Confidence Intervals

In this section, we investigate whether our previous results hold when examining average differences in percentage bid-ask spreads, rather than a non-parametric approach. We construct percentile-t bootstrap confidence intervals for the *average* effect of being interlisted on percentage bid-ask spreads. The double bootstrap procedure is described in the appendix. Table 4 reports the effect of being interlisted on the average percentage bid-ask spread.

The average changes in the bid-ask spread from interlisting and their associated bootstrap confidence intervals generally correspond with the nonparametric test results. Specifically, we find evidence that being interlisted on the NYSE significantly decreases trading costs on the TSE. The change in percentage bid-ask spreads is economically significant, around 0.2 to 0.4 percent. The effect is also negative for AMEX- and Nasdaq-interlisted stocks, although their bootstrap confidence intervals include zero. Importantly, the confidence intervals for 1-NN estimates are generally larger than those using kernel-based estimates. This reflects the higher variance of standard nearest neighbor estimation relative to approaches that have positive weights on distant firms.

Finally, we investigate whether our confidence intervals can be narrowed by eliminating the largest interlisted firms for which there are no good matches. To do this, we exclude the 11 largest NYSE-interlisted firms and the largest AMEX-interlisted firm (Imperial Oil Ltd.) from the sample and re-estimate the bootstrap confidence intervals.[17] The estimated

[17]Ideally, one would like to introduce a propensity score adjustment, similar to those normally used in the labor economics literature, in order to eliminate the largest firms which "almost always" are interlisted. Unfortunately, this is difficult to do in this context due to the small number of firms which become interlisted in any given year

confidence intervals are similar – suggesting that our results are not driven by the largest firms.

7 Conclusion

Despite their apparent simplicity, standard nearest neighbor (1-NN) matching estimation techniques typically have less bias and comparable power to more complex matching estimation techniques for measuring differences in bid-ask spreads. When estimating differences using a small number of matched pairs, however, it is desirable to use matching estimates that place weight on more distant firms (e.g. k-NN ($k > 1$) nearest-neighbor matching estimates or kernel-based matching estimates). Essentially, there is an important trade-off between estimation bias and variance.

Bootstrap confidence intervals of changes to average bid-ask spreads are very wide – suggesting that it is preferable to use non-parametric approaches rather than calculating averages to compare the impact of listing. Narrower confidence intervals can be obtained by using matching estimates that place weight on more distant firms relative to the standard nearest neighbor approach.

We show that interlisting on the NYSE or Nasdaq has a significant negative effect on percentage bid-ask spreads posted in Toronto and results in significantly higher share of order flow from non-client (institutional) accounts. RRT participation decreases for NYSE-interlisted firms but increases for Nasdaq-interlisted firms. US listing status does not have a direct impact on RRT gross trading revenues. These results are verified for robustness by using a variety of different matching estimates.

and because of the small number of firms in general.

A Appendix: Bootstrap Confidence Intervals

Percentile–t bootstrap confidence intervals for the estimate $\hat{M}(L,p)$ are constructed using a "double" bootstrap procedure.[18] The double bootstrap procedure is necessary because of the lack of a tractable analytical expression for the standard error of the first level bootstrap matching estimate.

Denote the number of first-level bootstraps by B_1, indexing them by b_1, and the number of second-level bootstraps by B_2, indexing them by b_2. B_1 is chosen such that $\alpha(B_1+1)$ is an integer, where 2α is the desired confidence level. We select $B_1 = 999$ and $B_2 = 199$. For each bootstrap repetition $b_1 = 1, \ldots, B_1$, the **first-level bootstrap** proceeds as follows:

1. N_0 stocks are randomly selected with replacement from the set of non-interlisted stocks $\mathbf{I}_0$. Also, N_L stocks are randomly selected with replacement from the set of interlisted stocks $\mathbf{I}_L$. Denote the set of indices for the bootstrap sample of non-interlisted stocks by $\mathbf{I}_0^*(b_1)$ and the set of indices for the bootstrap sample of stocks interlisted on US exchange L by $\mathbf{I}_L^*(b_1)$.

2. Using these bootstrap samples, construct the matching weights, $W_{b_1}^*(i,j)$. Estimate $M_{b_1}^*(L,p)$ as follows:

$$M_{b_1}^*(L,p) = \frac{1}{N_L} \sum_{i \in \mathbf{I}_L^*(b_1)} \left(Y_{Li}^p - \sum_{j \in \mathbf{I}_0^*(b_1)} W_{b_1}^*(i,j) Y_{0j}^p \right). \tag{10}$$

3. Using the sample of stocks $\mathbf{I}_0^*(b_1)$ and $\mathbf{I}_L^*(b_1)$, a **second-level bootstrap** is conducted. Each repetition, $b_2 = 1, \ldots, B_2$ of the second-level bootstrap proceeds as follows:

   (a) Randomly select with replacement N_0 stocks from the set of stocks $\mathbf{I}_0^*(b_1)$ and randomly select with replacement N_L stocks from the set of stocks $\mathbf{I}_L^*(b_1)$. Denote the set of indices for the second-level bootstrap sample of non-interlisted stocks by $\mathbf{I}_0^{**}(b_2, b_1)$ and the set of indices for the bootstrap sample of stocks interlisted on US exchange L by $\mathbf{I}_L^{**}(b_2, b_1)$.

[18] We also consider percentile bootstrap confidence intervals based on a "single" bootstrap procedure. Similar results are obtained.

(b) Using these second-level bootstrap samples, construct the matching weights, $W^{**}_{b_2,b_1}(i,j)$. Estimate $M^{**}_{b_2,b_1}(L,p)$ as follows:

$$M^{**}_{b_2,b_1}(L,p) = \frac{1}{N_L} \sum_{i \in \mathbf{I}^{**}_L(b_2,b_1)} \left(Y^p_{Li} - \sum_{j \in \mathbf{I}^{**}_0(b_2,b_1)} W^{**}_{b_2,b_1}(i,j) Y^p_{0j} \right). \tag{11}$$

4. Using the estimates $M^{**}_{b_2,b_1}(L,p)$ from the second-level bootstrap, the standard error $\sigma^*_{b_1}$ is estimated as follows:

$$\sigma^*_{b_1} = \sqrt{\frac{1}{B_2} \sum_{b_2=1}^{B_2} \left(M^{**}_{b_2,b_1}(L,p) \right)^2 - \left(\frac{1}{B_2} \sum_{b_2=1}^{B_2} M^{**}_{b_2,b_1}(L,p) \right)^2}. \tag{12}$$

5. Using the estimated standard error, $\sigma^*_{b_1}$, the bootstrap t statistic is constructed as: $t^*_{b_1} = [M^*_{b_1}(L,p) - \hat{M}(L,p)]/\sigma^*_{b_1}$.

Using the estimates $M^*_{b_1}(L,p)$ from the first-level bootstrap, the standard error $\hat{\sigma}$ is estimated as follows:

$$\hat{\sigma} = \sqrt{\frac{1}{B_1} \sum_{b_1=1}^{B_1} \left(M^*_{b_1}(L,p) \right)^2 - \left(\frac{1}{B_1} \sum_{b_1=1}^{B_1} M^*_{b_1}(L,p) \right)^2}. \tag{13}$$

The bootstrap t statistics $t^*_{b_1}$ are sorted from smallest to largest such that $t^*_1 \leq t^*_2 \leq \ldots \leq t^*_{B_1}$. Define $\hat{t}^*_\alpha = t^*_{\alpha(B_1+1)}$ and $\hat{t}^*_{1-\alpha} = t^*_{(1-\alpha)(B_1+1)}$. The percentile–t bootstrap confidence interval with 2α level of confidence is defined as $\left[\hat{M}(L,p) - \hat{t}^*_{1-\alpha}\hat{\sigma}, \;\; \hat{M}(L,p) - \hat{t}^*_\alpha \hat{\sigma} \right]$.

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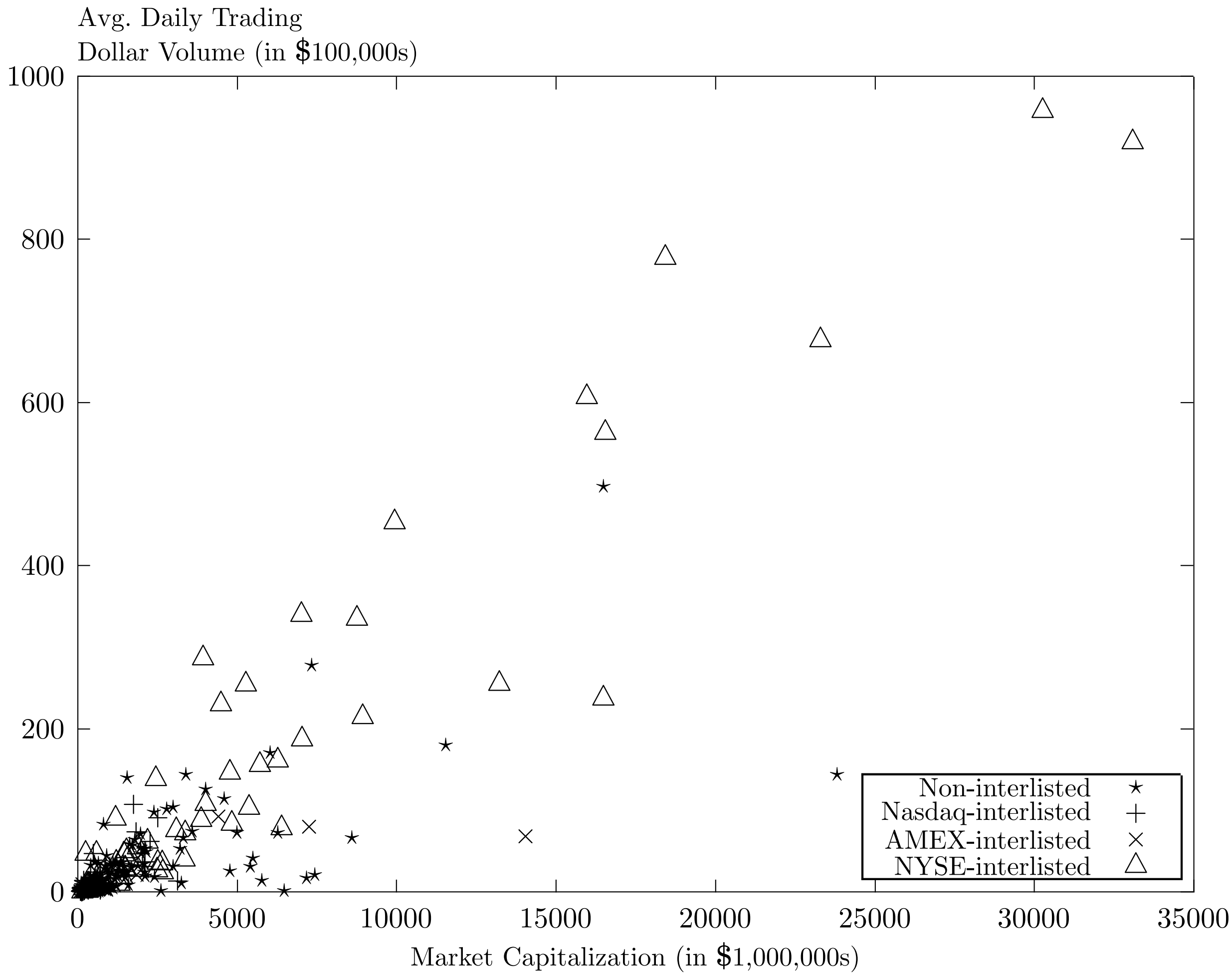

Figure 1: Scatter plot of distribution of firms by market capitalization and average daily dollar trading volume on the TSE.

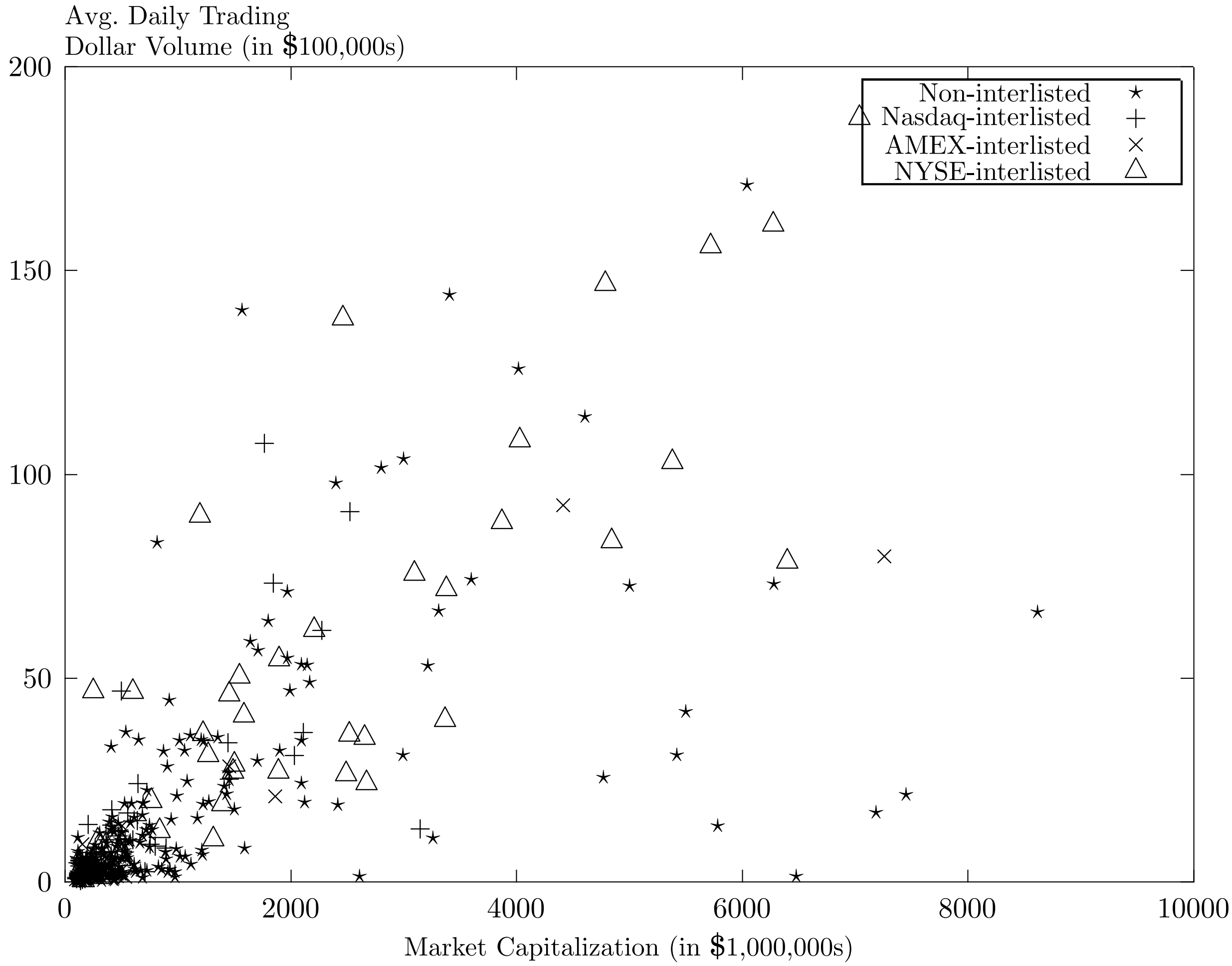

Figure 2: Scatter plot of distribution of firms by market capitalization and average daily dollar trading volume on the TSE (focusing on smaller firms).

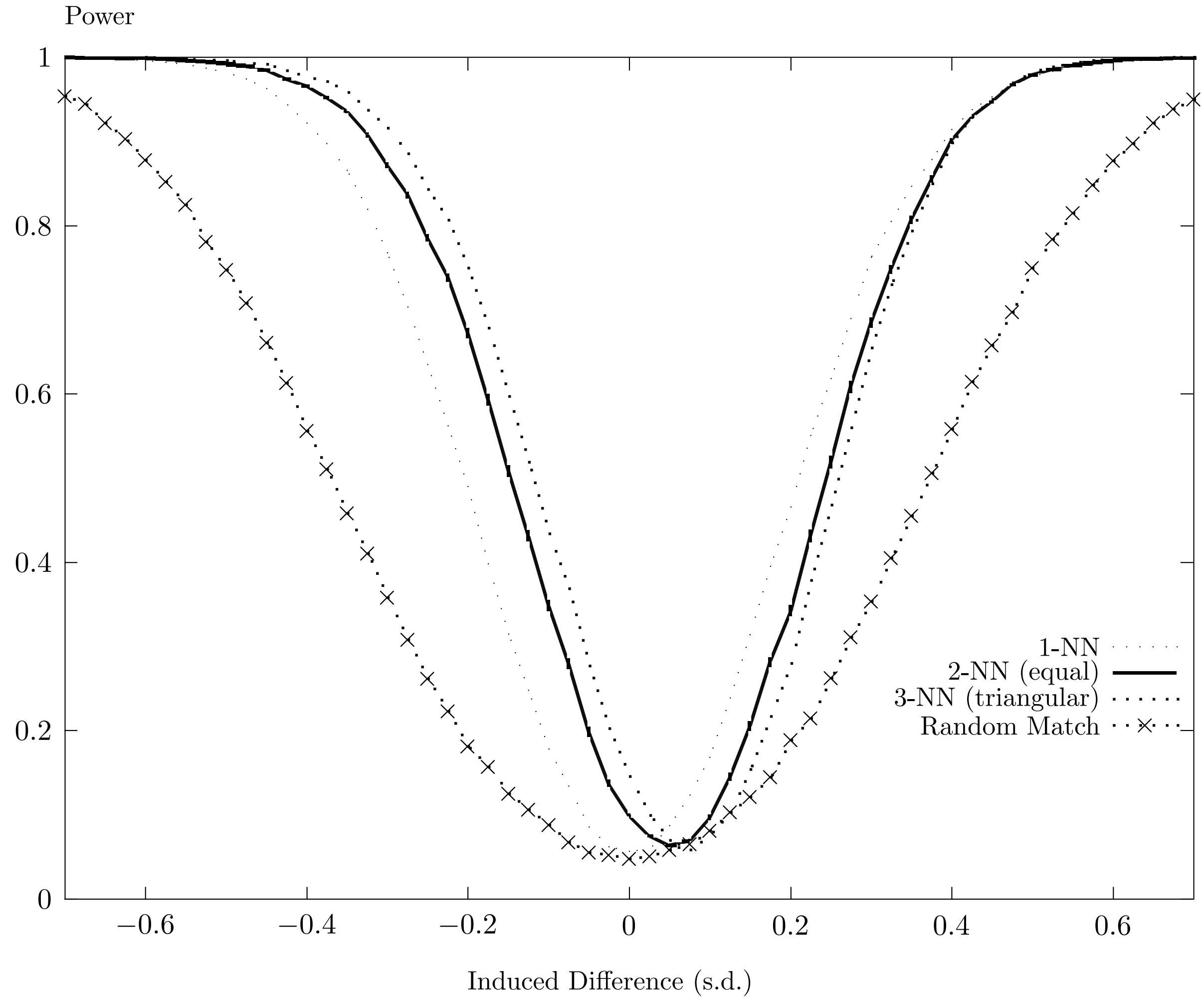

Figure 3: Power graph of two-sided Wilcoxon signed rank test ($\alpha = 0.05$) based on 1-NN, 2-NN (equal weights) and 3-NN (triangular weights) matching estimates. Random Match indicates a test based on matched pairs randomly selected wihtout reference to any matching characteristics. Power is plotted as a function of the induced difference (expressed in standard deviation terms). Based on 10,000 Monte Carlo replications and 50 matched pairs.

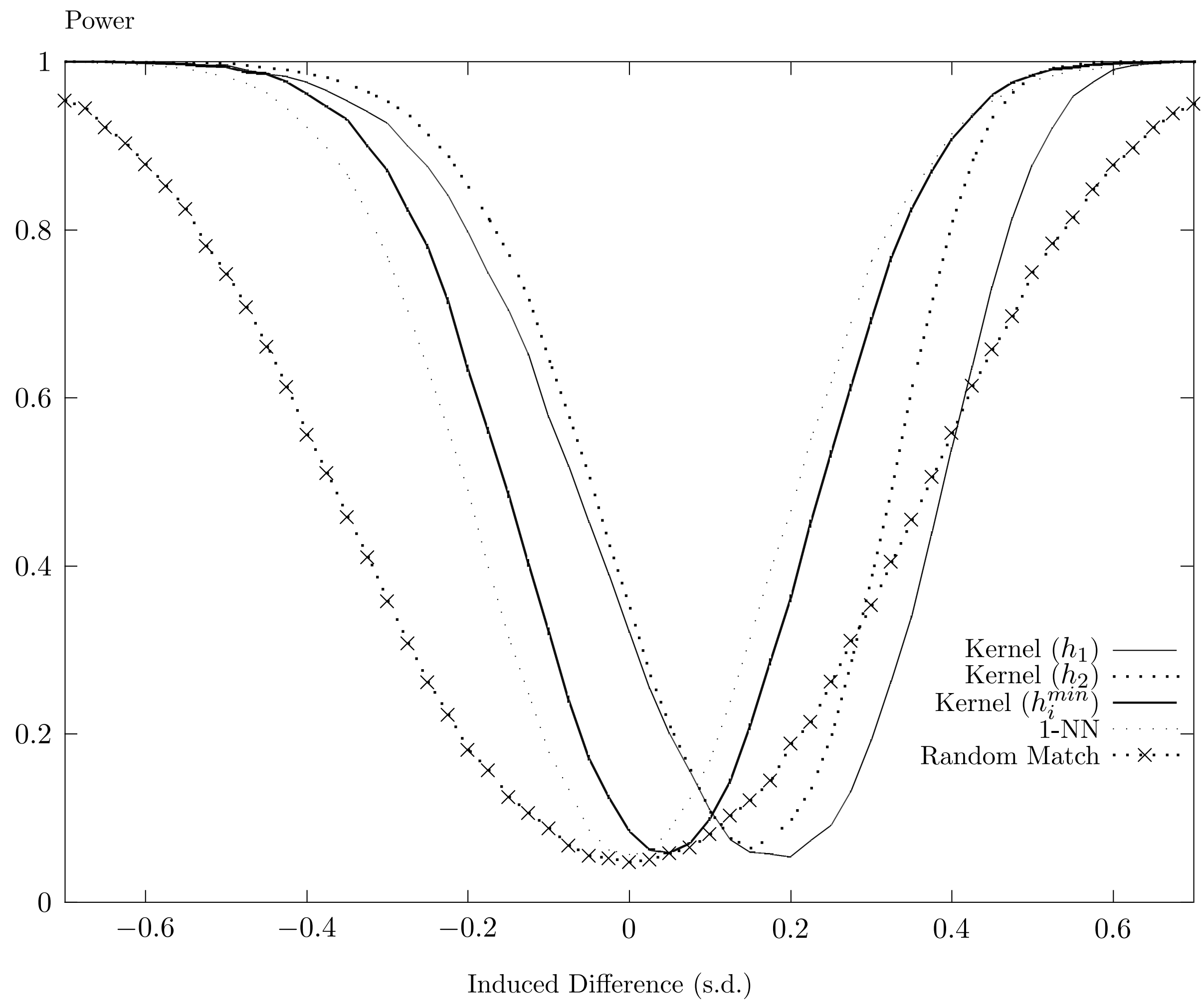

Figure 4: Power graph of two-sided Wilcoxon signed rank test ($\alpha = 0.05$) based on kernel-based matching estimates with bandwidth parameters: $h_1 = 1.059sN_0^{-1/5}$, $h_2 = 1.059sN_0^{-1/3}$, and h_i^{min} (variable bandwidth). The power of 1-NN matching estimates are also reported for comparison purposes. Power is plotted as a function of the induced difference (expressed in standard deviation terms). Based on 10,000 Monte Carlo replications and 50 matched pairs.

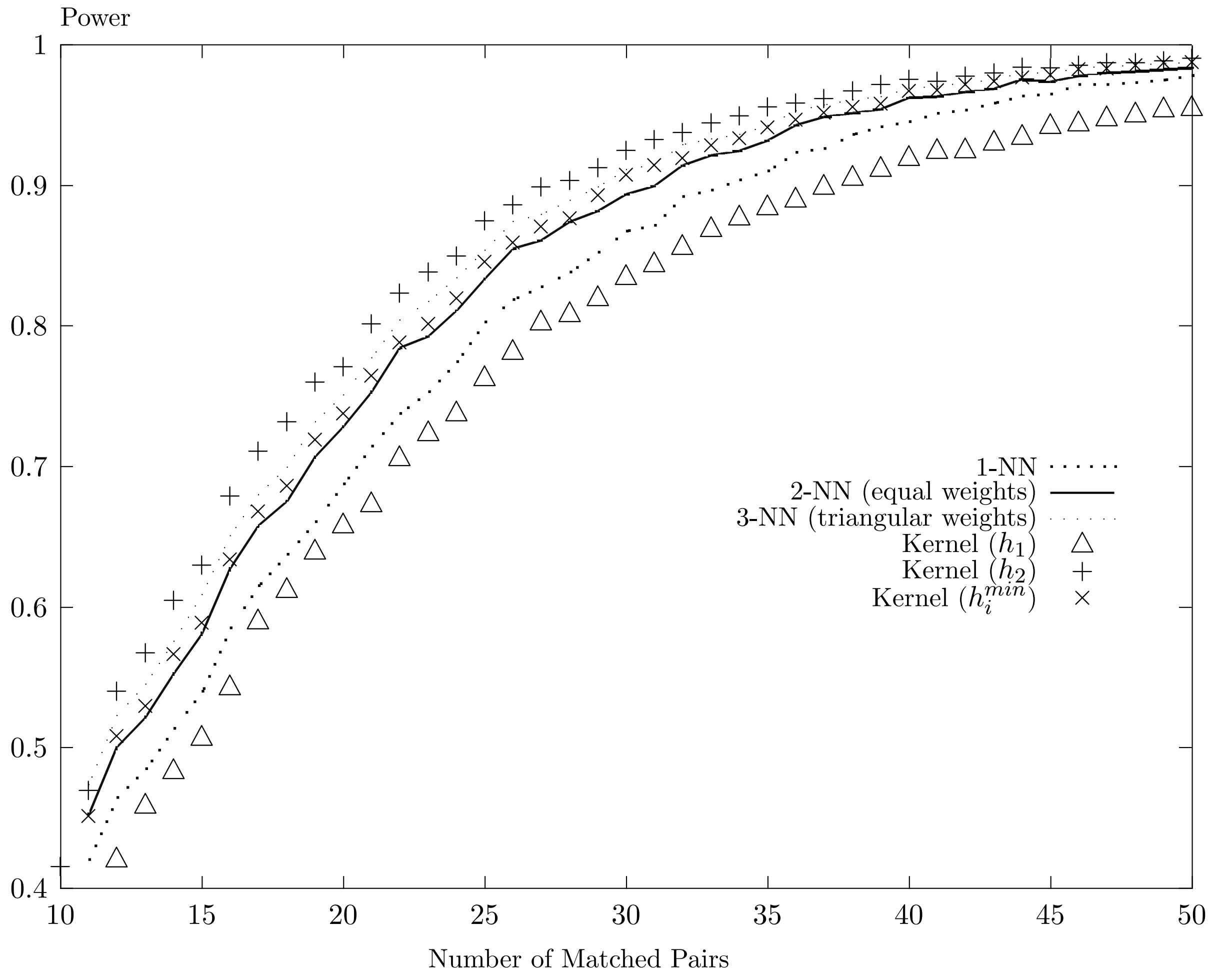

Figure 5: Power graph of two-sided Wilcoxon signed rank test ($\alpha = 0.05$) based on 1-NN, 2-NN (equal weights), and 3-NN (triangular weights) nearest neighbor matching estimates and the $h_1 = 1.059sN_0^{-1/5}$, $h_2 = 1.059sN_0^{-1/3}$ and h_i^{min} (variable bandwidth) kernel-based matching estimates. The power of the test is plotted as a function of the number of matched pairs. Based on 20,000 Monte Carlo replications. The induced difference is $+0.5s(Y)$ for 50% of the replications and $-0.5s(Y)$ for 50% of the replications.

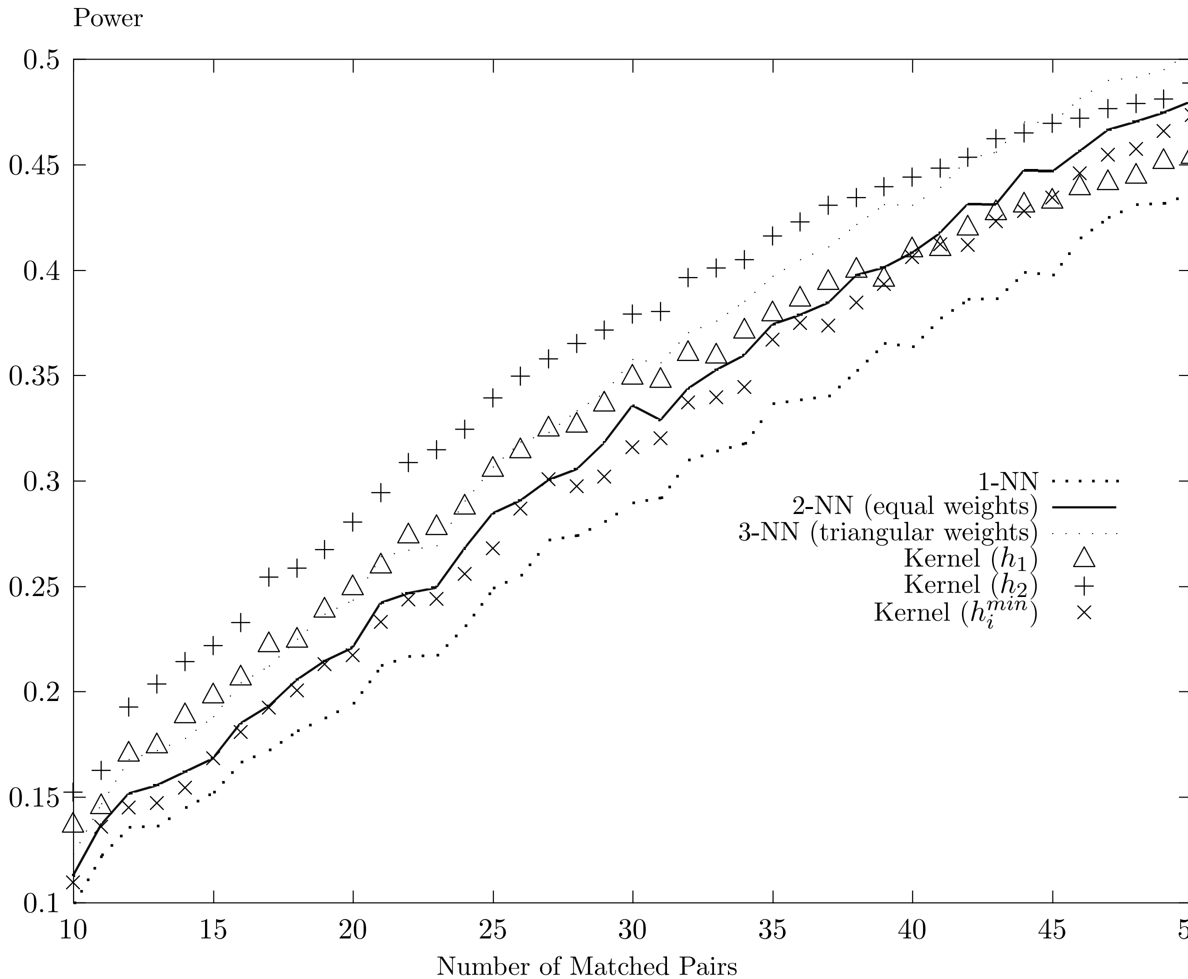

Figure 6: Power graph of two-sided Wilcoxon signed rank test ($\alpha = 0.05$) based on 1-NN, 2-NN (equal weights), and 3-NN (triangular weights) nearest neighbor matching estimates and the $h_1 = 1.059 s N_0^{-1/5}$, $h_2 = 1.059 s N_0^{-1/3}$ and h_i^{min} (variable bandwidth) kernel-based matching estimates. The power of the test is plotted as a function of the number of matched pairs. Based on 20,000 Monte Carlo replications. The induced difference is $+0.2s(Y)$ for 50% of the replications and $-0.2s(Y)$ for 50% of the replications.

Table 1: **Wilcoxon signed rank tests of the impact of interlisting on percentage bid-ask spread.** The average percentage bid-ask spread is calculated using observations at 5 minute intervals during regular trading hours. W is the smaller of the positive and negative rank sums. Sign indicates whether the impact of interlisting was positive or negative when the Wilcoxon test is significant at the 5% level.

Method	NYSE-Interlisted $N = 60$			AMEX-Interlisted $N = 19$			Nasdaq-Interlisted $N = 55$		
	W	p-value	Sign	W	p-value	Sign	W	p-value	Sign
1-NN	496.5	0.000	[−]	86	0.738		547	0.062	
2-NN (equal)	354	0.000	[−]	58	0.145		415	0.003	[−]
3-NN (triangular)	322	0.000	[−]	56	0.123		416	0.003	[−]
Kernel (h_1)	180	0.000	[−]	23	0.002	[−]	333	0.000	[−]
Kernel (h_2)	218	0.000	[−]	34	0.012	[−]	314	0.000	[−]
Kernel (h_i^{min})	410	0.000	[−]	67	0.275		438	0.005	[−]

Table 2: **Wilcoxon signed rank tests of the impact of interlisting on the percentage of total order flow involving non-client accounts.** W is the smaller of the positive and negative rank sums. Sign indicates whether the impact of interlisting was positive or negative when the Wilcoxon test is significant at the 5% level.

Method	NYSE-Interlisted $N = 60$			AMEX-Interlisted $N = 19$			Nasdaq-Interlisted $N = 55$		
	W	p-value	Sign	W	p-value	Sign	W	p-value	Sign
1-NN	245	0.000	[+]	54	0.104		427	0.002	[+]
2-NN (equal)	192	0.000	[+]	72	0.374		331	0.000	[+]
3-NN (triangular)	178	0.000	[+]	59	0.156		329	0.000	[+]
Kernel (h_1)	93	0.000	[+]	48	0.060		215	0.000	[+]
Kernel (h_2)	137	0.000	[+]	55	0.113		220	0.000	[+]
Kernel (h_i^{min})	218	0.000	[+]	68	0.293		372	0.000	[+]

Table 3: **Wilcoxon signed rank tests of the impact of interlisting on RRT gross trading revenues and the percentage of total order flow involving RRT accounts.** W is the smaller of the positive and negative rank sums. Sign indicates whether the impact of interlisting was positive or negative when the Wilcoxon test is significant at the 5% level.

Method	NYSE-Interlisted $N = 60$			AMEX-Interlisted $N = 19$			Nasdaq-Interlisted $N = 55$		
	W	p-value	Sign	W	p-value	Sign	W	p-value	Sign
RRT gross trading revenues									
1-NN	805	0.209		76	0.465		714	0.319	
2-NN (equal)	842	0.295		79	0.541		675	0.213	
3-NN (triangular)	787	0.173		81	0.594		680	0.225	
Kernel (h_1)	737	0.095		66	0.258		655	0.168	
Kernel (h_2)	789	0.177		68	0.293		678	0.220	
Kernel (h_i^{min})	787	0.173		84	0.679		717	0.328	
Percentage of total order flow involving RRT accounts									
1-NN	765	0.134		81	0.594		606	0.084	
2-NN (equal)	680	0.041	[−]	80	0.567		494	0.010	[+]
3-NN (triangular)	664	0.032	[−]	86	0.738		484	0.008	[+]
Kernel (h_1)	530	0.002	[−]	79	0.595		581	0.030	[+]
Kernel (h_2)	563	0.005	[−]	85	0.567		576	0.031	[+]
Kernel (h_i^{min})	699	0.056		84	0.738		510	0.014	[+]

Table 4: **Estimates of the impact of interlisting on average percentage bid-ask spread.** Results are reported for the sample of all interlisted firms and for the sample excluding the largest 12 interlisted firms. Reported percentile–t bootstrap confidence intervals are generated using $B_1 = 999$ and $B_2 = 199$. The average percentage bid-ask spread is calculated using observations at 5 minute intervals during regular trading hours.

Method	NYSE-Interlisted		AMEX-Interlisted		Nasdaq-Interlisted	
	$\triangle$ (Average percentage bid-ask spread) [%]					
Entire sample of interlisted firms:						
$h_1 = 1.059s[N_0]^{-1/5}$	-0.435	$[-0.642, -0.218]$	-0.498	$[-0.759, -0.167]$	-0.400	$[-0.650, 0.113]$
$h_2 = 1.059s[N_0]^{-1/3}$	-0.269	$[-0.428, -0.067]$	-0.434	$[-0.692, -0.152]$	-0.386	$[-0.634, 0.066]$
h_{min}	-0.205	$[-0.350, 0.121]$	-0.318	$[-0.926, 0.222]$	-0.357	$[-0.772, 0.088]$
1-NN	-0.213	$[-0.462, -0.009]$	-0.543	$[-1.518, 0.007]$	-0.224	$[-0.548, 0.356]$
2-NN	-0.168	$[-0.395, 0.019]$	-0.488	$[-1.389, 0.020]$	-0.222	$[-0.521, 0.314]$
3-NN	-0.187	$[-0.402, -0.010]$	-0.453	$[-1.291, 0.020]$	-0.279	$[-0.564, 0.232]$
Sample excluding largest 12 interlisted firms (11 NYSE-interlisted, 1 AMEX-interlisted):						
$h_1 = 1.059s[N_0]^{-1/5}$	-0.508	$[-0.747, -0.259]$	-0.529	$[-0.781, -0.188]$		
$h_2 = 1.059s[N_0]^{-1/3}$	-0.304	$[-0.479, -0.082]$	-0.463	$[-0.747, -0.120]$		
h_{min}	-0.213	$[-0.447, 0.023]$	-0.336	$[-0.948, 0.240]$		
1-NN	-0.236	$[-0.524, 0.019]$	-0.442	$[-1.301, 0.235]$		
2-NN	-0.171	$[-0.429, 0.057]$	-0.526	$[-1.292, 0.080]$		
3-NN	-0.204	$[-0.446, 0.012]$	-0.490	$[-1.207, 0.077]$		