Cross-subsidizing liquidity[*]

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Abstract

In modern markets, liquidity supply is dominated by endogenous liquidity providers, who tend to focus on the most profitable securities — those of large, frequently-traded firms. Securities of thousands of smaller firms are often neglected and remain relatively illiquid. We examine a recent initiative by the Toronto Stock Exchange that aims to improve small stock liquidity by bundling market making assignments in large and small stocks. The data show that such bundling significantly reduces trading costs in small stocks without harming large stocks. Cross-subsidization emerges as a vital channel for liquidity improvement.

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Liquidity supply in modern financial markets is dominated by endogenous liquidity providers (ELPs) — trading firms that supply liquidity voluntarily, when it is profitable. ELPs typically focus on high-volume stocks, those of large firms. As a result, liquidity in such stocks is generally abundant, while in small stocks it is often lacking.[1] Meanwhile, in most equity markets around the globe, small stocks make up the vast majority of listings and represent a vital source of capital for many businesses. How can liquidity provision in such stocks be encouraged?

To shed light on this question, we study a recent initiative by the Toronto Stock Exchange (TSX) to revitalize market making in small securities. In 2018, the TSX gradually adds a new designated market maker (DMM) to every one of its listings. Recognizing the challenge of encouraging ELPs to supply liquidity in small securities, the TSX revives a somewhat forgotten practice of allocating DMMs one high-activity security (denoted *Tier A*) for every four less attractive, low-activity *Tier B* securities. In the assigned stocks, the DMMs are expected to maintain narrow spreads, provide competitive quotes, and facilitate price continuity. In return, the TSX provides the DMMs with a compensation package that includes a cross-subsidy from bundling Tier A and Tier B stocks. In this study, we use a difference-in-differences approach to examine liquidity around the launch of this initiative. The data show that the cross-subsidy substantially enhances market making and improves market quality in small stocks without adversely affecting large stocks.

More specifically, the incentives provided by the TSX program are associated with a significant increase in liquidity provision by the newly assigned market makers. In an average Tier B security, their presence on the passive side of trades almost doubles. Perhaps more importantly, quoted spreads in Tier B stocks decline by 30%, while trading costs

[1] A rich literature examines the ability and willingness of ELPs to provide liquidity. The broad conclusion of this literature is that hiring or designating market makers improves liquidity in small firms (e.g., Venkataraman and Waisburd (2007), Anand, Tanggaard, and Weaver (2009), Menkveld and Wang (2013), Bessembinder, Hao, and Zheng (2015), Clark-Joseph, Ye, and Zi (2017), Bessembinder, Hao, and Zheng (2020)). We provide a comprehensive review of this literature later in this section.

decline by 24%. This decline is due entirely to the reduction in realized spreads, a metric that proxies for liquidity provider revenues. As such, the results are consistent with the possibility that the new DMMs increase the competitiveness of liquidity provision.

To better understand the effects of the cross-subsidy, we examine the revenues of a well-known trading firm, Citadel Securities, whose market making activities are partly visible in Canadian public data. Citadel is renowned for its market making expertise and advanced technological capabilities. It is a leading liquidity provider in many markets around the globe. For instance, in the U.S., Citadel provides liquidity in more than 20% of all trades.[2] As such, studying Citadel's revenue breakdown is of interest not only in the context of cross-subsidization on the TSX, but also more generally — as that of a key liquidity provider. The data show that the cross-subsidy from Type A stocks is vital for Citadel's revenue stream. More specifically, the revenue from Tier A securities allows Citadel to compensate for losses in Tier B securities, corroborating the notion that the cross-subsidy is important for incentivizing liquidity provision in less liquid stocks.

Enhancing liquidity provision in smaller stocks is among the main items on regulatory agendas in many jurisdictions around the globe. The most recent large-scale attempt to improve small-stock liquidity is the Tick Size Pilot administered by the U.S. Securities and Exchange Commission (SEC) in 2016-2018. The Pilot mandated widening of spreads in a select sample of small stocks in the hope that ELPs, able to earn greater profits, would enhance liquidity supply. Upon evaluating the results of the Pilot, the SEC concluded that widening tick sizes is not an optimal policy for liquidity enhancement.[3] In this study, we show that cross-subsidization represents a viable alternative to the approach explored by the SEC for enhancing liquidity in less active securities.

[2] "Equities flow market-maker of the year: Citadel Securities," Risk, November 26, 2019 (`https://bit.ly/2PYNCkw`) and "Stock exchanges backed by Virtu and Citadel moves closer to launch," by R. Henderson, Financial Times, October 31, 2019: `https://on.ft.com/2Vch60a`.

[3] Hu, Hughes, Ritter, Vegella, and Zhang (2018), Albuquerque, Song, and Yao (2019), and Rindi and Werner (2019) provide comprehensive analyses of the SEC Pilot.

A uniquely useful feature of the TSX program is that it is introduced in three staggered phases. In each phase, a diverse subset of securities from both Tier A and Tier B is assigned a new secondary market maker. The staggered introduction allows us to employ a difference-in-differences design, similar to that used by Hendershott, Jones, and Menkveld (2011), to control for potentially confounding effects. The stages are sufficiently spaced in time, with the first group entering the program on March 1st, 2018, the second group — on June 1st, and the last group — on September 19th. The data reveal rapid changes in market maker participation, displayed liquidity, and trading costs for securities entering the new market making program compared to the control securities.

Our work contributes to a rich literature on endogenous liquidity provision and designated market making. This literature recognizes that the competitive market for liquidity provision tends to fail for firms, for which the fundamental value uncertainty and information asymmetry are high. Bessembinder, Hao, and Zheng (2015) (hereafter BHZ) show theoretically that under such circumstances engaging a market maker may improve liquidity as well as increase firm value and welfare. The predictions of BHZ are foreshadowed by the results of early empirical studies that aim to understand the benefits of designating a market maker. These studies focus on European firms that choose to hire market makers to improve liquidity in their stocks.[4] Overall, young small firms with high information asymmetries see substantial liquidity improvements upon hiring a market maker (e.g., Nimalendran and Petrella (2003), Venkataraman and Waisburd (2007), Anand, Tanggaard, and Weaver (2009)). In addition, Perotti and Rindi (2010) show that when market makers are required to facilitate information disclosure, the firms employing their services benefit from a reduction in adverse selection. Furthermore, market making contracts are viewed favourably by the market, as evidenced by positive returns around hiring announcements. Menkveld and Wang (2013) suggest that the returns may be explained by expected liquidity

[4]Hiring of market makers is prohibited by securities regulation in many other jurisdictions, including Canada and the U.S.

improvements and, particularly, the expected reduction in liquidity risk.

An important caveat associated with the above-mentioned early studies is that the subject firms self-select into contracting with a market maker. These firms are often unique in that they expect to soon interact with financial markets by raising capital or repurchasing shares (e.g., Anand, Tanggaard, and Weaver (2009), Skjeltorp and Ødegaard (2015)). This caveat is overcome in two recent studies based on U.S. data. Clark-Joseph, Ye, and Zi (2017) show that when an unexpected technological glitch disrupts the NYSE, liquidity in the stocks with high participation of the NYSE DMMs declines significantly more than liquidity in the control stocks. In turn, Bessembinder, Hao, and Zheng (2020) use a unique feature of the NYSE DMM system, whereby DMM obligations are enhanced if a stock crosses a pre-defined volume threshold. Using a regression discontinuity design, they show that DMMs improve market quality and, importantly, find evidence of strategic complementarity in liquidity supply.

Taking a holistic view, the literature has made substantial advances in understanding the value of designated market makers. We posit that it is less clear how exchanges, regulators, or firms may incentivize modern ELPs to assume DMM roles aside from directly hiring them to do so — a practice not permitted in many jurisdictions. Our work is an attempt to fill this gap and is therefore complementary to the above-mentioned studies.

Bundling of market making assignments is a well-established, although somewhat forgotten, practice. Such assignments were ubiquitous in the days of the old NYSE specialist system. Every specialist was assigned one or two large stocks and was also expected to oversee trading in several small stocks. When this system was operational, there was some discussion in the literature about the existence of the cross-subsidy from the large to small stocks. Cao, Choe, and Hatheway (1997) argue conceptually, and Huang and Liu (2004) show theoretically, that such a cross-subsidy may be important for small-stock liquidity. Comerton-Forde, Hendershott, and Jones (2007) point out that the value of the cross-subsidy should increase in the fixed costs of market making. Because these studies examine an already established bundling system that does not undergo changes during their respective sample periods, they apply caution when drawing conclusions. Our difference-in-differences setting allows us to revisit this issue with new causal evidence. As far as we know, this is the first study that directly examines the effects of stock bundling and the resulting cross-subsidisation of liquidity.

Our results are also complementary to those in a recent study by Bellia, Pelizzon, Subrahmanyam, Uno, and Yuferova (2019), who examine an incentive program administered by Euronext Paris that aims to increase market maker competitiveness. Their findings point to the program's success in increasing the number of market makers in an average stock from six to eight, leading to liquidity improvements. Rather remarkably, the improvements are concentrated in large, frequently-traded securities, while the above-mentioned theory predicts that liquidity provision by competitive ELPs should have already been sufficient in such stocks. Meanwhile, in our setting large securities experience no change, while small stocks see sizable improvements. Our results may therefore be viewed as complementing those of Bellia, Pelizzon, Subrahmanyam, Uno, and Yuferova (2019), as we focus on cross-subsidization between highly liquid and less liquid securities as a means to improve liquidity in the latter.

Although this study focuses on equity market structure, it may deliver valuable lessons that transcend beyond this area. For instance, there is a strong push in the FinTech domain, and in particular among blockchain enthusiasts, to build infrastructure that allows financial services to be delivered via decentralized, disintermediated platforms. Trading small stocks on modern equity exchanges may be viewed as the approximate form of interaction on such platforms, in that liquidity demanders and liquidity suppliers often have to find each other without an intermediary. The world of equity trading therefore has potentially important lessons for platform-based finance. In equities, there are areas of the market where there is strong competition, low costs, and high throughput. At the same time, other areas exhibit low activity and low levels of interaction, and it is often unclear whether the lack of activity stems from the underlying asset, the market structure, or if the asset and market structure effects reinforce each other. What the TSX initiative shows is that platform providers (or, alternatively, the platform organization) can enhance interactions by incentivizing market participants to provide a bundle of services across both more and less active assets.

I. Hypothesis Development

For most of its history, the TSX has retained the status of Canada's premier listing venue. As the market evolved, and new trading platforms started making dents in the TSX market share, the exchange began seeking ways to improve its value proposition. It believed that a market maker program could improve liquidity, especially in the small stocks that are often neglected by the ELPs. In turn, improved liquidity could attract more volume to the exchange, either from traders who previously stayed on the sidelines due to high trading costs, or from the rival exchanges.

Whether the DMM program is successful in improving liquidity and attracting volume is an empirical question. We examine this question in the following hypotheses:

Hypothesis 1 (Liquidity) *The DMM program leads to liquidity improvements, resulting in lower bid-ask spreads, greater quoted depth, lower trading costs, and more frequent TSX presence at the NBBO.*

Hypothesis 2 (Volume) *TSX trading volume and market share increase after the implementation of the DMM program.*

Consistent with $H1$, the DMM program improves posted liquidity and reduces trading costs. The latter is achieved in part by boosting competition that reduces market maker rents, as measured by realized spreads. In addition, consistent with $H2$, the TSX market share increases. In the remaining hypotheses, we examine the economic mechanisms that drive these results.

The DMM program includes four market making incentives: (i) access to odd lots, which are generally believed to originate from retail traders and therefore to be relatively uninformed; (ii) lower liquidity taker fees and higher liquidity provider rebates; (iii) bonus payments that apply when market making goals are met in Tier B stocks; and (iv) the cross-subsidy from Tier A stocks. We assess these incentives starting with access to odd lots.

Hypothesis 3 (Odd lot revenues) *Odd lot trades have lower price impacts, and market makers face lower adverse selection in the DMM program stocks, in which they have privileged access to odd lots.*

The data support $H3$ in that odd lots indeed incur negligible adverse selection costs and also provide an important market maker revenue boost in both Tier A and Tier B stocks. Next, to examine the effect of the above-mentioned incentives, we estimate DMM trading revenues in two ways: (i) with enhanced maker-taker fees and access to odd lots in Tier A stocks and (ii) with enhanced fees, bonus payments, and access to odd lots in Tier B stocks. Finally, we note that the DMM program assigns market makers four illiquid securities for each highly liquid security. Such assignments suggest that market making in illiquid securities may not be sufficiently profitable, requiring cross-subsidization. To shed light on these issues, we test the following hypotheses:

Hypothesis 4 (Enhanced fees and odd lots) *In Tier A stocks, market maker revenues are negative without enhanced maker-taker fees and access to odd lots.*

Hypothesis 5 (Enhanced fees, bonus payments, odd lots, and the cross-subsidy)

In Tier B stocks, market maker revenues are negative without enhanced maker-taker fees, bonus payments, access to odd lots, and the cross-subsidy from Tier A stocks.

Our results corroborate $H4$ and $H5$, in that Tier A stocks are profitable only after accounting for the enhanced fees and access to odd lots, while Tier B stocks are only profitable upon accounting for the enhanced fees, bonus payments, access to odd lots, and the cross-subsidy. As such, the cross-subsidy emerges as a vital component in incentivizing liquidity provision for small stocks. In the remainder of this study, we provide a detailed description of the analyses and methods that allow us to arrive at this conclusion.

II. The DMM Program, Data, and Sample Selection

Through most of history, equity markets relied on DMMs to maintain a stable supply of liquidity. For instance, on the New York Stock Exchange, the Toronto Stock Exchange, and Deutsche Boerse, monopolistic *specialists* maintained limit order books and were expected to provide liquidity. The specialists commonly had market making assignments that included a mix of attractive and less attractive securities — a bundle. In the early 21st century, when monopolistic specialists were replaced by ELPs, stock bundling was abandoned. It is often argued that small stocks were the casualty of the new liquidity provision paradigm. Since then, a common theme in public discussions is the need to encourage liquidity supply in such stocks.

The TSX market rules refer to five DMM obligations that must be met in each assigned security every month. (1) The Spread Goal must be maintained 95% of the time or more. (2) The DMM must ensure that the TSX is at the (protected) NBBO for a minimum amount of time. (3) The DMM must quote a certain number of shares at the NBBO. (4) The DMM must ensure that the book is lined with reasonable amounts of liquidity such that excessive price gaps do not occur. (5) Finally, the DMM must provide quotes in the pre-opening session, with the intention of facilitating a smooth market opening.

A DMM assignment is for at least 50 securities, and for each high-volume (Tier A) security a market maker is assigned 4 less attractive names (Tier B). The TSX kindly provided us with a list of the primary and secondary market maker assignments for the respective entry dates. In total, nine institutions participate in the new DMM program, from large banks such as the Royal Bank of Canada to smaller trading firms such as WD Latimer. Table I reports the share of DMM assignments for each participating institution.

A notable representative of the DMM group is Citadel, a well-known high-frequency trading firm. Citadel's importance for the markets is difficult to overstate, as it represents more than 20% of all market making in the U.S. and captures similar market shares around the globe. Consistent with its typical involvement, it is awarded close to 28% of all DMM assignments in our sample. In the following sections, we pay special attention to Citadel as a representative of modern high-speed ELPs.

A. Canadian Equity Market Structure

During the sample period, Canada has five listing venues: the Toronto Stock Exchange (TSX), TSX Venture, Alpha Exchange, Neo Exchange, and the Canadian Securities Exchange (CSE). The TSX is the main market and lists all securities — from large to small — aside from the microcaps. Our analysis covers only the TSX-listed stocks. Canada also has nine trading venues that operate as public limit order books: the TSX, TSX Alpha, CSE, NASDAQ CXC, NASDAQ CX2, Omega, Lynx, Neo-L and Neo-N. In addition, there are five dark pools: MatchNow, Neo-D, NASDAQ CXD, ICX, and Liquidnet.[5] One peculiar feature of the Canadian market structure is that the order protection rule applies only to a subset of venues whose volume share exceeds a predefined threshold for several months. In addition, limit orders on the TSX Alpha are not protected because the market operates

[5]For a thorough description of the dark trading environment in Canada, see Foley and Putnins (2016)

a random delay, a speedbump.[6] At the time of our study, the protected markets are: the TSX, NASDAQ CXC, NASDAQ CX2, Omega, and the CSE. We use trade and quote data from all of these markets.

B. Data

The data for this study is sourced from the Thomson Reuters Tick History (TRTH) database. For every protected market, we obtain (i) all trade records and (ii) reports on the state of the limit order book at each quote update, time stamped to the millisecond. Overall, the structure of the data is similar to the NYSE DTAQ database, with one exception. In Canadian public data, most venues identify the participating brokers on both sides of a trade. In a later section, we use these broker identities to draw inferences for one of the DMMs, Citadel Securities.

This study is the result of a merger of two independent projects. Prior to the merger, one of the projects used the TSX subscription-based Grapevine data platform, and the other used TRTH. Upon careful comparison, we are confident that the results obtained from the two datasets are similar. To facilitate replication, we report the results based on TRTH since it is more commonly used in the academic community.

C. Sample

When building the sample of securities, we exclude warrants, preferred shares, and exchange traded funds (ETFs). Warrants and preferred shares are part of the DMM program, but trade exceptionally infrequently. ETFs are not part of the DMM program. We also remove (i) U.S. market holidays and half-days, (ii) trades identified as off-market crossings, (iii) midpoint dark trades, and (iv) instances of locked and crossed markets. Finally, we

[6]More details on the Alpha speedbump introduction can be found in Chen, Foley, Goldstein, and Ruf (2016)

winsorize all variables at 5% to mitigate the effects of outliers that are occasionally observed in small stocks.

We split the analysis by Tier A and Tier B securities. Many Tier B securities, or Bs for short, are low-priced, that is trade at prices below \$1. Academic studies usually exclude such stocks, concerned with their volatility. We have a similar concern, but also note that over 35% of Bs (225 in total), are low-priced. To learn from this sizeable group, we retain these stocks in the sample. For robustness, we examine the low-priced Bs separately. The results are similar to those obtained for the full sample of Bs. Table II reports summary statistics for the sample securities.

The TSX implemented the DMM program in three stages: on March 1st, 2018, for 191 securities, then on June 1st, 2018, for 250 securities, and finally on September 19th, 2018, for the remaining 499 securities. For each stage, we focus on the $[-30; +30]$ trading day windows surrounding the implementation dates. In the main analysis, we examine all three implementation events together. During robustness checks, we separate them and find both qualitatively and quantitatively similar results.

D. Statistical Analysis

The basis of our statistical approach is a conventional difference-in-differences analysis of a panel data set (securities$\times$days). We clarify this approach using the quoted bid-ask spread as an example. The dependent variable DV_{it} is the value of the quoted spread for the treated security i at time t. Using this dependent variable, we estimate the following regression:

$$DV_{it} = \alpha + \beta \cdot DMM_{it} + controls_{it} + \delta_i + \gamma_t + \epsilon_{it}, \tag{1}$$

where DMM_{it} is an indicator variable set to 1 on the date of the DMM introduction for security i, δ_i is a security fixed effect, and γ_t is the date fixed effect. Using two-way fixed effects allows us to compare the changes experienced by the stocks that have migrated to the DMM program to the changes in the control stocks that have not yet migrated.[7] The coefficient of interest β captures the effect of the introduction of the TSX DMM program on treated securities. We use two additional control variables; the security's dollar volume and volatility, computed as the day's high minus low price, scaled by the average price. All regression coefficients are estimated using double-clustered standard errors that are robust to both cross-sectional correlation and idiosyncratic time-series persistence.

III. Empirical Results

A. *Market Maker Activities*

The DMM program aims to incentivize market making. As such, in the first step of our analysis we ask if the newly appointed DMMs adopt behaviors consistent with market making. To answer this question, we compare trader account activity on the passive side of trades both before and after these accounts are assigned as DMMs. If such presence increases, it is likely due to enhanced market making. We focus our analyis on trades because TRTH does not contain broker IDs for quotes.

Figure 1 plots the time series of passive trading before and after the DMM assignment. Once the program begins, passive trading in the assigned stocks more than doubles, consistent with the notion that the program increases incentives to provide liquidity. We confirm this result in a more formal setting by estimating equation (1) with the share of passive volume as the dependent variable. Table III confirms that liquidity provision increases significantly, both economically and statistically.

[7]Hendershott, Jones, and Menkveld (2011) use a similar regression setup to examine the introduction of the NYSE Autoquote, an event that was staggered similarly to the implementation of the DMM program.

B. Displayed Liquidity

The previous section suggests that the new DMMs increase their share of liquidity providing trades. In this section, we ask if this increased activity leads to meaningful improvements in quoted liquidity as asserted in H1.

To understand the impact of DMMs on displayed liquidity, we compute four metrics. The first is the quoted spread, or the difference between the Canada-wide best ask and bid prices (the NBBO). Spreads usually vary in the stock price, so we scale them by the corresponding midpoint defined as the average of the NBBO bid and ask quotes. The second metric is the NBBO depth computed as the natural logarithm of dollar volume posted at the best prices. Following convention, we time-weight both metrics. Finally, to understand if the DMM program makes the TSX more competitive with its rivals, we study the percentage of time the exchange is at the NBBO and its share of total NBBO depth.

Tables IV and V examine quoted liquidity for Tier A and Tier B securities, with the former table reporting the univariate tests and the latter the regression results. We observe a decline in quoted spreads subsequent to the introduction of a DMM for all Tier B securities, but not for Tier A securities. More specifically, controlling for volume and volatility in Table V, quoted spreads decline by 19.9 bps in Tier B stocks, a reduction of more than 30%. The lack of improvement for Tier A securities is not surprising. Liquidity provision in these securities is already very competitive, and it is difficult to expect that a DMM should cause dramatic changes.

Notably, quoted depth declines in Tier B securities, while remaining unchanged in the As. These results are consistent with the literature on liquidity provision by modern ELPs that put substantial focus on keeping inventories low (e.g., Brogaard, Hagströmer, Nordén, and Riordan (2015), Brogaard, Carrion, Moyaert, Riordan, Shkilko, and Sokolov (2018)). As such, although they tend to quote better prices, ELPs are usually not associated with substantial increases in quoted depth. In this context, it is important to remember that, in Tier B securities, the NBBO itself improves significantly, and as such the results do not point to a decline in posted liquidity, but rather to smaller depth at the improved prices.

When it comes to relative competitiveness with the other exchanges, the TSX increases its presence at the NBBO in both As and Bs (Table V). These increases are statistically significant, yet may appear economically trivial. For Tier A, the NBBO presence increases by 0.86%, and for Tier B — by about 1.26%. These results are due in part to the already strong TSX presence at the NBBO; 92% in As and 87% in Bs before the DMM program launch. In addition, when interpreting the statistics for the Bs, it is important to keep in mind that the TSX increases its presence at the new narrower NBBO compared to the wider, pre-DMM NBBO. Finally, consistent with the results for quoted depth discussed earlier, we observe no change in the TSX share of posted depth.[8]

C. Trading Cost and Its Components

Displayed liquidity metrics suggest that the DMM program improves prices at which the average liquidity provider is willing to transact. To understand if this improvement results in lower trading costs realized by liquidity demanders, we examine effective spreads. As is conventional, effective spreads are computed as twice the signed difference between the traded price and the prevailing NBBO midpoint. We further scale the effective spreads by the midpoint to account for price differences across securities and also weight them by dollar volume. We use the Lee and Ready (1991) algorithm to sign trades.[9]

Table VI reports estimation results, which generally mimic those for the quoted spreads. Namely, effective spreads for Tier A securities do not change upon the introduction of

[8]Time share estimates the fraction of time each exchange quotes at the NBBO. Depth share computes the proporiton of depth quoted at the NBBO which is present on a particular exchange. Further information on their construction may be found in Foley, Liu, and Jarnecic (2019)

[9]Chakrabarty, Pascual, and Shkilko (2015) show that the Lee-Ready algorithm, despite its age, works well in modern limit order book settings.

DMMs, whereas for Bs there is a significant decline. Specifically, the effective spreads decline by 15.2 bps, equivalent to a 24% change.

To better understand the source of the changes in the effective spread, we decompose it into its two components: price impact and realized spread. The price impact captures the adverse selection cost that liquidity providers incur by trading with informed liquidity demanders. It is defined as twice the signed difference between the current midquote (at time t) and the midquote at a future time $t+\tau$. The time horizon τ is typically set according to the frequency with which a security trades.[10] In the manuscript, we report the results for the 1-minute horizon. The results do not qualitatively change when we use 1-second, 30-second, and 5-minute horizons.

In turn, the realized spread is the difference between the effective spread and the price impact, capturing liquidity provider revenue net of adverse selection costs. We scale both the price impacts and realized spreads by the prevailing midquote and weight them by dollar volume.

Table VI suggests that the previously documented reduction in effective spreads in Bs is attributable entirely to the reduction in realized spreads. This result is consistent with the notion that the introduction of DMMs results in lower rents for an average liquidity provider. There is thus some evidence that the DMM presence results in more competitive market making in support of H2.

D. Trading Activity Levels on the TSX

The TSX derives a large portion of its revenues from trading fees. As such, one of the DMM program goals, even if not officially stated, is to increase the TSX trading volume. Two channels may contribute to such an increase. First, lower trading costs attributable to the program may encourage more economic agents to trade, increasing volume across

[10] For more detailed discussion on the selection of an appropriate horizon over which to compute realized spreads and price impact, see Conrad and Wahal (2020)

the entire market and/or specifically on the TSX. Second, volume may migrate from the rival markets to the TSX due to its more competitive quotes and more frequent presence at the NBBO. To examine these possibilities, we estimate equation (1) using trading volume across all markets and the TSX volume share as dependent variables.

Table VII shows that the TSX's volume share increases subsequent to the introduction of the DMM program, though only in Tier B securities. This result is expected given that the reduction in trading costs is observed exclusively for the Bs. For all tiers, there is no evidence of an increase in market-wide volume. The TSX is therefore able to increase its market share to some degree, potentially justifying the DMM program from a revenue standpoint.

IV. Subsidies and the Cross-subsidy

In the final part of the analysis, we examine the payoffs to the DMMs. We are particularly interested in how the subsidies offered by the TSX stack up, and whether they potentially allow for DMM profitability. The subsidies include enhanced maker-taker fees, monthly incentive payments (in Tier B stocks only), and access to odd-lots. In addition, the cross-subsidy for assuming a DMM role in four Tier B securities is the ability to assume such a role in one Tier A security. We discuss these subsidies in turn, starting with odd lots.

Odd lots. The TSX allows DMMs to access 50% of odd-lots, which are relatively uninformed, thereby boosting DMM revenue. Two characteristics of Canadian equity trading ensure that the odd-lot flow indeed has low information content. First, retail order flow must be routed to lit markets, unlike for instance in the U.S., where such flow is often purchased by wholesalers. Second, the TSX, through a set of rules, ensures that odd-lots come predominantly from retail brokers. Broker compliance with these rules is regularly monitored. To support the claim that odd-lots in our sample are indeed relatively uninformed, we estimate the following regression:

$$DV_{it} = \alpha + \beta \cdot Odd_{it} + \delta_i + \gamma_t + controls_{it} + \epsilon_{it}, \tag{2}$$

where DV_{it} are the average price impact, realized spread, and effective spread computed separately for the odd-lot and non-odd-lot trades in stock i on day t; Odd_{it} is a dummy variable equal to 1 if the DV_{it} is for the odd-lot trades and 0 otherwise; and the remaining variables are as previously defined. As such, the model contains, for each stock-day, two observations: one for the odd-lots and the other for the remaining trades. The variable of interest is β, capturing the differential effect of odd-lots.

Table VIII shows that the price impacts of odd-lots are substantially lower than they are for the other trades. More specifically, the latter have price impacts of 22.59 bps, while the odd-lots — of only 0.98 bps (= 22.59 - 21.61). Meanwhile, the realized spreads for odd-lots are 48.89 bps (= 19.62 + 27.27), 2.39 times greater than those for the other trades, consistent with odd-lots providing a substantial revenue subsidy for the DMMs. Gaining access to the odd-lots through the DMM program, therefore, represents a valuable incentive for the liquidity improvement effects previously documented. In what follows, we aim to understand just how much of an incentive the odd-lots and other subsidies represent, and whether the cross-subsidy from As to Bs is important.

Estimating DMM revenue. Our data are broker-level, so for most DMM firms, such as large banks, distinguishing between proprietary trading volume, which includes DMM activity, and client volume is not possible. One exception is Citadel Securities, as all of its activity is proprietary, and its main focus is market making. We use Citadel to gain some understanding of possible DMM revenues. Prior to the launch of the DMM program, Citadel is highly active in Tier A securities, but barely participates in the trading of Tier B securities as should be expected from an ELP. As such, we focus on the period after the program launch, when Citadel's participation in the Bs ramps up. To shed light on revenues, we start with a raw intraday revenue metric, adjust it for inventory risk, and then, one by one, add DMM incentives. Specifically, we begin by following Brogaard, Hendershott, and Riordan (2014) and compute Citadel's raw intraday revenue as follows:

$$\text{revenue}_{it} = \text{sell \$ vol}_{it} - \text{buy \$ vol}_{it} + \text{closing price}_{it} \cdot (\text{buy vol}_{it} - \text{sell vol}_{it}), \tag{3}$$

where the first component, sell \$ vol_{it} − buy \$ vol_{it}, is the net trading revenue for the day, and the second component is the end-of-day inventory evaluated at the day's closing price. Because odd-lots represent a market making incentive, we omit them from this calculation and account for them separately in what follows.

The revenue calculation described above is usually performed for relatively liquid securities and therefore assumes that end-of-day inventory positions may be easily exited at the closing price. In conversations with us, market participants however point to substantial inventory risk in Tier B stocks. Due to relatively infrequent trading in these stocks, bringing inventories to zero at the end of the day is difficult, and market makers are often forced to hold large overnight positions. Such positions are subject to price changes overnight and during the following day while being unwound.

To proxy for the cost associated with this inventory risk, we turn to a conventional value-at-risk (VaR) approach. First, for each stock i on each day t, we compute possible changes in the dollar value of inventory, ΔINV, by multiplying the end-of-day inventory values by the expected close-to-close return for each stock. To proxy for expected return, we use the average of all close-to-close returns from 2017. Second, using last year's average daily volume numbers, we compute the expected time to unwind each overnight position. The data suggest that the vast majority of inventory balances may be unwound within a day. Third, using the expected time to unwind, we prorate ΔINV to obtain expected inventory values once unwound. Fourth, we compute the mean and the standard deviation of expected inventory values and randomly draw 10,000 observations from a normal distribution with these parameters. Finally, we use the conventional 1% threshold to estimate VaR (the cost of inventory risk) and adjust the above-mentioned revenues for estimated inventory risk. To calculate the average market making revenue for each stock i on day t, we compute the following:

$$\mathrm{R0}_{it} = \text{revenue}_{it} + \text{inventory risk}_{it}. \tag{4}$$

The resulting R0 calculation effectively has two inventory components: the value of the inventory position at the end of the day and the additional cost associated with the risk of not being able to unwind the position quickly. Figure 2 reports the results. As should be expected in a competitive market for liquidity provision, raw revenues without subsidies are negative in both the As and Bs at, respectively, −$74.21 and −$20.77 per stock-day. This result is consistent with the earlier literature, in that profit margins in modern market making are rather thin, and liquidity providers are unprofitable without incentives such as rebates.[11]

Next, to assess the extent to which including rebates alters the revenue estimates, we augment R0 with DMM liquidity taker fees and maker rebates:

$$\begin{aligned}\mathrm{R1}_{it} &= \mathrm{R0}_{it} + \text{fees/rebates}_{it} \qquad (5)\\ &= \mathrm{R0}_{it} + \text{passive vol}_{it} \cdot \text{maker rebate} - \text{aggressive vol}_{it} \cdot \text{taker fee},\end{aligned}$$

where the latter two terms add DMM fees and rebates to the inventory risk-adjusted revenue. In Figure 2, we report that the addition of these fees reduces the DMM stock-day

[11]Further discussion on the importance of maker-taker fees to the trading environment may be found in Malinova and Park (2015).

losses to, respectively $-\$24.84$ and $-\$8.61$.

Next, we compute revenues accounting for the monthly performance rewards paid to the DMMs (applicable for Tier B stocks only) if they meet the requirements of the program:

$$\begin{aligned} \text{R2}_{it} &= \text{R1}_{it} + \text{performance reward}_{it} \qquad (6) \\ &= \text{R1}_{it} + \text{monthly reward/\# trading days}_{it}, \end{aligned}$$

where monthly reward/# trading days is the daily share of the average monthly performance reward. Figure 2 shows that adding the bonuses in Bs further reduces Citadel's losses in Bs, to $-\$2.91$ per stock-day.

As the final step, we examine the effect of odd lots, which we have until now excluded:

$$\text{R3}_{it} = \text{R2}_{it} + \text{odd-lot revenue}_{it} + \text{odd-lot inventory risk}_{it}, \qquad (7)$$

where odd-lot revenue and inventory risk are computed as in eq. (4). Inventory risk associated with odd lots is negligible, as retail order flow is usually both small and balanced (the volume of buys approximately equals the volume of sells), with little or no inventory accumulation (i.e., Boehmer, Jones, Zhang, and Zhang (2019)). The final revenue figures are \$14.44 and $-\$0.39$ per stock-day in, respectively, Tier A and Tier B securities. As such, Citadels activities in As are only profitable once all market making incentives are accounted for, even after recognizing that our analysis represents an upper bound, as it ignores fixed cand non-exchange based fees, such as connectivity, market data, and personell. In the meantime, direct incentives do not appear sufficient to achieve profitability in Bs.

We therefore conclude that market making in Bs is only profitable in conjunction with a cross-subsidy from As.

V. Discussion and Conclusion

For markets to work, it is essential that buyers and sellers are able to find one another. For the most liquid, frequently traded securities this is usually not an issue. In less liquid, smaller securities on the other hand, the search for a counterparty is often difficult, in particular if the need to trade is urgent. This is where intermediaries can step in and bridge the gap. Notably, small stocks are difficult to intermediate; it can take a while to trade out of an inventory position, the fixed costs are often large, and the rewards from balanced trading are low. Endogenous liquidity providers — the dominant intermediaries in today's market — typically ignore small securities, potentially contributing to a chicken and egg problem, whereby there is no liquidity for a lack of trading activity and vice versa.

How should liquidity provision in small securities best be encouraged? The U.S. Congress attempted to accomplish this goal with the Tick Size Pilot. The idea was that by forcing larger price increments, market makers would find it more attractive to post liquidity in the Pilot securities. The trade-off, of course, was that this move would likely increase trading costs. The results of the Pilot were generally mixed, and the regulators chose not to proceed with widening tick sizes across the board.

In pursuit of improved liquidity in small stocks, the Toronto Stock Exchange chose to revive a somewhat forgotten market-driven solution, rendering market-making a bundled product. The idea of such an approach is to create cross-subsidization, from large and profitable stocks to the small unprofitable ones. The market maker is only allowed to keep the attractive assignments in large stocks as long as they ensure that there is a functioning market in small stocks.

In this paper, we show that the TSX initiative was successful in the sense that it led to an improvement in liquidity for the less liquid stocks without creating a disruption in large stocks. Whether this move also accomplishes the broader goal of keeping the market active in less liquid stocks is a question for a longer-run study that is beyond the current scope of this paper. For now, however, we believe that there is some indication that a bundled approach to market making has merit in modern markets.

A Appendix: Expected Impact as presented by TMX to the Ontario Securities Commission

The following is an excerpt from the TMX Group's Submission to the Ontario Securities Commission regarding their new market making program.[12]

"TSX believes that appropriate incentives are required to ensure the Canadian market continues to thrive and adequate support is provided to many of the smaller and growing Canadian companies listed on TSX. The Proposed Amendments and accompanying program structure contains several additional nuances that promote a healthy and viable market for Market Makers, investors, listed companies and TSX over the long term.

While it may be argued that the role of a Market Maker is less important for Canada's most liquid securities, Market Makers provide invaluable support for less liquid securities. The TSX market making program remains an important driver for price discovery and liquidity for less liquid securities and achieves this through careful structuring of program policies, which require that Market Makers commit capital to both liquid and less liquid security assignments in the current ratio of 1:4 respectively. This unique proposition creates additional and often overlooked commitments made by Market Makers in the form of additional costs and increased risks associated with non-borrowable securities, buy-in requirements, heightened volatility and longer position holding times. Therefore, the perceived benefits associated with market making for a liquid security are effectively balanced against the commitments associated with market making in less liquid securities at the same time.

Through this balance, the expected impact of the Proposed Changes are expected to enhance the quality of execution for all MGF-eligible investors' and market participants' orders through an increase in guaranteed liquidity at the Protected NBBO and a reduction

[12] https://www.tsx.com/resource/en/1489/

in the need to seek liquidity across multiple venues. Through increased competition for security assignments, more robust processes for performance evaluation and an additional committed Market Maker per security, TSX also anticipates tighter spreads and more liquidity available across both liquid and less liquid securities in the TSX Central Limit Order Book (CLOB) to the benefit of all investors."

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Table I
DMM Program Participants

The table contains the names of institutions selected to participate in the 2018 TSX DMM program together with percentage shares of stocks (from the filtered sample) assigned to them. The filtered sample excludes preferred shares and warrants that trade too infrequently to allow for meaningful statistical testing.

Caldwell	1.7
Canacord	1.9
Citadel	27.9
Independent Trading Group	4.7
Jitney Trading	1.9
National Bank Financial	8.0
Royal Bank of Canada	13.9
Toronto Dominion	35.3
WD Latimer	4.7

Table II
Summary Statistics for the Sample Firms

The table reports summary statistics for the sample securities. We first compute stock-day averages for all variables, and then aggregate them into pre- and post-event statistics for thirty trading days before and thirty trading days after the introduction of the DMM program on March 1, June 1, and September 19, 2018.

	Tier A				Tier B			
	Before	After	Difference		Before	After	Difference	
Price	51.45	54.65	3.20		28.94	36.76	7.83	
Market Cap ($M)	13 955.87	13 525.28	−430.59		4 246.68	4 327.60	80.92	
Volume (million shares)	3.29	2.70	−0.59		0.92	1.05	0.13	***
Volatility (%)	3.37	3.10	−0.27	***	5.13	3.88	−1.25	

Table III
DMM Trading Share: Regression Analysis

The table contains the results from panel estimation of equation (1) using the DMM passive volume share as the dependent variable. Controls include a stock-day measure of volatility computed as (High Price – Low Price)/((High Price + Low Price)/2). The regressions include stock and date fixed effects, and standard errors are double-clustered by security and date. The asterisks *** and * indicate significance at the 1% and 10% levels; t-statistics are in parentheses.

	Tier A	Tier B
Intercept	2.02***	1.05***
	(11.07)	(11.30)
DMM	2.46***	0.92***
	(3.91)	(4.04)
Volatility	0.08*	0.03
	(1.91)	(1.33)
N	69734	97137
R^2	0.04	0.00

Table IV
Quoted Liquidity and Trading Costs: Summary Statistics

The table contains the pre- and post-event liquidity statistics averaged across all three DMM roll-out events. The Quoted Spread is the difference between the national best offer and the national best bid, divided by the midquote. NBBO Depth is the natural log of the average number of shares at the NBBO bid and the NBBO ask. These metrics are time-weighted when computing daily averages. The Effective Spread is the signed difference between trade price and the prevailing midquote multiplied by two and scaled by the prevailing midquote. Trades are signed using the Lee-Ready algorithm. The Price Impact is calculated as the signed difference between the current midquote and the midquote one minute after the trade scaled by the current midquote. The Realized Spread is the difference between the Effective Spread and the Price Impact. To compute daily averages, we volume-weight the effective spreads, price impacts, and realised spreads. Asterisks *** indicate statistical significance of post-event changes at the 1% level.

	Tier A				Tier B			
	Before	After	Difference		Before	After	Difference	
Quoted Spread bps	7.06	6.60	−0.46		53.12	36.18	−16.94	***
NBBO Depth	6.91	6.73	−0.18		6.91	6.67	−0.24	***
Effective Spread bps	8.72	9.60	0.88	***	56.47	42.27	−14.21	***
Realized Spread bps	1.34	2.79	1.45	***	18.50	14.25	−4.25	***
Price Impact bps	7.38	6.80	−0.57		37.94	27.94	−10.00	

Table V
Quoted Liquidity: Regression Analysis

The table contains the results from the panel estimation of equation (1) using Quoted Spreads (QS), log NBBO depth, % of time at NBBO, and % of NBBO depth, as dependent variables. Controls are the stock-day measures of share volume/100000 and volatility*100. The regressions include stock and date fixed effects, and standard errors are double-clustered by security and date. The asterisks ***, ** indicate significance at the 1%, and 5% levels. *t*-statistics are in parentheses.

	quoted spread	NBBO Depth	% of time at NBBO	% of NBBO Depth
Panel A: Tier A				
Intercept	16.33***	7.01***	93.14***	48.46***
	(58.77)	(516.27)	(753.45)	(250.39)
DMM	−1.04	0.03	0.86**	0.11
	(−1.58)	(1.11)	(2.55)	(0.25)
Volume	−0.34***	0.02	0.13**	0.44**
	(−3.01)	(1.63)	(1.98)	(2.18)
Volatility	0.57***	−0.01***	−0.43***	0.24***
	(5.40)	(−2.58)	(−8.56)	(3.67)
N	50033	50032	50032	50031
R2	0.01	0.01	0.01	0.01
Panel B: Tier B				
Intercept	193.24***	7.83***	92.53***	71.36***
	(203.36)	(870.84)	(783.96)	(586.72)
DMM	−19.90***	−0.05**	1.26***	−0.13
	(−7.10)	(−1.97)	(4.87)	(−0.32)
Volume	−6.44**	0.10**	0.17**	0.48
	(−2.48)	(2.02)	(2.03)	(1.50)
Volatility	2.45***	−0.01***	−0.29***	−0.38***
	(9.35)	(−4.48)	(−8.95)	(−11.94)
N	86986	86986	86986	86986
R2	0.02	0.01	0.01	0.01

Table VI
Trading Costs: Regression Analysis

The table contains the results from panel estimation of equation (1) using the effective spread, realized spread, and price impact as dependent variables. The controls are as previously defined. We do not report the estimates for the controls or the intercept to save space. The regressions include stock and date fixed effects, and standard errors are double-clustered by security and date. The asterisks *** indicate statistical significance at the 1% level. The t-statistics are in parentheses.

	Effective Spread	Realized Spread	Price Impact
Panel A: Tier A			
Intercept	14.13***	3.52***	10.39***
	(20.21)	(5.84)	(20.73)
DMM	−0.87	−0.76*	−0.24
	(−1.18)	(−1.69)	(−0.52)
Volume	0.09	0.88	−0.77***
	(0.29)	(1.64)	(−2.73)
Volatility	1.28***	−0.92***	2.25***
	(6.37)	(−4.52)	(10.17)
N	50033	50033	50033
R2	0.02	0.00	0.09
Panel B: Tier B			
Intercept	173.62***	103.20***	62.94***
	(125.47)	(138.29)	(53.49)
DMM	−15.16***	−12.13***	0.61
	(−6.04)	(−5.11)	(0.40)
Volume	−6.46**	−4.16***	−3.05**
	(−2.48)	(−3.52)	(−2.02)
Volatility	5.07***	−1.34***	6.90***
	(12.56)	(−6.00)	(20.12)
N	86986	86986	86986
R2	0.04	0.00	0.08

Table VII
Trading Volume: Regression Analysis

The table contains the results from panel estimation of equation (1), using the TSX Volume Share and Market-wide dollar volume as dependent variables. Volatility, as defined previously, is a control. The regressions include stock and date fixed effects, and standard errors are double-clustered by security and date. Asterisks *** and ** indicate significance at the 1% and 5% levels. t-statistics are in parentheses.

	TSX Volume Share	Market log $-Volume
Panel A: Tier A Securities		
Intercept	66.08***	16.60***
	(555.21)	(847.78)
DMM	0.56	0.03
	(1.72)	(1.17)
Volatility	0.40***	0.14***
	(6.94)	(17.35)
N	67928	67936
R2	0.01	0.17
Panel B: Tier B Securities		
Intercept	82.89***	10.52***
	(1 209.12)	(426.98)
DMM	0.68**	0.03
	(2.30)	(1.19)
Volatility	0.05**	0.12***
	(2.19)	(16.42)
N	97129	97137
R2	0.00	0.14

Table VIII
Adverse Selection for Odd-Lot Trades

The table presents the results from panel estimation of equation (2) using price impacts and realized spreads as dependent variables. All variables are calculated per stock-day, for odd lot transactions and the remaining (nonodd lot) transactions separately. ODD = 1 for stock-day observations that include only odd-lot trades, and ODD = 0 for stock-day observations that consist of the remaining trades. The control variables are as previously defined. Regressions include stock fixed effects, and standard errors are double-clustered by security and date. The asterisks *** and * indicate significance at the 1% and 10% levels. *t*-statistics are in parantheses.

	Price Impact	Realized Spread
Intercept	22.59***	19.62***
	(11.51)	(8.92)
ODD	−21.61***	27.27***
	(−13.40)	(14.56)
Volume	−2.63	4.63***
	(−1.54)	(3.42)
Volatility	7.33***	−1.23*
	(11.62)	(−1.69)
N	288593	288593
R^2	0.02	0.00

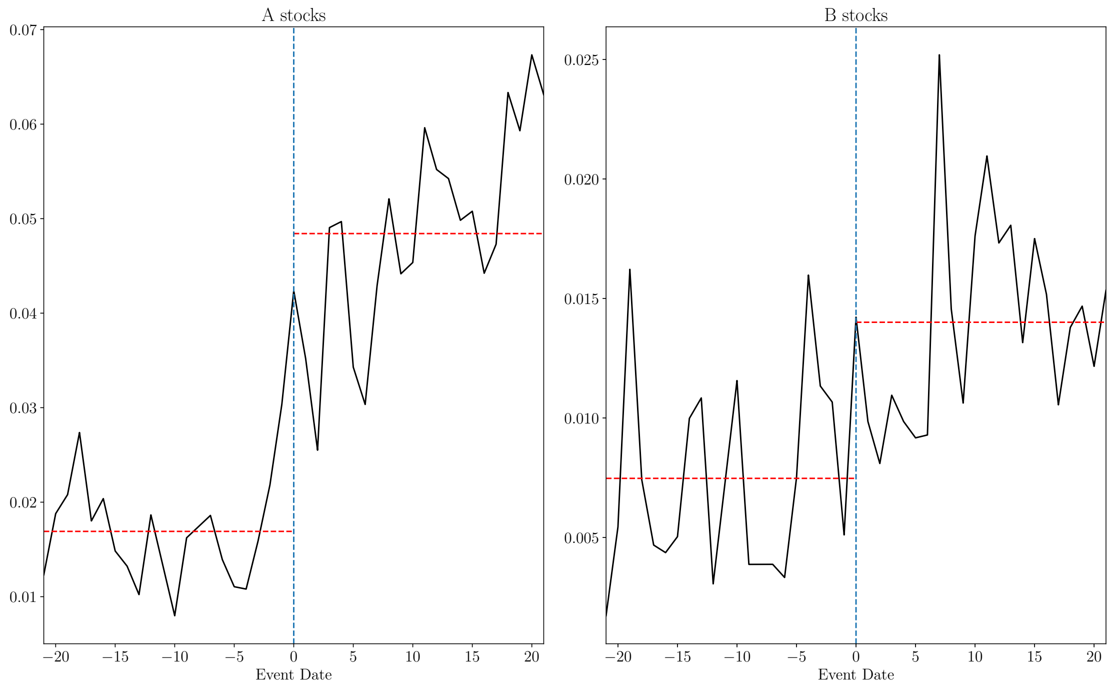

Figure 1
Fraction of Volume traded by Market Makers

This plot illustrates the percentage of passive liquidity provided by the DMMs aggregated across all stocks in Tiers A and B. Event date is the date a stock is included in the DMM program.

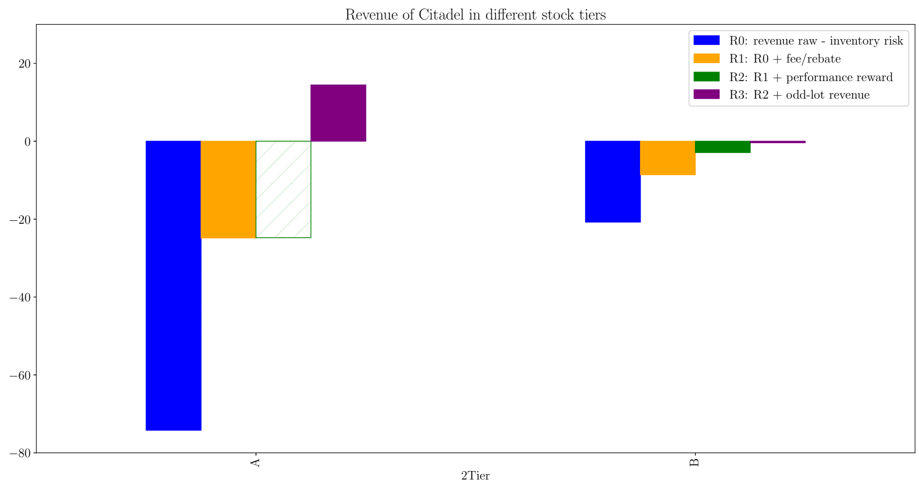

Figure 2
Citadel Revenues

The figure displays average daily Citadel revenues estimated in the 30 days post-launch of the DMM program for Tier A and Tier B securities. The blue bars represent raw intraday revenue adjusted for the end-of-day inventory risk. The orange bars include an adjustment for liquidity taker fees and liquidity maker rebates. The green bar for the Tier B stocks accounts for the monthly performance rewards in these stocks. To stipulate that such rewards are not available in the Tier A stocks, we use a hollow green bar. Finally, the purple bars account for additional revenue derived from preferential interactions with retail order flow allowed as one of the DMM program incentives.