In Good Times and in Bad: High-Frequency Market Making Design, Liquidity, and Asset Prices*

Simon N. M. Schmickler† Pedro Tremacoldi-Rossi‡

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Abstract

How can exchanges and regulators improve the liquidity and stability of modern financial markets through liquidity provision obligations and incentives? We exploit two market maker programs as natural experiments using unique message-level trade and quote data from the Brazilian stock exchange that reveal market participants' identities. We find combining obligations and incentives improves and stabilizes liquidity which attracts volume and lifts asset prices. In normal times, these positive effects are driven by the program incentives, while tight obligations constrain market makers and decrease market quality. In crises, however, the results flip: stocks with larger incentives experience worse liquidity dry-ups because voluntary liquidity providers withdraw; in contrast, tight obligations mitigate liquidity dry-ups because mandatory intermediaries step in as the liquidity providers of last resort. Finally, which market makers are assigned to which stocks is consequential: market makers' cross-asset hedging behavior causes excess co-movement of returns, liquidity, and volume, highlighting a trade-off between liquidity and excess co-movement. Overall, our results suggest that exchanges and regulators should combine incentives with countercyclical liquidity provision obligations.

Keywords: Market Making; High-Frequency Trading; Market Design; Liquidity; Market Stability; Volatility; Excess Co-movement; Crises

JEL Codes: G01; G11; G12; G18; G23

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†Department of Economics and Bendheim Center for Finance, Princeton University, Julis Romo Rabinowitz Building, Princeton, NJ 08544; e-mail: Simon.Schmickler@princeton.edu

‡University of Illinois at Urbana-Champaign

1 Introduction

A key purpose of financial markets is liquidity provision. The intermediaries that supply liquidity are market makers (MMs), which are specialized firms that stand ready to both buy and sell. Today, market making is dominated by high-frequency traders (HFTs). Exchanges and regulators are concerned that these voluntary liquidity providers can simply exit during crises, causing liquidity to evaporate when traders need it the most, as for example during the 2010 Flash Crash (e.g. Kirilenko et al., 2017). As a solution, major exchanges including the NYSE, Euronext, London Stock Exchange, Deutsche Börse, and Brazil's B3 enroll designated market makers (DMMs) that accept liquidity provision obligations in return for incentives such as preferential trading fees. Since the 2018 legislative framework MiFID II, EU regulators even require exchanges to enter DMM agreements with voluntary market makers.

However, market making design is challenging: obligations guarantee a minimum of liquidity provision but also constrain DMMs; incentives encourage voluntary liquidity provision but also harmful strategies; and despite their potentially large consequences for the functioning of financial markets, the separate effects of the elements of these policies and consequently the optimal policy design are largely unknown.

This paper tackles this challenge by empirically investigating how exchanges and regulators can improve the liquidity and stability of modern financial markets. In particular, should exchanges and regulators use liquidity provision obligations or incentives? Does the answer differ in good times and crises? How can they prevent liquidity dry-ups? And how should they assign MMs to assets?

We address these questions using unique full-depth message-level trade and quote data from the Brazilian exchange B3, one of the largest exchanges in the world with a total stock market capitalization of 1 trillion USD. The key advantage of these data is that they reveal market participants' identities. The data cover the universe of activity on B3: all trades and quotes in all assets from 2014 to 2020 timestamped to the millisecond. In total, the raw message data include 50 billion observations. While our analysis is set in Brazil, the MMs include the most sophisticated algorithmic traders in the world, such as Citadel Securities and Virtu Financial.

For identification, we use two market maker programs that provide abrupt exogenous variation in MM activity as well as liquidity provision obligations and incentives. In 2018 and 2019, the exchange implemented centralized programs assigning 2 to 5 out of 13 global high-frequency MMs to each included stock. The programs impose stock-specific liquidity provision obligations: DMMs must maintain continuous, two-sided quotes within maximum bid-ask spreads and at minimum lot sizes. In return, DMMs receive incentives to voluntarily provide liquidity: B3 grants DMMs stock-specific trading fee discounts on *all* trades in their designated stocks. B3 decided program stock selection, obligations, and incentives two months in advance and quasi-randomly conditional on few observable variables.

We exploit the various features of the MM programs using several difference-in-differences designs which identify the effects of the overall programs, and separately estimate the effects of liquidity provision obligations and incentives, in normal times and in crisis. We examine effects on the behavior of market makers as well as the level, volatility, and co-movement of liquidity, volume, and returns. While the programs provide random variation in many program elements, the identifying assumption underlying our research design is not random assignment; it is that outcomes would have trended in parallel absent the programs. Consistent with this assumption, we find the relevant outcomes for treated and control groups evolve in parallel before the shocks.

We begin by examining how DMMs behave during normal times. We find each DMM simultaneously runs two strategies for each asset. The first strategy only serves to fulfill their obligations. We call this strategy the "mandatory activity." We can isolate the mandatory activity because the programs require DMMs to post very large and uncommon quantities, which is a special advantage of our setting. The strategy is very active; e.g., Citadel Securities sends about one program-quantity message per second per stock. But as the quantity requirement exposes DMMs to substantial execution risk, this strategy quotes wide spreads and consequently generates little volume: total mandatory passive trades from all DMMs combined amount to only 1% of trading volume. Simultaneously, DMMs run a second strategy that we call the "voluntary activity." As a reward for fulfilling their obligations, DMMs receive a fee discount for all trading in their assigned stocks. This gives them a competitive advantage over all other liquidity providers, an advantage they exploit with a strategy that quotes smaller quantities but at aggressive prices which attracts large volume: the voluntary activity intermediates 30% of total volume. The voluntary activity also crosses the spread, but more often provides liquidity.

Next, we study how the programs affect market outcomes. We start by investigating the programs' overall effects using a difference-in-differences methodology comparing stocks that were newly included in the MM programs to those that were not. The combination of obligations and incentives is overall beneficial for stocks. Liquidity improves: quoted and effective spreads decline by up to 17%, and depth increases by 50%. In particular, the fee discount fully passes through into lower spreads. We find this large liquidity improvement is partly driven by strategic complementarity in liquidity provision. In addition to the DMMs, other traders that do not receive the fee discount also tighten spreads and provide more depth after the programs start. The liquidity improvement attracts volume, which rises by 15%, and lifts asset prices by 4%. In addition to the programs' effects on levels, we examine their effects on stability. We find DMMs drastically lower the volatilities of liquidity and volume, but there is no substantial effect on return volatility. DMMs stabilize liquidity, which also stabilizes volume because trading demand depends on liquidity. Overall, the programs are win-win-win-win-lose situations: investors and stocks benefit from improved liquidity, the increase in volume overcompensates the exchange for the fee discounts, DMMs profit from the fee discount, and MMs that were not selected as DMMs lose business.

Our next step is to disentangle the effects of liquidity provision obligations and incentives. To this end, we exploit abrupt changes in stock-specific obligations and incentives from the 2018 to the 2019 program. We find tightening liquidity provision requirements, intended to improve market quality, has the opposite effect. Tight obligations decrease liquidity, volume, and asset prices, likely by exposing MMs to higher execution risk which lowers inventory capacity and inhibits MMs' ability to voluntarily provide liquidity. Incentives to voluntarily provide liquidity, by contrast, are beneficial. Together, these results show that in normal times, the positive effects are driven by the incentives, not the obligations.

However, these results flip in crises. Specifically, we examine the COVID-19 market crash during which stock prices fall by over 40% and liquidity dries up: within days and at the 95th percentile, program stocks' quoted spreads surge seven-fold from 0.15% to 1%. We find that during the crash, the voluntary activity withdraws and the mandatory activity becomes the liquidity provider of last resort. As market conditions worsen, liquidity provision by the voluntary strategy exhibits an abrupt absolute drop of 8% of total volume, a change that fully reverses as market conditions normalize. At the exact same time, the share of volume intermediated by the mandatory strategy quintuples from 1% to 5% and drops back to 1% as market conditions normalize.

We investigate whether this MM behavior affects stocks' resilience in crises by exploiting variation generated by the 2019 market maker program. First, we document that tighter program requirements mitigate the liquidity dry-up during the crash. MM obligations act as insurance, costly in normal times but beneficial in crises. Second, we find that larger incentives, i.e. more reliance on voluntary HFT liquidity provision, exacerbate the liquidity dry-up because the voluntary activity withdraws. Finally, we find the program overall mitigates the liquidity dry-up. In sum, the programs are beneficial during both normal times and crises, but the effects of obligations and incentives are inverted. This suggests that exchanges and regulators should combine incentives with countercyclical liquidity provision obligations.

Another important choice exchanges make is how to assign MMs. Here, we document a dark side of the programs: MMs hedge across assets causing excess co-movement of liquidity, volume, and returns. Hence, by choosing which MMs to assign to which stocks, exchanges create co-movement clusters. We begin by examining how MMs behave. In practice, MMs act as intermediaries in several assets, making joint portfolio and liquidity supply decisions (Easley et al., 2020). Indeed, theoretical models of market making with multiple assets predict that MMs' demand for one stock depends negatively on inventory of the stock itself and, crucially, negatively on inventory of other stocks as well (Andrade, Chang, and Seasholes, 2008). We test whether MMs' quoting behavior is consistent with this prediction. In particular, we test how MMs revise price quotes in response to inventory shocks in the stock itself and in other stocks. Concretely, we examine MMs' quoting behavior in event time which preserves the temporal ordering of market events and MMs' quote revisions and only consider MMs' reactions in excess of any market reaction by controlling for stock returns.

We find MMs revise quotes aggressively after their passive orders are hit. Consider a MM who does not currently hold inventory; in response to accommodating a market sell order, the MM decreases quotes and widens spreads for that asset and for other assets. This cross-asset quoting behavior gives rise to a spillover effect through the portfolios of MMs; and as the shock moves all assets intermediated by the MM in the same direction, this mechanism can cause nonfundamental co-movement.

We estimate the causal effect of common intermediation on co-movement by exploiting exogenous variation in market making activity created by the two MM programs. Our difference-in-differences estimator compares stock pairs that are assigned a common MM to stock pairs that are assigned disjoint sets of MMs. We find common intermediation raises co-movement across all three dimensions: liquidity, volume, and returns. The increases are economically meaningful, up to 20% of the mean. Overall, there is a trade-off: DMMs boost and stabilize liquidity but cause excess co-movement.

Our results are robust to a battery of additional tests. Most importantly, we estimate all difference-in-differences models separately for the 2018 and the 2019 programs. For all 15 variables we consider, levels, volatilities, and correlations of liquidity (measured as quoted spreads, effective spreads, and depth), volume, and returns, the results are consistent across the two natural experiments, which gives us high confidence in the robustness of the findings.

Related Literature. This paper relates to the literature studying the effects of DMMs. The literature finds DMMs improve market quality and benefit asset prices (Nimalendran and Petrella, 2003; Venkataraman and Waisburd, 2007; Anand, Tanggaard, and Weaver, 2009; Comerton-Forde et al., 2010; Perotti and Rindi, 2010; Menkveld and Wang, 2013; Skjeltorp and Odegaard, 2015; Clark-Joseph, Ye, and Zi, 2017; Bellia et al., 2020; Bessembinder, Hao, and Zheng, 2020). In contrast to the literature, we observe DMM behavior at the message level, as well as the exact DMM contract parameters. Our setting allows us to separate DMMs' mandatory and voluntary activity and disentangle their effects, in normal times and crises. These differences are policy relevant because exchanges and regulators can choose obligations and incentives.

We also contribute to the extensive literature exploring the behavior and effects of HFTs (e.g. Brogaard, Hendershott, and Riordan, 2014; Menkveld, 2016; Gider, Schmickler, and Westheide, 2019; Kervel and Menkveld, 2019; Korajczyk and Murphy, 2019). Specifically, recent work documents that HFTs often withdraw during crises (Anand and Venkataraman, 2016; Kirilenko et al., 2017; Brogaard et al., 2018; Raman, Robe, and Yadav, 2021). We contribute to this literature by showing that this behavior and its adverse effects can be mitigated by imposing affirmative obligations on HFTs. Another contribution of this paper is that HFTs hedge across assets which generates excess co-movement.

Next, this paper is related to the vast literature on the economics of market making (e.g. Stoll, 1978; Amihud and Mendelson, 1980; Hasbrouck and Sofianos, 1993; Madhavan and Smidt, 1993; Comerton-Forde et al., 2010; Hendershott and Menkveld, 2014). While existing findings are typically based on trade data from NYSE specialists, we observe algorithmic MMs' behavior at the message level. Moreover, research in market microstructure predominantly examines markets one asset at a time, yet market participants make decisions across assets, especially with the rise of algorithmic trading (Easley et al., 2020). Our analysis documents that, consistent with theoretical models (Andrade, Chang, and Seasholes, 2008), MMs hedge across assets and cause excess co-movement.

This paper also relates to the extensive literature that examines how financial institutions impact asset prices and market quality (e.g. Brunnermeier and Pedersen, 2009; He and Krishnamurthy, 2013; Adrian, Etula, and Muir, 2014; He, Kelly, and Manela, 2017; Koijen and Yogo, 2019). In particular, this paper contributes to the literature that connects intermediaries to commonality in asset returns and liquidity. Greenwood and Thesmar (2011) and Anton and Polk (2014) find common ownership by mutual funds is associated with higher return co-movement. Barberis, Shleifer, and Wurgler (2005) and Claessens and Yafeh (2013) document index inclusion increases stocks' correlation with said index, though Chen, Singal, and Whitelaw (2016) cast doubt on the result. While this literature shows how shocks to demand-side investors create low-frequency co-movement, our paper studies how sell-side intermediaries cause high-frequency spillover effects. Also related are papers that investigate cross-stock predictability (Hasbrouck and Seppi, 2001; Harford and Kaul, 2005; Andrade, Chang, and Seasholes, 2008; Tookes, 2008; Pasquariello and Vega, 2015).

Relatedly, Chordia, Roll, and Subrahmanyam (2000) document important commonality in liquidity. Building on their work, Coughenour and Saad (2004) and Anand and Venkataraman (2016) show commonality in liquidity between stocks handled by the same liquidity provider. Similarly, Malceniece, Malcenieks, and Putniņš (2019) find HFTs increase return and liquidity market betas. Complementing these supply-side results, Karolyi, Lee, and van Dijk (2012) and Koch, Ruenzi, and Starks (2016) provide evidence that commonality in liquidity is driven by correlated liquidity demand. We contribute to this literature by showing that cross-asset hedging by MMs causes excess co-movement in liquidity, volume, and returns.

2 Data and Empirical Strategy

We use message data for all listed assets traded on the Brazilian Stock Exchange (B3). Raw messages include every order submitted and track lifetime order status in a market-by-order fashion. B3 marks every order with a buy/sell indicator, order type, quantity, bid or offer price, and aggressor flag and then records all changes (e.g., partial fulfillment, cancellation, modification, rejection, etc.) sequentially. As our audit trail data record orders at all price levels, the raw messages allow us to reconstruct the full depth limit order book of every market at every moment. Messages are timestamped to the millisecond. Our sample spans 2014 to 2020. In total, the raw message data include about 50 billion observations.

A special feature of our data is that they contain unique entering firm IDs. These identifiers are assigned by B3 to exchange participants allowed to operate in the market and remain constant across time, assets, and firm lifespan. If a market participant stops trading, e.g. because of an acquisition, B3 freezes the identifier and never uses the same code again. The exchange provides the identities of all registered firms since 1980, which enables us to observe the actual firm behind the masked ID and hence, all orders and trades done by the firm in stocks, options, and futures.

2.1 Institutional Details

B3 – Brasil, Bolsa, Balcão, formerly BM&FBovespa – is the only exchange in Brazil and resulted from of a merger between the country's last exchanges in 2008. In 2017, then BM&FBovespa took over CETIP, Brazil's largest depository, clearinghouse, and over-the-counter (OTC) market. This acquisition made B3 the largest OTC market in the country. Today, B3's services include trading, clearing, and settlement of equities and derivatives as well as registration, clearing, settlement, and custody systems for OTC fixed-income securities and OTC derivatives. According to the CME, this wide range of product offerings makes B3 the world's third largest exchange and the largest in Latin America by total market value across all its products (stocks, options, futures, OTC fixed income, OTC derivatives). In terms of its total stock market capitalization of 1 trillion USD, B3 ranks about 20th in the world, similar to the main stock exchanges in Germany, Switzerland, Australia, and Singapore. B3 is a public company, trading in its own market with a market cap of about 15 billion USD, putting it in line with the world's top stock exchanges such as Nasdaq and Deutsche Börse.

B3 launched electronic limit order book platforms in the early 1990s, around the same time CME introduced its electronic trading platform Globex. Trading at B3 became fully electronic in 2009, when the last derivatives pits were shut down. B3's electronic trading platform is very similar to interfaces used at US exchanges, with market data feeds following standard FIX message protocols optimized for low latency. This allows B3 to route orders directly to CME, for example, which cross-lists several products with B3. Order priority allocation follows price, time, and quantity. For the same price level, orders entered first are entirely filled first (FIFO matching). The regular trading session starts at 10:00am and closes at 4:55pm. Stocks are traded at one-centavo increments and in 100-share minimum lot sizes. Odd lots are submitted and traded in a separate, parallel market – named "fractional" stocks by B3 – where investors may submit orders for fewer than 100 shares. We observe fractional stock trading but do not use it in this paper.

2.2 The Natural Experiments

We exploit B3's 2018 and 2019 MM programs as sources of exogenous variation in MM activity, obligations, and incentives. We obtain all program details directly from B3.

Timeline. In 2018 and 2019, B3 implemented centralized programs with standardized contract parameters to enroll MMs in stocks starting on one set date. MMs commit to maintaining minimum quantities at maximum spreads in exchange for fee discounts. Figure 1 provides a timeline of the two programs. The first program was announced in August 2018. Financial institutions could apply to the program until September 10. On September 12, B3 made and publicly released all program decisions. The program began on October 15, 2018 and ended on November 1, 2019. In September 2019, B3 announced a second program. Financial institutions had to apply by September 20 and B3 made and announced all program decisions on September 27. The program started on November 2, 2019, immediately following the end of the first program, and ended on April 30, 2021. For the 2018 and the 2019 programs, B3 chose program stocks and parameters two months and DMMs one month in advance. This means that B3's decisions are not based on changes occurring after the program start.

Program Inclusion. The 2018 program included 54 out of about 400 stocks while the 2019 program included 89. For the 2018 program, B3 selected program stocks quasi-randomly conditional on three observable variables. First, B3 selected stocks from the exchange's IBrX 100 index, which tracks the 100 top stocks based on average daily volume. Second, B3 excluded a small number of top stocks because of an internal notion that these stocks were already sufficiently liquid. Third, B3 gave preference to stocks without pre-existing bilateral DMM contracts (B3 has allowed issuing companies to enter bilateral agreements with trading firms for designated market making since 2003. About half of IBrX 100 stocks had entered these bilateral agreements which were unaffected by the market maker programs). While B3 did not use a random number generator to decide program inclusion, B3 explains the selection process as manual conditional stratified randomization; decision makers at B3 aimed to maximize variety across included stocks. While we confirm this empirically by showing that conditional on the three variables other stock characteristics are unrelated to treatment status, our identification strategy does not rely on random assignment. For the 2019 program, B3 increased the program's scope to all except the top IBrX 100 stocks.

DMM Assignment. The 2018 (2019) program divided included stocks into 2 (3) groups based on a liquidity cutoff. Group A included the 9 (13) stocks with historical average daily volume above R$80 (R$100) million. Group B included stocks below the cutoff, with the exception that the 2019 program further assigned stocks below R$30 million to group C. B3 offered two DMM slots for each stock in group A, three slots for group B, and five slots for group C. The 2018 volume cutoff reused an old value from a 2015 policy. B3 allowed trading firms to apply for stocks selectively. However, trading firms had to apply for five stocks in group B or C in order to submit one bid for a stock in group A. B3 had full discretion in choosing MMs and aimed to maximize variety across stocks; i.e. when given the choice between two trading firms, the exchange selected the firm with the lowest total number of slots. The 2018 program filled all DMM slots for each stock in the program. The 2019 program filled 96% of slots. The 2018 (2019) program selected 9 (13) trading firms as DMMs. The DMMs are mostly HFTs and include some of the most sophisticated algorithmic traders in the world, such as Citadel Securities, Virtu Financial, and Jane Street.

Activity Parameters. The programs set stock-specific minimum activity parameters. Specifically, the programs require DMMs to maintain continuous, two-sided quotes within maximum bid-ask spreads and at minimum lot sizes during at least 80% of each trading day. Moreover, DMMs must participate in at least 5% of daily trading volume. B3 set stock-specific parameters by applying mechanical rules to data covering the 12-month period ending three months before the programs. The rules aim to balance liquidity provision and execution risk. B3 set minimum quantities to about 0.3% of past average daily shares traded rounded to 1000s and maximum spreads to the past average round trip cost of each stock at the minimum quantity rounded up to the next 0.25%. Firms could propose stricter parameters, but final contract parameters remained unchanged from the values initially proposed by B3. Appendix Tables A1 and A2 detail the designated MMs and program parameters for each stock. Appendix Figure A1 shows histograms of program parameters.

Benefits and Enforcement. B3 fully waived trading fees for MMs in their designated stocks. The only exceptions are group A stocks in the 2019 program, for which MMs received a 75% instead of a 100% discount. B3 is a monopoly and consequently charges high fees. The fees range from 1.1 to 2.3 basis points. The more a market participant trades, the lower the fee. On average, B3 collects 1.85 basis points from each side of the trade. As market makers trade large volumes, they paid close to 1.1 basis points per transactions before the programs. For comparison, major stock exchanges typically charge less than 0.5 basis points. This means the fee discount is a very large competitive advantage and consequently, a very large shock. B3 evaluated DMMs after the first six months of each program, at which point B3 could sanction or replace firms that failed to fulfill their obligations. However, all MMs complied and by the end of the programs, no MMs had been substituted.

2.3 Observing Market Makers' Trades and Quotes

Figure 2 illustrates how traders access the Brazilian financial market. B3 gives direct market access to about 100 executing firms. End investors submit orders through executing firms. Importantly, executing firms merely transmit orders to the exchange; they do not trade with clients as in a dealer market. For example, Goldman Sachs executes orders for institutional clients and XP for retail investors. While we are working with B3 to obtain account IDs, our current data reveal the executing firm that sends the message to B3. However, while some MMs (highlighted in red) are executing firms (e.g. Credit Suisse), MMs and executing firms are not synonymous. Notably, foreign MMs are required to trade via domestic execution brokers. B3 reveals to us which execution brokers MMs use. MMs only use one execution broker for each stock. MMs may use different execution brokers for different stocks, but in practice they use one or only a few executing firms. E.g., Virtu Financial submits orders via UBS and QE Trading submits orders via Genial Institutional.

Execution brokers have multiple clients. Hence, while most activity originating from an executing firm that executes for a MM does stem from the MM because of MMs' high activity level, messages from other clients contaminate this inference. However, the programs' unique structure helps us identify messages from MMs. The programs require MMs to maintain high and unusual minimum quantities. While 100 is the most common (and required minimum) order quantity for most stocks, the programs set minimum quantities from 2,000 to 60,000 shares. MMs would not voluntarily provide such depth, which is why B3 incentivizes them. Therefore, MMs do not quote above the minimum quantity, meaning they quote *exactly* at the minimum quantity. As the minimum quantities are very uncommon lot sizes, messages at the minimum quantity from execution brokers serving MMs are quotes from MMs. Specifically, they are messages sent by MMs to fulfill their program obligations. We therefore call these messages their "mandatory activity".

While B3 confirms this logic, we also verify it empirically. Figure 3 shows the distribution of order quantities in 1000s for the first stock alphabetically, the large brewing company Ambev, on October 1, before the 2018 program begins, and on October 15th, the program's first day. The minimum quantity for Ambev is 25,000 shares. Before the shock, there are virtually no quotes at 25,000 shares. In fact, most quotes are for 1,000 shares or fewer. However, after the shock, a substantial fraction of messages enter at exactly 25,000 shares, while the rest of the distribution remains almost unchanged. This bunching at exactly 25,000 shares confirms that MMs quote exactly at minimum quantities. This pattern is not unique to Ambev, as shown in section 3.1.1, where we compare MMs' mandatory and voluntary activity.

We measure MMs' voluntary activity as quotes by MMs' execution brokers excluding messages at the minimum quantity. This measure contains MMs' voluntary activity, though it also contains some messages from other clients. However, as there are about 100 execution brokers and MMs are very dominant in the stocks they intermediate (e.g., about half of all messages come from MMs), the contamination is likely small. We are also working with B3 to obtain account instead of executing firm IDs, meaning our future inference will be exact.

2.4 Comparison to Alternative Data Sources

Trade and quote data from order-driven markets almost never reveal traders' identities. The fact that researchers have proxied trading by the same entity as trades that occur almost simultaneously (e.g. within 20 microseconds) in different products (e.g. Ernst, 2021) shows the difficulty of obtaining identified message data. This makes our ability to observe MM behavior at the message level an important feature of this paper.

Previously, researchers have gained insights based on other data sources. While we cannot list all papers that have used trader identities, several stand out as important. First, Madhavan and Smidt (1991) and Madhavan and Smidt (1993) obtain transactions directly from one NYSE specialist firm. Hasbrouck and Sofianos (1993) use the NYSE specialist equity trade (SPET) file which covers NYSE specialist trades. More commonly, researchers use the NYSE Specialist Equity Trade Summary (SPETS) file, which provides daily data on specialists' trades (e.g. Madhavan and Sofianos, 1998; Hendershott and Seasholes, 2007; Comerton-Forde et al., 2010; Hendershott and Menkveld, 2014). Further, NYSE Consolidated Equity Audit Trail Data (CAUD) are transaction-level data that contain a flag indicating whether the buyer or seller are institutional investors (e.g. Boulatov, Hendershott, and Livdan, 2013; Hendershott, Livdan, and Schürhoff, 2015). Similarly, NASDAQ, as well as the Trade Capture Report from the CME to the CFTC, supply transaction-level data that identify whether the buyer or seller are high-frequency traders (HFTs) (e.g. Brogaard, Hendershott, and Riordan, 2014; Kirilenko et al., 2017; Brogaard et al., 2018).

Next, the Investment Industry Regulatory Organization of Canada (IIROC) provides message-level data containing anonymous market participant IDs. Brogaard, Hendershott, and Riordan (2019) and Korajczyk and Murphy (2019) use the IDs to classify whether market participants are HFTs. Likewise, Aquilina, Budish, and O'Neill (2021) rely on message-level data with anonymous market participant IDs through a request of the Financial Conduct Authority (FCA) to the London stock exchange. Kervel and Menkveld (2019) and Meling (2021) obtain transaction-level data from Sweden and Norway, respectively, that reveal the executing firm that sends the order.

While our data share similarities with each of these data sources, our data have several advantages: first, they are at the message level, which is the most granular; second, they reveal identities; third, at least for the mandatory activity, they identify the market markers themselves, not just the executing firms which often execute trades for many clients; fourth, they cover algorithmic MMs instead of specialists (of course, each advantage only applies to a subset of the data sources listed above).

2.5 Variable Construction

In addition to the raw message data, we use other datasets. All MM program details are from B3, which also provides a mapping between anonymous market participant IDs and their identities as well as information on which market participant each MM uses as an execution broker in each stock. Finally, we obtain additional stock and accounting data from Compustat Global Fundamentals Annual and Compustat Global Security Daily.

We use the raw message data to reconstruct the complete limit order book at each instant, thereby allowing us to recover best bids and offers at that precise time. We use the data in this form to investigate MMs' high-frequency behavior at the message level. Further, we retain complete limit order book snapshots at the 5-minute frequency, which is the most common intraday frequency (e.g. Marshall, Nguyen, and Visaltanachoti, 2012). We also compute daily and monthly frequency data by aggregating from the 5-minute frequency. This ensures that our low-frequency measures capture intraday instead of end-of-day information.

We construct two key input datasets: stock x time data and trader x stock x time data. For the former, we construct several key variables. Brunnermeier and Pedersen (2009) define liquidity as the difference between transaction prices and fundamental values. While fundamental values are unobserved, Comerton-Forde et al. (2010) argue that effective spreads best capture the spirit of their model. Therefore, we measure liquidity as effective spreads and additionally examine quoted spreads and depth, all constructed following Marshall, Nguyen, and Visaltanachoti (2012). Effective spreads are volume-weighted mean 2*abs((trade price - midpoint) / midpoint) during the respective time period. Quoted bid-ask spreads are end-of-period (best offer - best bid) / midpoint. We construct three measures of depth: depth on the first five price levels, total depth, and depth within 0.5% of the midpoint. We choose the latter as our main measure of depth because we believe it best captures liquidity, but the results are qualitatively the same across the different measures of depth. We compute R$ depth by multiplying depth in number of shares with the open price. This prevents intraday volatilities and correlations of depth being driven by stock returns. Depth and volume are in log R$.

Returns are relative changes in end-of-period bid-ask midpoints. We winsorize returns cross-sectionally at the 1 and 99% levels. Next, we compute standard deviations and stock pair level correlation coefficients of log quoted spreads, log effective spreads, log depth, log volume, and returns by month. Quoted spreads, effective spreads, depth, volume, and returns in levels, standard deviations, and correlation coefficients form the main input data into our empirical exercises at the stock x time level. In all exercises, we exclude microcap stocks, which are defined as stocks with a market capitalization less than R$100M.

Next, we construct trader x stock x time data. We compute the number of trades, total number of shares traded, and total R$ value traded separately for buys vs. sells and for liquidity-taking vs. liquidity-providing trades. We also retain prices and quantities of end-of-period best active bids and offers. Finally, we count the number of messages independently for each message type. Importantly, we split MMs' mandatory and voluntary activity. To this end, we use the information provided by B3 to link market participant IDs to their identities. Then, we map these identities to the MMs for which they transmit orders.

Finally, we separate the mandatory and voluntary activities by whether a message is sent at the program quantity, as described in section 2.3.

2.6 Summary Statistics

Table 1 gives an overview of the 13 MMs in our sample. The table provides stock-day level summary statistics by MM, sorted alphabetically. Panel A summarizes their mandatory activity, panel B summarizes their voluntary activity. At the time, 1 USD buys about 4 R$s. We begin by looking at MMs' mandatory activity. Average stock-day trading volume ranges from R$300k for Credit Suisse to R$1.5M for Jane Street. The average trade size is large, around R$60k, meaning each MM's mandatory activity only trades about a dozen times a day in each stock. However, MMs send a large amount of messages. Citadel Securities sends the most messages, at 19,000 messages per stock per day, i.e. about 1 message per stock per second, and 1,700 messages per trade. Finally, by definition, the mandatory activity trades only passively.

We also examine MMs quoting styles by reporting the fraction of messages that are new orders, fills, cancels, and replace orders. Two distinct quoting styles emerge. Citadel Securities is a good example of the first style. Their share of new and cancel orders is 50% and their share of fill and replace messages is 0% (rounded to the first decimal place). Credit Suisse is a good example of the second style. Their share of new, fill, and cancel messages is close to 0 and their share of replace orders is close to 100%.

Panel B reports analogous statistics for the voluntary activity. Here, average stock-day trading volume is much larger, ranging from 12M for Green Post Trading to 52M for Headlands Technologies. At the same time, average trade size is much lower, typically less than R$10k. This means the voluntary activity trades much more often, thousands of times per stock per day. While the voluntary activity also sends an enormous amount of messages, from 8k to 95k messages per stock-day, the message to trade ratio is much lower, ranging from 3 to 25. Further, the voluntary activity often takes liquidity. The most aggressive institutions are Citadel Securities and Tucana Bay, which are the aggressor in almost 60% of their volume. Finally, new, fill, cancel, and replace orders account for about 40, 15, 35, and 10% of messages, respectively.

Table 2 reports summary statistics of monthly stock characteristics for the sample spanning the nine-month event windows around the MM programs. There are about 3600 observations, about 200 stocks during 18 months. The stocks in the sample have a mean market capitalization of R$12B. From the 5th to the 95th percentiles, stock prices range from R$2 to R$69. The natural experiments fall into a good period for stock prices. The average monthly return is 3%. The Brazilian stock market is very liquid: at the 5th percentile, quoted bid-ask spreads are only 5 basis points. Even at the median, bid-ask spreads are only 12 basis points. Only the very right side of the distribution is illiquid, with a 1.5% quoted spread at the 95th percentile. Effective spreads are similar to quoted spreads. Average depth is R$700k on the first five price levels, R$1.3M within 0.5% of the midpoint, and R$5M in the full-depth book. Average daily volume is R$50M, which increases to R$180M at the 95th percentile and to over R$2B for the most traded stock, the oil firm Petrobras. The average daily number of trades is 5400 and the average trade size is R$8400.

Next, we summarize the distributions of intraday (5-minute) standard deviations of log quoted spreads, log effective spreads, log depth, log volume, and returns. This differs from the standard deviations of the respective variables above because it is computed within instead of across stocks. Liquidity is volatile: quoted and effective spreads have a mean standard deviation of about 50% and depth of 80%. Further, volume is volatile with a mean standard deviation of 300%. Finally, mean intraday return volatility is 20 basis points.

Finally, we summarize correlations between program stocks. In contrast to the stock-level variables discussed above, correlations are *stock-pair-level* variables. This is why there are many more, 170k, observations. Table 3 reports the corresponding summary statistics. The variables are percent correlation coefficients of intraday (5-minute) log quoted spreads, log effective spreads, log depth, log volume, and returns. First, liquidity is correlated across stocks, with means of 17, 11, and 51% for quoted spreads, effective spreads, and depth. So is volume, as the mean correlation is 34%. Finally, returns have a mean correlation of 7%. Idiosyncratic volatility dominates at high-frequency.

3 Results

3.1 Liquidity Provision Obligations and Incentives in Normal Times

3.1.1 Market Maker Behavior

We begin by examining how DMMs behave. We find each DMM runs two strategies for the same asset at the same time. The "mandatory activity" fulfills the DMM obligations, and the "voluntary activity" exploits the fee discount to quote aggressive prices. Plots (a) and (b) of Figure 4 examine the voluntary and mandatory activity, respectively, in event time during a $\pm$ four-month event window around the programs. The red line in plot (a) shows the number of messages from the voluntary activity as a percent fraction of all messages sent by other executing firms for stocks included in the program. The line starts at 40% because B3 selected trading firms that were already making markets to be DMMs. Then, with the start of the program, this fraction jumps to 70%. The gray and black lines report trading instead of quoting activity. With the start of the program, the share of trades in which the voluntary activity participates jumps from 45 to 65% and its share of volume jumps from 35 to 50%. That the share of trades is greater than the share of volume means the average trade size is low, as reported by the summary statistics in Tables 1 and 2. Overall, plot (a) demonstrates that fee discounts incentivize MMs to increase their voluntary activity.

Plot (b) displays the analogous results for the mandatory activity. Quoting activity explodes. Two months before the program begins, the fraction is visually indistinguishable from 0. Only about 0.01% of messages are sent at the minimum quantity. This fraction increases to about 1% in the pre-treatment period, when MMs run live tests. When the program starts, this fraction jumps to 40% and then climbs to 60% over three months. In addition to demonstrating how active the mandatory strategy is, this finding also further demonstrates the validity of inferring the mandatory activity from minimum quantities (in combination with execution brokers) as described in section 2.3. In contrast, the share of trades and volume in which the mandatory activity participates stays close to zero. The mandatory activity participates in 1% of volume and 0.2% of trades. The fact that the share of volume is greater than the share of trades means the average trade size is high, as reported by the summary statistics in Tables 1 and 2. This is because the minimum quantities are large.

Finally, plot (c) separates the voluntary trading volume into active and passive trades. Passive volume increases from 20 to 30%, active volume rises from 15 to 20%. This shows that DMMs exploit their competitive advantage to intermediate large volume. However, they also trade actively, either to hedge or to take directional bets. Note that there is no analogue of plot (c) for the mandatory activity, which, by definition, only trades passively.

Next, Figure 5 digs deeper into DMMs' behavior by examining prices instead of quantities. It displays the fractions of time the voluntary and mandatory activity spend on different price levels. The red line in plot (a) shows that upon the programs' start, the share of time that the voluntary activity provides the best price in the market increases from 20 to 35%. This demonstrates that DMMs exploit their competitive advantage coming from the fee discount by quoting aggressive prices. The gray line denotes that the share of time during which the voluntary activity quotes on price levels 2 to 5 only rises slightly, from 15 to 17%. Plot (b) reports the analogous results for the mandatory activity, which usually quotes unattractive prices, almost never quoting at the top of the book.

In sum, Figure 6 illustrates DMMs' typical quoting behavior using an example snapshot of the bid-side of a limit order book. Price levels decrease from the top to the bottom and queue priority declines from left to right. We highlight orders from the mandatory and voluntary activity in red and blue, respectively. The figure illustrates that the mandatory activity quotes large quantities deep in the book while the voluntary activity quotes small quantities at the top of the book. Appendix Figure A2 contains a dynamic instead of a static example.

3.1.2 Designated Market Makers' Overall Effects

We begin by investigating the effects of combining liquidity provision obligations and incentives. To this end, we exploit exogenous variation in market making activity created by the MM programs using a difference-in-differences identification strategy to estimate DMMs' casual effects on the levels and volatilities of liquidity, volume, and asset prices. For the first program, we compare stocks included in the MM program to stocks that are not part of the program. We use the 2019 program to compare stocks newly included in the program to stocks included since the 2018 program. Hence, the treated stocks in the 2018 experiment are the control stocks in the 2019 experiment. We estimate DMMs' causal effects on stock-level outcomes separately for the 2018 and 2019 program using

$$y_{i,t} = \alpha_i + \phi_t + \beta MM_i \times Post_t + \delta' X_{i,t} + \epsilon_{i,t}, \tag{1}$$

where MM indicates that stock i is newly included in the MM program. X denotes a vector of control variables. When estimating this regression, we cluster standard errors by stock. The 2019 program starts almost 4 months before the COVID crisis begins. As this section examines the effects during normal times, we set the event windows to $\pm$ 4 months around the events and cut off the sample at the start of the COVID-19 stock market crash on February 21, 2020.

The validity of our difference-in-differences identification strategy relies on the assumption that outcomes for the treatment and control groups would have trended in parallel without the treatment. This assumption likely holds because B3 selected program stocks quasi-randomly conditional on being IBrX 100 index constituents, not being one of a few top stocks, and not having a pre-existing bilaterally contracted DMM. Table 4 confirms this selection procedure using regressions of the treatment indicator on an indicator for inclusion in the IBrX 100 index, an indicator for a pre-existing bilateral DMM relationship, and key stock characteristics. The characteristics include key outcome variables of our analysis; the Fama and French (2015) characteristics size, value, profitability, and investment; and major additional firm characteristics. As expected, the coefficient on the IBrX 100 indicator is positive and statistically significant for both programs; the coefficient on the indicator for the bilateral DMM relationship is negative and significant for the 2018 experiment and positive and significant for the 2019 experiment; the top stock indicator is statistically significant and negative for the 2018 experiment and missing for the 2019 experiment because the top stocks are not in the sample; and importantly, the coefficients on all other characteristics are small and statistically insignificant. Motivated by this empirical fact, we choose the three variables B3 used to determine treatment as the set of control variables. The fact that treated and control firms have similar stock characteristics, at lest conditional on the control variables, also suggests that the parallel trends assumption is likely fulfilled. We further document the absence of differential pre-trends when examining dynamic treatment effects.

DMMs' Effects on Liquidity, Volume, and Asset Prices. Table 5 reports estimates of equation 1 for the two natural experiments separately. The rows report results for different dependent variables: log quoted spreads, log effective spreads, log depth, log volume, and cumulative abnormal returns. We begin by examining the 2018 experiment in panel A. First, stocks in the program experience a statistically significant 10% decline in quoted bid-ask spreads. Similarly, effective spreads drop by 10%. Next, row 3 finds a 50% increase in depth. These three effects demonstrate that DMMs increase liquidity. Row 4 shows the liquidity improvement attracts volume, which increases by 15%. To interpret the size of this effect, recall that Figure 4 documents that the programs also increase the share of volume in which MMs participate by 15%. As MMs only take one side of each trade, this means that the programs increase trading volume even after stripping out the trading volume of MMs.

Finally, we examine pricing effects. Stock prices react when the relevant information is revealed; therefore, in all exercises involving price reactions, we examine returns around the announcement, not the start, of the program. We find program stocks experience positive cumulative abnormal returns of 3%. Panel B shows that the results are very similar for the 2019 experiment. In fact, the confidence intervals overlap in most cases. This further corroborates the robustness of the findings.

We also estimate dynamic treatment effects using

$$y_{i,t} = \alpha_i + \phi_t + \sum_{s \neq 0} \beta_s MM_{i,t} \times \mathbb{1}\{s = t - E + 1\} + \delta' X_{i,t} + \epsilon_{i,t}, \tag{2}$$

where E is the time of the event and the β_s are the dynamic treatment effects. Figure 7 reports estimates of equation 2, pooling the two program samples. Plots (a) and (b) trace out the effects on quoted and effective spreads, respectively. The pattern is the same in both plots. Treated and control stocks trend in parallel before the shock. When the shock begins, program stock spreads fall sharply relative to control stocks. After a few months, there seems to be a partial reversal, though the confidence intervals overlap for all post-treatment effects. Plot (c) reports effects on depth. Treated and control stocks trend in parallel from period -4 to -1. In period 0, depth increases for treated stocks. This is expected because MMs run live tests before the program starts. Next, when the program starts, depth rises sharply and remains elevated. Plots (d) and (e) show the effect on volume and asset prices. Again, there are no differential pre-event trends, but volume and asset prices increase after the shock. Overall, DMMs are beneficial for stocks. They boost liquidity, which attracts volume and lifts asset prices.

The fee discount fully passes through into lower spreads: the spread decrease is about the same as the fee discount for a roundtrip transaction; 2 basis points (a 10% decline of a pre-treatment mean of the treated group of 20 basis points) in comparison to saving the 1 basis point trading fee in two transactions. We find this large liquidity improvement is partly driven by strategic complementarity in liquidity provision. In particular, we examine how other liquidity providers respond to the MM program by constructing hypothetical limit order books that ignore DMMs. We use the hypothetical books to compute quoted spreads and depth provided by non-DMMs. Appendix Table A3 reports the results. We find non-DMMs tighten spreads and provide more depth after the programs start even though they do not receive the fee discount.

Designated Market Makers' Effects on Volatility. In addition to the programs' effects on levels, we examine their effects on stability. In particular, we examine the volatilities of liquidity, volume, and returns. Table 6 reports the results for the two natural experiments separately. The rows report results for volatilities of different dependent variables: intraday (5-minute) quoted spreads, effective spreads, depth, volume, and returns. The columns differ by including different sets of fixed effects. We begin by examining the 2018 experiment in panel A.

First, rows 1 to 3 present the results for percent volatilities of liquidity measures. For the volatility of quoted spreads, we find a negative and statistically significant coefficient of -6 across all specifications, a large effect amounting to a third of a standard deviation. Similarly, we find that the volatilities of effective spreads and depth also decline. DMMs stabilize liquidity. Next, row 4 shows a negative and statistically significant coefficient of -50 for the volatility of volume, a large effect amounting to 70% of a standard deviation. This is consistent with the decreased volatility of liquidity. The demand for trading depends on its cost. And as the cost of trading stabilizes, so does volume. Finally, the effect on return volatility is positive but small and statistically insignificant. Panel B demonstrates the 2019 experiment yields very similar results. In fact, the confidence intervals overlap in most cases, which further supports the robustness of these findings.

Next, we examine the effects' dynamics by estimating equation 2. Figure 8 reports the results. Plots (a) to (d) display the results for the intraday volatilities of quoted spreads, effective spreads, depth, and volume. The patterns are very similar across the four graphs. There are no differential pre-treatment trends, followed by a sharp, concave drop when the event begins. The effect plateaus quickly and does not reverse. Plot (e) shows that there is no statistically significant response of intraday return volatility. Overall, DMMs stabilize liquidity and volume.

3.1.3 Effects of Liquidity Provision Obligations and Incentives

The MM programs combine the two major elements exchanges use to improve market quality: liquidity provision obligations and incentives. Which of these two elements is responsible for the improvement in market quality? We answer this question by exploiting abrupt variation in obligations and incentives generated by the MM programs. First, B3 changes stock-specific maximum spreads and minimum quantities from the 2018 to the 2019 program. For some stocks, maximum spreads decrease (increase) and/or minimum quantities increase (decrease), i.e. requirements tighten (loosen). For other stocks, the program parameters remain unchanged. Second, in an attempt to boost fee revenue, B3 lowers the fee discount from 100% to 75% for the 13 most traded program stocks, a negative treatment reducing the incentive for voluntary liquidity provision. We exploit each change using a difference-in-differences identification strategy based on equation 1.

Table 7 reports the results. Panel A displays the effects of tightening DMM requirements. We estimate equation 1 for the following shock: stocks for which B3 tightens requirements are positively treated; stocks for which B3 loosens requirements are negatively treated; stocks for which B3 does not change the requirements or changes the maximum spread and minimum quantity in the same direction (i.e. tightens one and loosens the other) form the control group. We find increases in quoted and effective spreads, decreases in depth and volume, and negative cumulative abnormal returns. The effects are statistically significant for spreads and volume, but not for returns and depth. Tight obligations, intended to improve market quality, have the opposite effect, likely because they expose MMs to higher execution risk which lowers inventory capacity and inhibits their ability to voluntarily provide liquidity.

Panel B displays the effects of the incentive to voluntarily provide liquidity. Again, we estimate equation 1, now for the following shock: stocks for which B3 reduces the fee discount are *negatively* treated, and the remaining program stocks form the control group. We find the opposite effects from panel A, i.e. incentives are beneficial: fee discounts lower quoted and effective spreads and increase depth, volume, and asset prices. Overall, this shows that in normal times the positive effects are driven by the incentives, not the obligations.

3.2 Liquidity Provision Obligations and Incentives During Crises

Thus far we have examined effects during normal times. However, crises are particularly important to exchanges and regulators because liquidity often evaporates during crises which can be detrimental to welfare because crises are when investors have the largest and most immediate trading needs. Therefore, we now explore MM behavior as well as market outcomes during the COVID-19 stock market crash. Figure 9 demonstrates the severity of the crash in our setting. Panel (a) shows cumulative returns on the equal-weighted program stock portfolio. The downturn begins on February 21, 2020. Stock prices fall by 10% until March 4, when asset prices crash, falling by 40% until they reach the bottom on March 23. After that, they partially recover.

Panel (c) shows how the crisis affected liquidity. We plot the time series of the median and 95th percentile quoted spreads of program stocks. We also plot the fraction of time for which the program maximum spread is binding. Before the crisis, program stocks are very liquid. Median spreads are 0.1%, 95th percentile spreads are 0.15%, and the maximum spread never binds. Then, at the beginning of the crisis, the market looks resilient, only displaying modestly increased spreads. However, on March 12, the day of the global "Black Thursday" crash, liquidity suddenly dries up: median quoted spreads of program stocks quadruple from 0.1 to 0.4% and at the 95th percentile, quoted spreads surge seven-fold from 0.15% to 1%. In normal times, the maximum spreads imposed by the MM programs never bind, but on March 12, maximum spreads are binding 20% of the time. After that, liquidity remains scarce but improves slowly. Finally, panel (c) examines trading volume. Despite the liquidity dry-up, average daily volume rises from R$60M to R$80M, highlighting how desperate investors are to trade.

3.2.1 Market Maker Behavior

As before, we first investigate MMs' behavior. We find that voluntary liquidity providers withdraw and mandatory intermediaries become the liquidity providers of last resort. Figure 10 plots the time series of the liquidity provision shares of the mandatory and voluntary activities, i.e. passive trading volume of the respective activity scaled by total trading volume. Before the shock, the voluntary activity is responsible for a large share, 40%, of liquidity provision. However, during the crash this share abruptly drops to 32%, reaches its minimum almost exactly at the height of the crisis, and fully reverses when market conditions normalize. The mandatory activity follows the opposite pattern. It starts very low, at less than 1% of liquidity provision. Then, at the exact same time as the voluntary activity withdraws, the average share of liquidity provision by the mandatory activity quintuples to 5%, peaking very close to the crisis' worst point, after which it drops back to pre-crises levels as market conditions normalize.

3.2.2 Effects on Stocks' Resilience in Crises

In parallel to the preceding analysis of normal times, we now examine the effects of the overall program, obligations, and incentives during the crisis. We exploit variation across stocks generated by the 2019 MM program to investigate whether MMs' crisis behavior affects market outcomes. Concretely, we estimate dynamic treatment effects using equation 2, where the time of the shock is the start of the crash, the 21st February of 2020, and the treatment indicator isolates different stock subgroups depending on the effect of interest. Causal inference is more difficult in this setting than in the preceding analysis of normal times because the MM programs start during normal times and are already in place when the crisis begins. One particular concern is that the subgroups we compare differ in additional dimensions that may be correlated with their sensitivity to crashes. We address this concern by comparing subgroups that are as similar as possible and by controlling for time-specific effects of known differences.

Figure 11 reports the results. Most importantly, we study the effects of affirmative liquidity provision obligations during crises by comparing stocks with tight to stocks with loose obligations. While the exchange sets maximum spreads based on historic liquidity levels, we exploit that B3 rounds maximum spreads to the next 0.25%, which generates quasi-random variation in liquidity provision obligations. Picture two nearly identical stocks that would have been assigned maximum spreads of 0.5% and 0.51%. The former would have a relatively tight maximum spread at 0.5%, while the latter would have been rounded up to a relatively loose maximum spread of 0.75%. Specifically, we compare stocks in the top and bottom halves of the rounding error and control for historic pre-rounding spread $\times$ time heterogeneous slopes. Plots (a), (b), and (c) report the estimated effects of tighter obligations. We find tight obligations mitigate the liquidity dry-up: quoted spreads of stocks with tight obligations spike by 0.1% less during the crash, a large effect of 100% of the pre-crisis median. The effects on volume and returns are small.

Next, the 2019 program generates variation in voluntary liquidity provision incentives by granting DMMs 100% fee discounts in most program stocks and 75% fee discounts in the 13 program stocks for which historic average daily trading volume exceeded R$100M. While this cutoff is arbitrary, it does mean treated (100% fee discount) and control (75% fee discount) stocks differ according to historic trading volume. We address this by controlling for historic trading volume $\times$ time heterogeneous slopes. Plots (d), (e), and (f) report the results. We find that stocks with larger incentives experience worse liquidity dry-ups: quoted spreads of stocks with higher incentives spike by 0.1% more during the crash, a large effect of 100% of the pre-crisis median. Consistently, volume also declines. Again, there are no effects on returns. These results indicate that strong reliance on voluntary HFT liquidity provision is harmful during crises because these liquidity providers withdraw.

Finally, we examine the program's overall effects by comparing program stocks to the most similar non-program stocks, i.e. stocks right outside the IBrX 100 cutoff, ranked 101 to 150. The only reason the control stocks are not part of the program is that they are not part of the index, i.e. because their historic trading volume fell just short of an arbitrary cutoff. This means treated and control stocks differ according to the metric used for index inclusion. We address this by controlling for index metric $\times$ time heterogeneous slopes. Further, the fact that treated and control stocks differ by IBrX 100 index inclusion raises the concern that they differ along additional dimensions such as their investor base. However, attenuating this concern, the IBrX 100 is not a top index. The most important index in the Brazilian stock market is the Ibovespa, and the largest Brazil ETF (EWZ) tracks the MSCI Brazil 25/50 Index, both of which track substantially fewer stocks than the IBrX 100. Panels (g), (h), and (i) report the program's estimated effects on liquidity (quoted spreads), volume, and returns. Before the crash, treated and control stocks trend in parallel, but when the crisis begins, program stocks experience a significantly less severe liquidity dry-up. The effects on volume and returns are small.

While the program is overall beneficial in both normal times and crises, the effects of obligations and incentives invert. In normal times, exchanges can increase market quality by encouraging voluntary liquidity provision. By contrast, imposing tight liquidity provision requirements constrains MMs and can decrease market quality. During crises, however, tight obligations are beneficial while strong reliance on HFT liquidity is harmful. This suggests that exchanges and regulators should combine incentives with countercyclical liquidity provision obligations. Of course, it may be difficult to dynamically adjust obligations. If obligations have to be static, our results suggest that obligations should be set such that they do not bind during normal times but become binding during crises, as is the case for the program we examine in this paper.

3.3 How to Assign Market Makers to Assets?

Another important choice exchanges have to make when designing liquidity provision programs is how to assign MMs. Here, we document a dark side of these programs: MMs hedge across assets which causes excess co-movement of liquidity, volume, and returns. Hence, by choosing which MMs to assign to which stocks, exchanges create co-movement clusters.

3.3.1 Market Maker Behavior

We begin by examining how MMs behave. In practice, MMs act as intermediaries in several assets, making joint portfolio and liquidity supply decisions (Easley et al., 2020). Indeed, theoretical models of market making with multiple assets predict that MMs' demand for one stock depends negatively on inventory of the stock itself and, crucially, negatively on inventory of other stocks as well (Andrade, Chang, and Seasholes, 2008). We test whether MMs' quoting behavior is consistent with this prediction. Specifically, we test how MMs revise price quotes in response to inventory shocks in the stock itself and in other stocks.

Our approach addresses two challenges. First, our specification allows us to focus on MMs' reactions in excess of market reactions by controlling for stock returns. Second, we address a reverse causality problem: algorithmic MMs respond to market events in fractions of a second. Therefore, market events and quote revisions happen simultaneously in data synchronized to regular time periods. But the causality may run both ways: MMs respond to market events and MM quotes attract volume. Our high-frequency, message-level data allow us to address this reverse causality problem by examining MMs' quoting behavior in event time, which preserves the temporal ordering of market events and quote revisions.

Concretely, we conduct this analysis by MM $\times$ stock $\times$ trading day for computational reasons and treat the bid and ask side of the market separately. We denote the liquidity provider by i, the stock by n, and the day by d. There are two event time clocks. The first clock is only needed for variable definitions; every trade is an event and event time is denoted by $\tilde{t}$. The second clock is the frequency at which we estimate MM behavior; each active change in a MM's best standing quote starts a new period and event time is denoted by t. We only start a new event period after *active* changes to avoid the mechanical effects of passive execution on standing quotes. We denote the set of stocks in which i is a MM as $\mathcal{I}_i$. $\mathcal{T}$ is the set of all trades. A trade is described by the tuple $(i, n, \tilde{t})$.

The MM may react to any market event that occurred since the last quote update, including market events in other stocks. Therefore, we construct explanatory variables that summarize all trades that occur between event time $t-1$ and event time t in all stocks intermediated by MM i. We denote the set of these trades by

$$\mathcal{M}_{i,t} = \{(j,m,s) \in \mathcal{T} : t-1 < s < t, m \in \mathcal{I}_i\}. \tag{3}$$

Depending on the stock under consideration, we divide this set into four disjoint subsets

$$\begin{aligned}
\mathcal{M}^{OF}_{i,n,t} &= \{(j,m,s) \in \mathcal{M}_{i,t}, j \neq i, m = n\} \\
\mathcal{M}^{OFabsorbed}_{i,n,t} &= \{(j,m,s) \in \mathcal{M}_{i,t}, j = i, m = n\} \\
\mathcal{M}^{OFother}_{i,n,t} &= \{(j,m,s) \in \mathcal{M}_{i,t}, j \neq i, m \neq n\} \\
\mathcal{M}^{OFabsorbedOther}_{i,n,t} &= \{(j,m,s) \in \mathcal{M}_{i,t}, j = i, m \neq n\}.
\end{aligned} \tag{4}$$

The OF and $OFabsorbed$ subsets only contain trades in the stock itself, the $OFother$ and $OFabsorbedOther$ subsets only contain trades in other stocks. The $OFabsorbed$ and $OFabsorbedOther$ subsets only contain trades where the MM was the liquidity provider, the OF and $OFother$ subsets only contain trades where the MM was not the liquidity provider. There are four main dependent variables, one summarizing each subset. These four variables are all defined in the same way by

$$x_{i,n,t} = \frac{1}{\sum_{\{m \in \mathcal{M}^x_{i,n,t}\}} R\$\overline{Vol}_m} \sum_{(j,m,s) \in \mathcal{M}^x_{i,n,t}} OrderSide_{j,m,s} R\$Vol_{j,m,s}, \tag{5}$$

where $x \in \{OF, OFabsorbed, OFother, OFabsorbedOther\}$. We normalize by dividing by past average daily R\$ volume, $R\$\overline{Vol}$, summed over all stocks in the respective set. $OrderSide$ is 1 if the buyer is the aggressor, -1 if the seller is the aggressor. $R\$Vol$ is the R\$ value of the trade. The only difference across the four variables is which trades are included in the summation, the $\mathcal{M}^x$. OF is order flow intermediated by other liquidity providers. $OFabsorbed$ is order flow absorbed by the MM (i.e. changes in inventory). $OFother$ is order flow in other stocks intermediated by other liquidity providers. $OFabsorbedOther$ is order flow absorbed by the MM in other stocks (i.e. changes in inventory of other stocks). We use these variables to estimate

$$\begin{aligned}
\Delta p_{i,n,t} = {} & \alpha_{i,n,d} + \beta_{1,i,n,d} OF_{i,n,t} + \beta_{2,i,n,d} OFabsorbed_{i,n,t} \\
& + \beta_{3,i,n,d} OFother_{i,n,t} + \beta_{4,i,n,d} OFabsorbedOther_{i,n,t} + \beta_{5,i,n,d} r_{n,t} + \epsilon_{i,n,t},
\end{aligned} \tag{6}$$

where p denotes log best price quotes of the MM. We treat the two sides of the market separately: p is the best bid of the MM in one dataset and the best ask in another dataset. For estimation, we then append the two datasets which imposes symmetry. We control for log stock returns, r, the analogue of the dependent variable at the stock level instead of the MM level. This makes this specification particularly stringent because we only attribute quote revisions unexplained by market movements to the independent variables of interest.

The coefficient estimates are subscripted because we estimate equation 6 separately for each MM x stock x day combination. This is conceptually equivalent to including MM x stock x day fixed effects. We report mean coefficients and compute Fama-MacBeth standard errors robust to within MM x day correlation from the distribution of the coefficient estimates (Fama and MacBeth, 1973). This accounts for correlations across stocks as well as for autocorrelation within stocks during the trading session. Our approach is broadly similar to Brogaard, Hendershott, and Riordan (2019).

β_1 measures the relationship between MM quotes and order flow. The similar relationship between stock returns and order flow is well-studied and known to be positive (e.g. Hasbrouck and Sofianos, 1993; Madhavan and Smidt, 1993). Here, we control for stock returns and examine how MMs respond to order flow in excess of market movements. β_2 measures how MMs react to order flow when they were the liquidity providers. Researchers have examined the relationship between quote revisions and specialist trades (e.g. Hasbrouck and Sofianos, 1993; Madhavan and Smidt, 1993) but not at this level of granularity because market data almost never reveal trader identities. Existing findings are typically based on daily trade data (e.g. Comerton-Forde et al., 2010). In contrast, our data allow us to examine MM behavior at high frequency. Finally, β_3 and β_4 measure the analogous effects across stocks. Research in market microstructure usually examines markets one asset at a time. Yet, market participants make trading decisions across assets, even more so with the rise of algorithmic trading (Easley et al., 2020). Our two cross-asset variables take this into account and allow us to study how MMs respond to information and inventory shocks in other stocks.

Table 8 reports estimates of equation 6. Quote revisions and stock returns are in percent. The sample spans the MM programs' duration. Columns 1 and 2 report results for the mandatory activity, columns 3 and 4 for the voluntary activity. Columns 2 and 4 control for stock returns, columns 1 and 3 do not. The estimated coefficients are qualitatively similar, just smaller once we control for stock returns. All relevant coefficient estimates are statistically significant.

In the main specification for the mandatory activity, column 2, the coefficient on order flow is 0.7, indicating MMs are more sensitive to order flow than the market. Second, the coefficient on absorbed order flow is much larger, 8. This means MMs revise quotes much more aggressively when they are on the other side of the order flow, likely to revert inventory. In response to providing liquidity amounting to 1% of daily volume, MMs revise quotes by 8 basis points in excess of the market response. Third, the coefficient on order flow in other stocks is very close to zero. However, MMs revise quotes when their limit orders in other assets are hit. The coefficient on order flow absorbed in other stocks is much larger, 4. In response to a 1% shock in other stocks, MMs revise quotes by 4 basis points, again in excess of any market response. Finally, the coefficient on returns is 0.9. This simply captures that MMs move their quotes with market prices. The coefficient is close to but less than one because MMs do not always react to market events when quoting deeper in the book. Column 4 reports the analogous results for the voluntary activity. The results are qualitatively the same, except that the coefficients are larger, meaning that the voluntary activity revises quotes more aggressively. This makes sense, because the orders of the voluntary activity are more exposed.

3.3.2 Effects of Common Intermediation on Co-Movement

Market events spill over to other assets through MMs' cross-asset hedging behavior and as the shocks move all assets intermediated by the MM in the same direction, this mechanism can cause nonfundamental co-movement. Using a difference-in-differences identification strategy, we exploit exogenous variation in market making activity created by the MM programs to estimate the causal effect of common intermediation on the co-movement of liquidity, volume, and asset prices. Figure 12 illustrates the programs as shocks to common intermediation. The nodes in the graph are the ticker symbols of 10 randomly selected program stocks. Nodes are connected if they have a common MM. The color of the connection indicates when the two stocks were connected. Before the program, there are no connections. The 2018 program introduces the gray and red connections. Then, from the 2018 to the 2019 program, the red connections are severed and the blue connections are added. Hence, there are positive and negative shocks to common intermediation.

We use this shock to estimate the causal effect of common intermediation on co-movement. This analysis is analogous to that described in section 3.1.2, except it is at the stock pair level instead of the stock level. Similar to equation 1, we estimate the difference-in-differences regression,

$$\rho_{i,j,t} = \alpha_{i,j} + \phi_t + \beta Connected_{i,j} \times Post_t + \delta' X_{i,j,t} + \epsilon_{i,j,t}, \tag{7}$$

separately for each MM program. Importantly, the panel variable is the stock pair, i.e. the combination of stock i and stock j. The dependent variable is the correlation between stock i and stock j. The main explanatory variable is the interaction between a binary variable that indicates whether stocks i and j have a common MM and a post-shock indicator. β is the average treatment effect. In the main specification, we include stock pair and time fixed effects and cluster standard errors by stock pair.

We run this analysis on the stock pair sample in which stock i and stock j are both part of the MM program. Hence, the treatment group consists of stock pairs that were assigned a common MM and the control group consists of stock pairs for which each stock was assigned a DMM, but their DMM sets are disjoint. This means the results cannot be driven by the direct effects of having a MM.

Table 9 reports estimates of equation 7 for the two natural experiments separately. The rows report results for different dependent variables: the correlation of intraday (5-minute) quoted spreads, effective spreads, depth, volume, and returns. The columns differ by the inclusion of different sets of fixed effects. We begin by examining the 2018 experiment in panel A. First, for liquidity co-movement, the estimated average treatment effects are positive, and statistically significant across all specifications, for all three measures of liquidity. The treatment effect estimates imply increases between 5 and 20% of the mean. For trading volume, we find a statistically significant effect of 10% of the mean. Finally, for return co-movement, the estimated average treatment effect is positive, statistically significant, and implies that common intermediation raises the correlation coefficient of high-frequency returns by 10% of the mean, a significant increase. Panel B demonstrates the 2019 experiment yields very similar results. In fact, the confidence intervals overlap in most cases, further confirming the robustness of the findings. Overall, common intermediation raises co-movement across all three dimensions: liquidity, volume, and returns.

4 Conclusion

We study how exchanges and regulators can improve the liquidity and stability of modern electronic financial markets, in good times and in bad. We address this question using unique message-level trade and quote data from the Brazilian exchange B3 that reveal market participants' identities. Further, we exploit two natural experiments that provide rich and abrupt exogenous variation in market maker (MM) activity as well as liquidity provision obligations and incentives: two MM programs that prescribe stock-specific maximum bid-ask spreads and minimum lot sizes and grant trading fee discounts in return. While the experiments occur in Brazil, the MMs include the most sophisticated algorithmic traders in the world, such as Citadel Securities, Virtu Financial, and Jane Street.

During normal times, each designated market maker (DMM) simultaneously runs two strategies for each asset. The first strategy, the "mandatory activity," only serves to fulfill their obligations. This strategy quotes wide spreads and consequently generates little volume. Simultaneously, DMMs run a second strategy, the "voluntary activity," which exploits their competitive advantage due to the trading fee discount by quoting aggressive prices and intermediating large volumes.

At the stock level, the combination of obligations and incentives improves and stabilizes liquidity which attracts volume and lifts asset prices. In normal times, these positive effects are driven by the program incentives, while tight obligations, intended to improve market quality, have the opposite effect, likely because they expose MMs to higher execution risk which lowers inventory capacity and inhibits MMs' ability to voluntarily provide liquidity.

In crises, however, the results flip: stocks with larger incentives experience worse liquidity dry-ups because the voluntary activity withdraws; in contrast, tight obligations mitigate liquidity dry-ups because the mandatory activity steps in as the liquidity provider of last resort. These results suggest that exchanges and regulators should combine incentives with countercyclical liquidity provision obligations. Of course, it may be difficult to dynamically adjust obligations. If obligations have to be static, our results suggest that obligations should be set such that they do not bind during normal times but become binding during crises.

Finally, which market makers are assigned to which stocks is consequential: consistent with theoretical models of market making, we document empirically that inventory shocks in one asset shift MMs' demand for the asset itself and other stocks they intermediate. This cross-asset hedging behavior of MMs gives rise to a spillover effect through MMs' portfolios that causes nonfundamental co-movement. We confirm this mechanism by documenting that stock pairs that are assigned a common DMM experience increases in the correlations of liquidity, volume, and returns. This shows a trade-off: on the one hand, DMMs increase liquidity, on the other hand, they cause excess co-movement.

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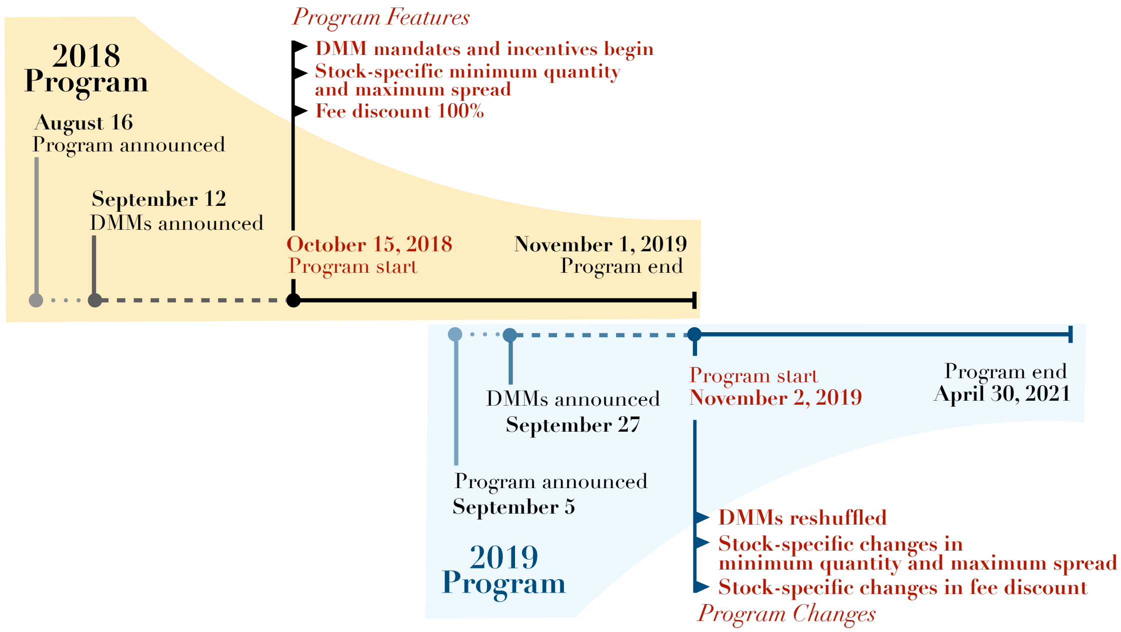
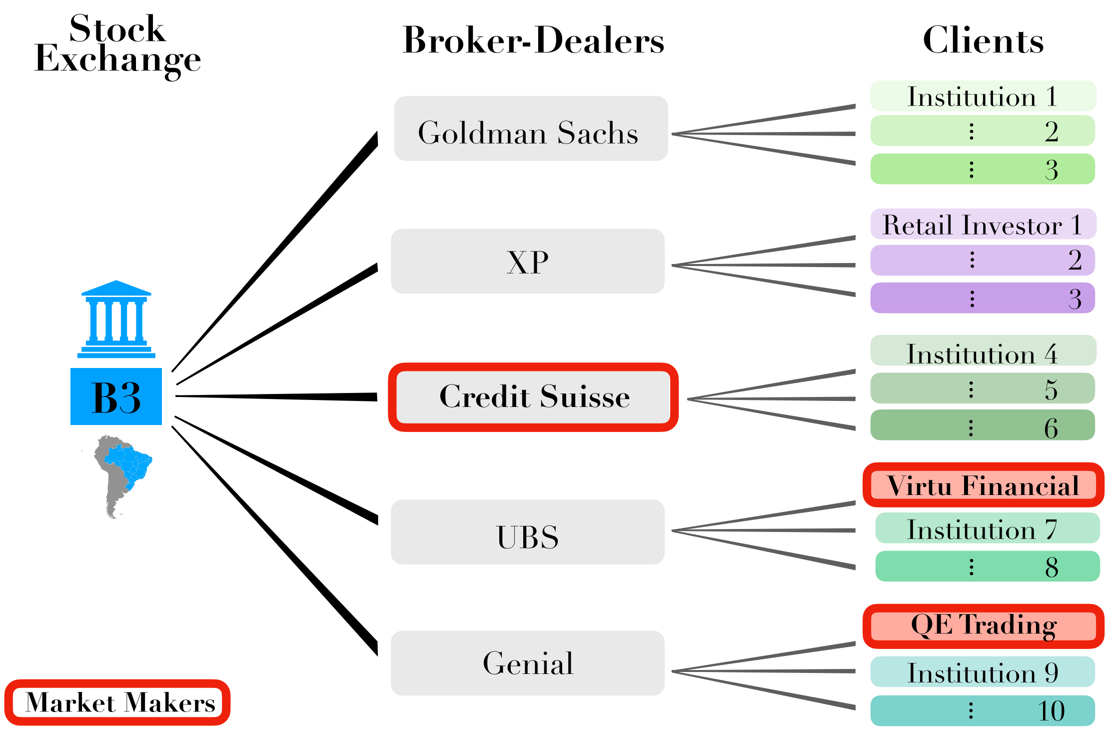
Figure 1: The Timeline of B3's Market Maker Programs



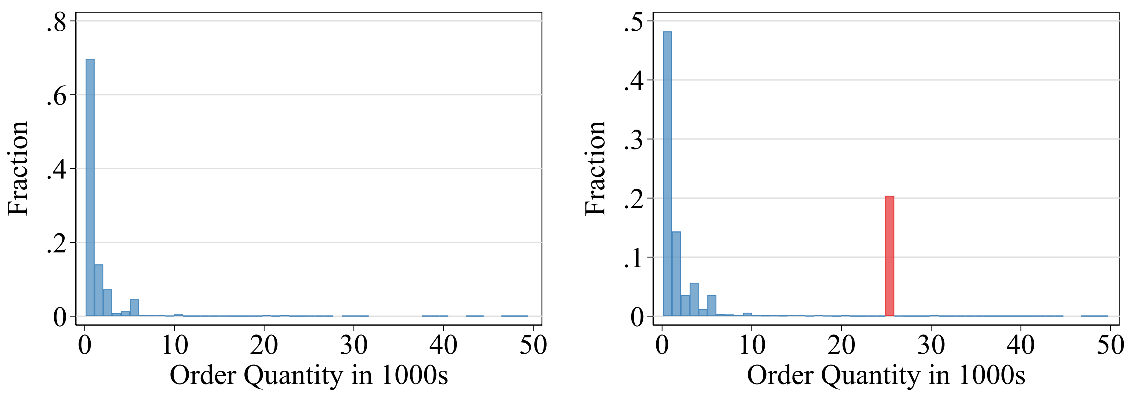
This figure illustrates the timeline of B3's 2018 and 2019 market maker program. B3 publicly announced the 2018 (2019) program on August 16, 2018 (September 5, 2019). Market making firms had until September 10, 2018 (September 20, 2019) to apply for each stock they were interested in. B3 made and publicly released all program decisions on September 12, 2018 (September 27, 2019). The program began on October 15, 2018 (November 2, 2019). It ended on November 1, 2019 (April 30, 2021).

Figure 2: Institutional Background



This figure illustrates how traders access Brazilian financial markets. B3 gives direct market access to about 100 broker-dealers. We observe broker-dealer identities in the message data. End investors submit orders through broker-dealers. For example, Goldman Sachs executes orders for financial institutions and XP does so for retail investors. Some broker-dealers are themselves market makers, e.g. Credit Suisse. In addition, Credit Suisse executes orders for institutional clients. Some market makers are not broker-dealers and submit orders via broker-dealers. E.g., Virtu Financial submits orders via UBS and QE Trading submits orders via Genial Institutional. Additionally, UBS and Genial Institutional both also execute orders for other institutional clients.

Figure 3: Example of Bunching at the Minimum Quantity (at 25)

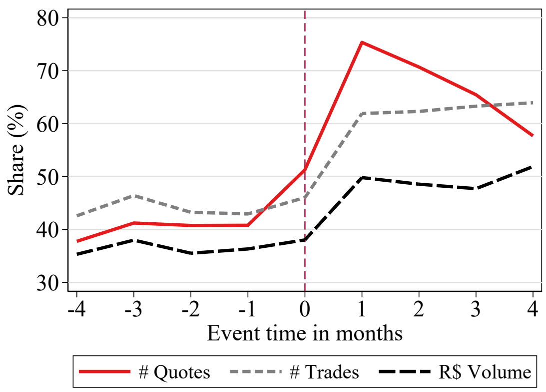


(a) Before the Program

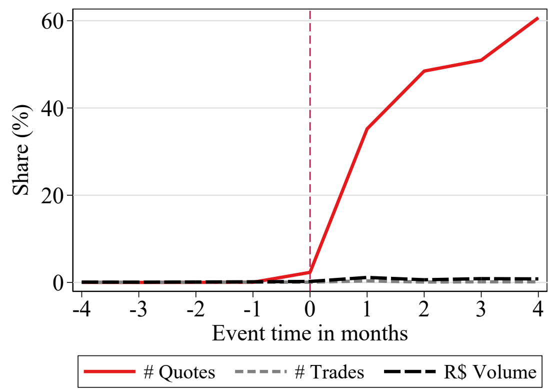
(b) After the Program

This figure illustrates that DMMs quote exactly at the minimum quantity the market maker programs require. The example shows the distribution of order quantities in 1000s for the first stock alphabetically, ABEV3, on October 1st, 2018, before the shock and on October 15th, the first day after the shock. The minimum quantity for ABEV3 is 25,000 shares.

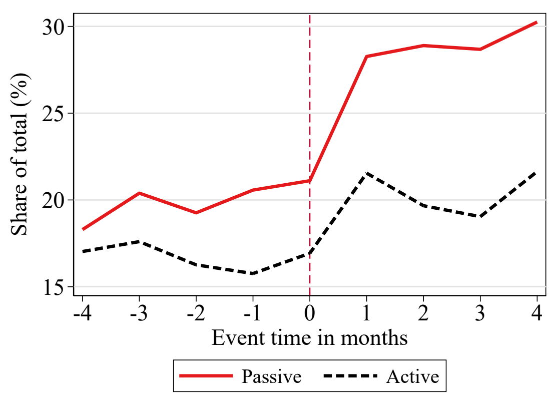
Figure 4: Quoting and Trading: Mandatory vs. Voluntary Activity



(a) Voluntary activity



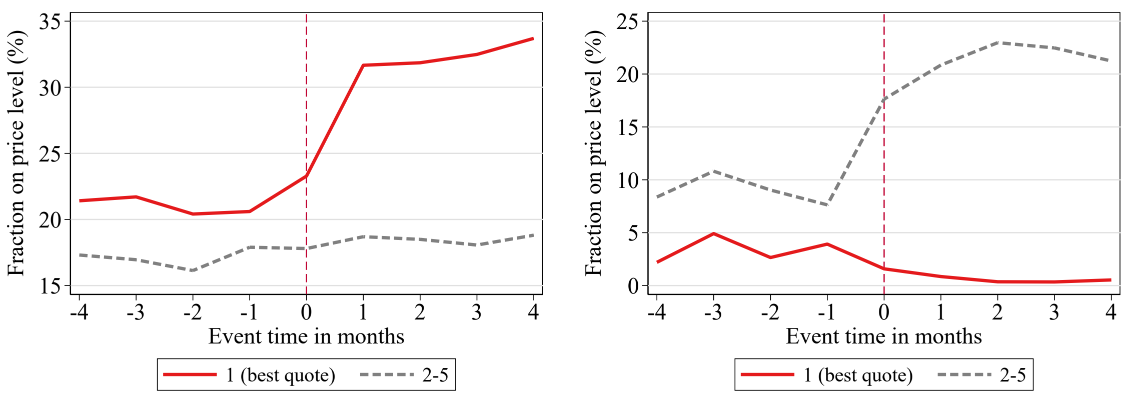
(b) Mandatory activity



(c) Voluntary activity: active vs. passive

This figure compares the quoting and trading of the mandatory and voluntary activity. Panels (a) and (b) plot the number of quotes as the percent fraction of all quotes from other market participants, trading volume as the percent fraction of total volume, and the number of trades as the percent fraction of the total number of trades, all for the voluntary and mandatory activity, respectively. Panel (c) shows total passive and total active trades separately as the percent fraction of total volume. We only show this split for the voluntary activity because, by definition, the mandatory activity only trades passively. Event time is in months around the market maker programs.

Figure 5: Fraction of Time On Each Price Level: Mandatory vs. Voluntary Activity

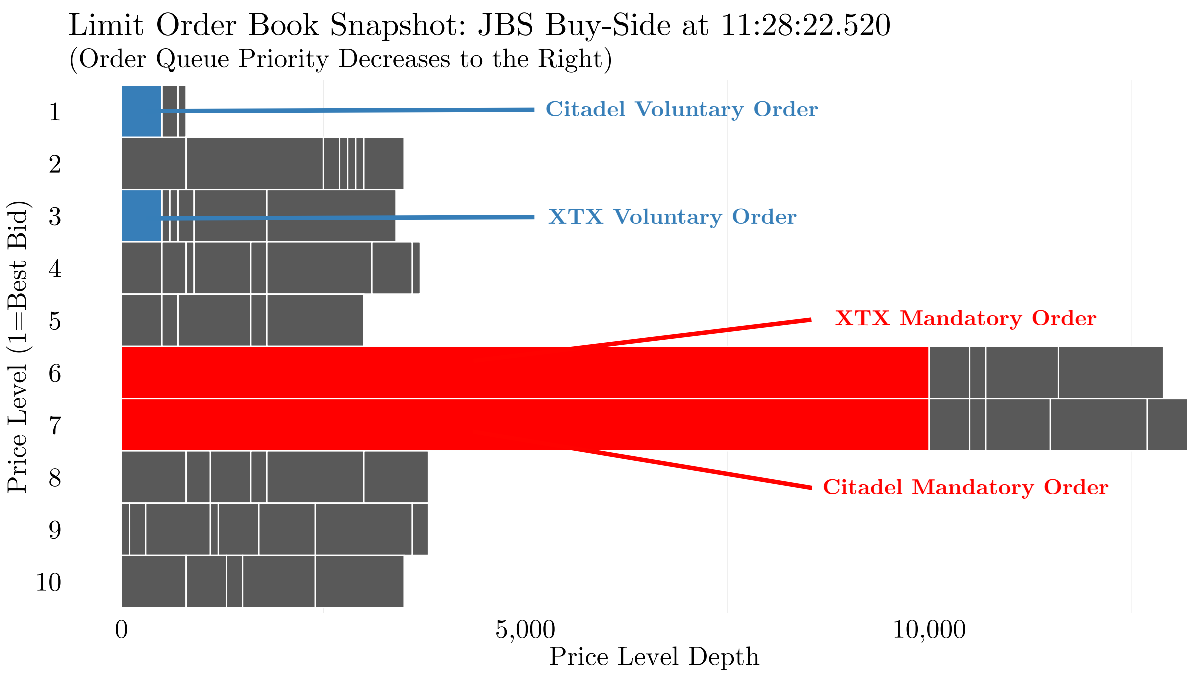


(a) Voluntary activity

(b) Mandatory activity

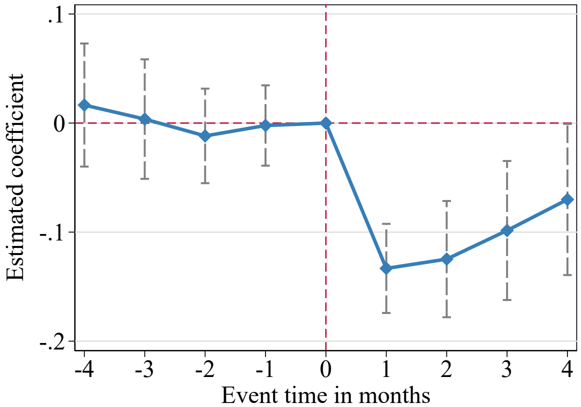
This figure shows the percent fraction of time market makers quote on different price levels. Panel (a) shows results for the voluntary activity, panel (b) for the mandatory activity. The red line corresponds to the best price. The gray line corresponds to price levels 2, 3, 4, or 5. We average across the two sides of the market. Event time is in months around the market maker programs.

Figure 6: Illustration of the Mandatory vs. Voluntary Activity

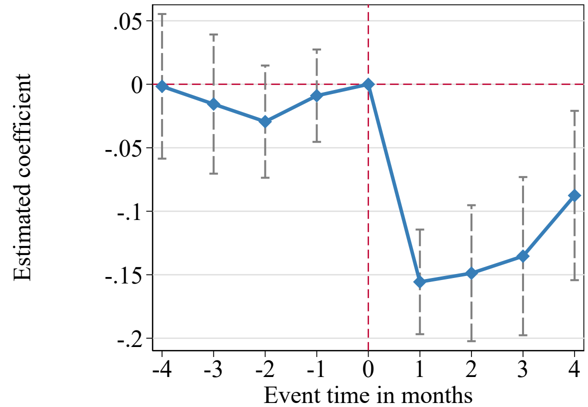


This figure illustrates the typical quoting behavior of the mandatory vs. voluntary activity using an example limit order book snapshot, JBS at 11:28:22.520 on the first day of the 2019 market maker program, 11/04/2019. We only show the first 10 price levels of the bid side. Each block corresponds to one order, with its width indicating its lot size and queue priority decreasing to the right. The market makers in this stock are Citadel Securities and XTX Markets. We highlight their mandatory orders in red and their voluntary orders in blue. The figure shows that, typically, the mandatory orders provide large quantities deep in the book, while the voluntary orders provide small quantities at the top of the book.

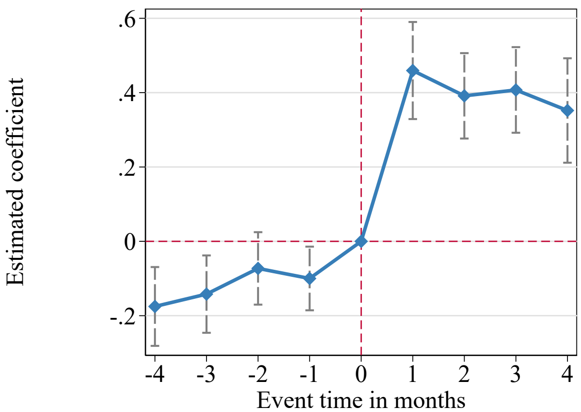
Figure 7: Dynamic Treatment Effects of DMMs on Liquidity, Volume, and Asset Prices



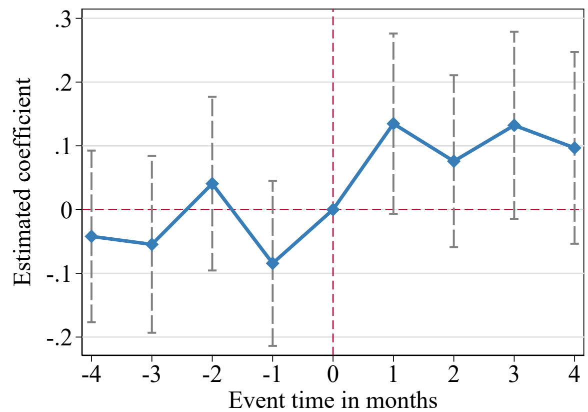
(a) Log Quoted Spread



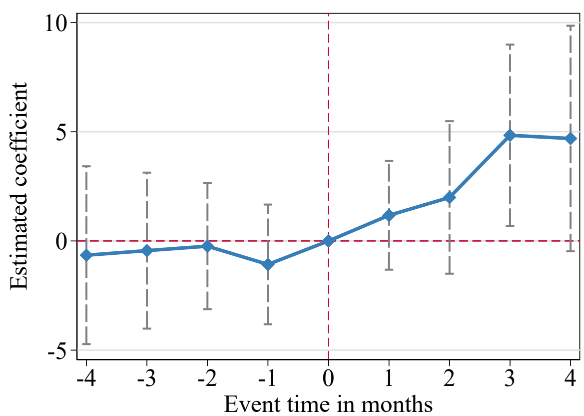
(b) Log Effective Spread



(c) Log Depth



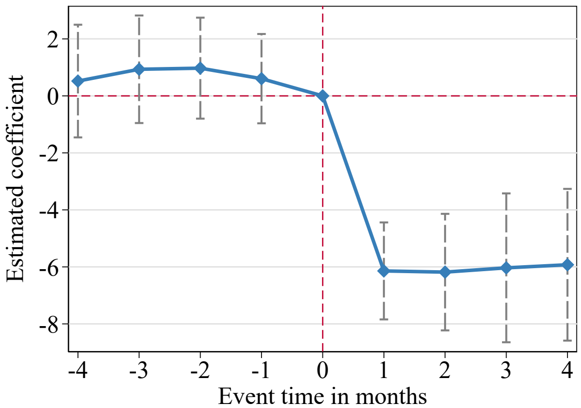
(d) Log Volume



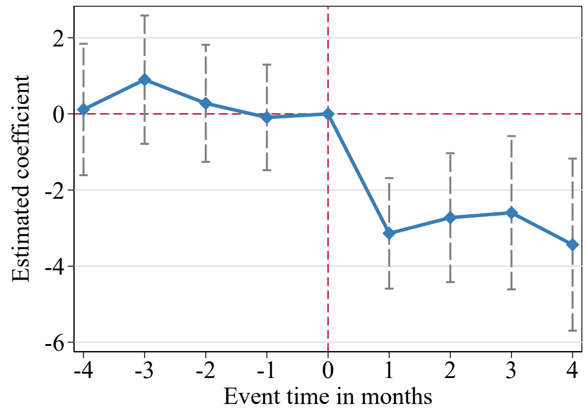
(e) Cumulative Abnormal Returns

This figure reports estimates of equation 2 and shows dynamic treatment effects of the market maker assignment on log quoted bid-ask spread, log depth, log R$ volume, and percent cumulative abnormal returns. Standard errors are clustered by stock. The gray lines span 95% confidence intervals. Event time is in months around the market maker programs.

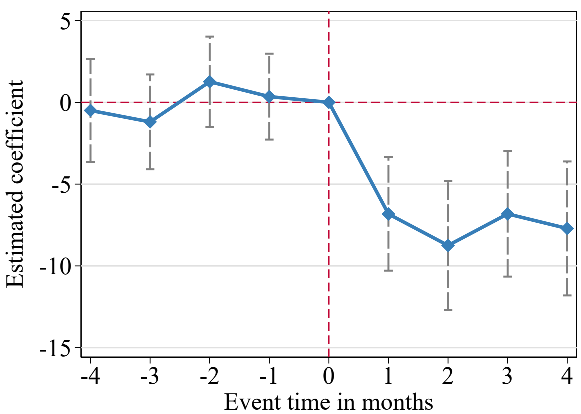
Figure 8: Dynamic Treatment Effects of Designated Market Makers on Volatilities



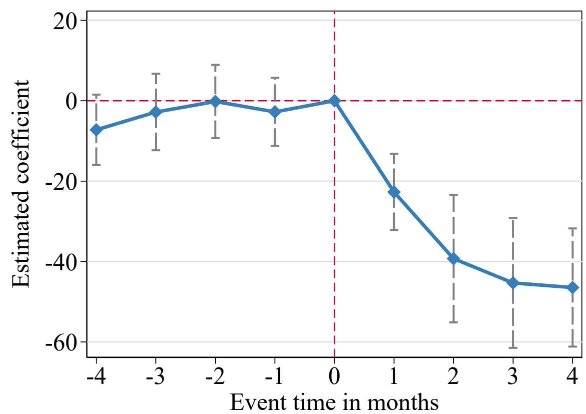
(a) Sd(Log Quoted Spread)



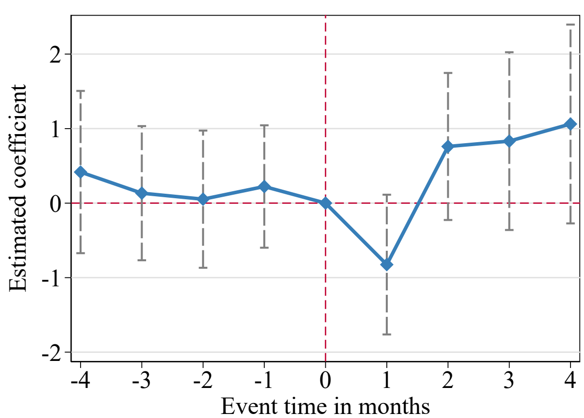
(b) Sd(Log Effective Spread)



(c) Sd(Log Depth)



(d) Sd(Log Volume)

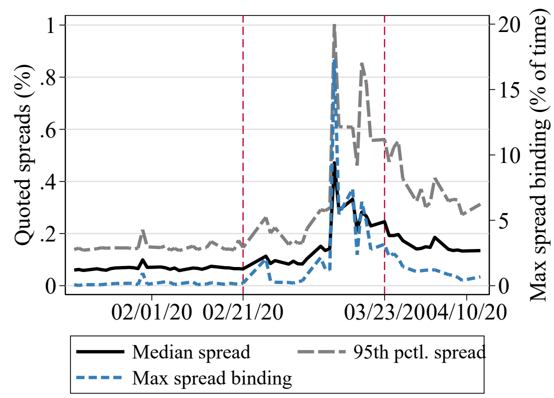


(e) Sd(Returns)

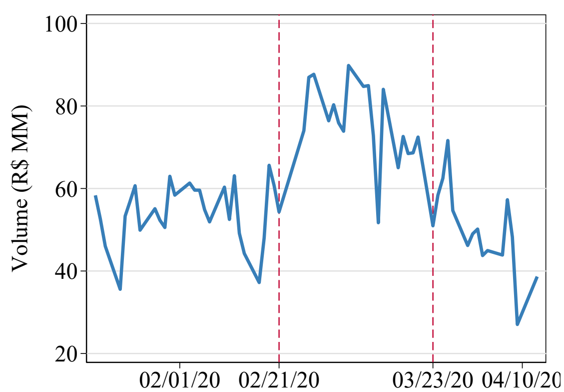
This figure reports estimates of equation 2 and shows dynamic treatment effects of the market maker assignment on the percent intraday (5-minute) volatilities of log quoted bid-ask spreads, log depth, log R$ volume, and returns. Standard errors are clustered by stock. The gray lines span 95% confidence intervals. Event time is in months around the market maker programs.

Figure 9: The Anatomy of the COVID-19 Crash

(a) Cumulative Returns



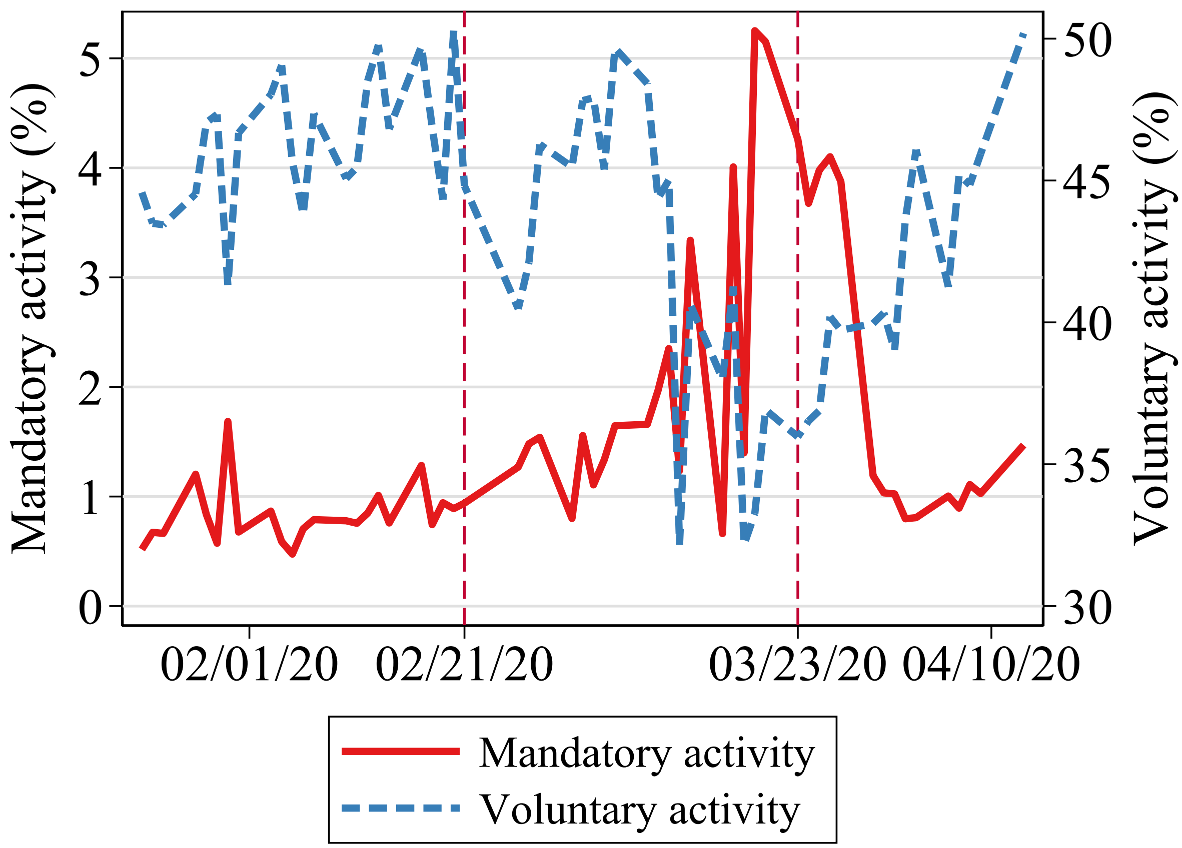
(b) Liquidity



(c) Volume

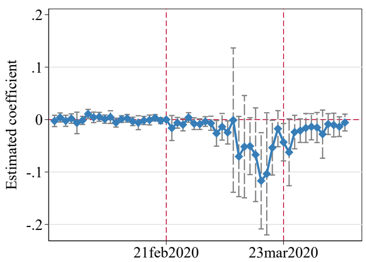
This figure shows time series of summary statistics for stocks in the 2019 market maker program during the 2020 stock market crash. Panel (a) plots cumulative returns on the equal-weighted portfolio of program stocks. Panel (b) plots median and 95th percentile quoted spreads as well as the fraction of time the program spread is binding. Panel (c) plots average daily trading volume. The variables in panels (b) and (c) are smoothed using a 5-day moving average. The red vertical lines indicate the start and the end of the COVID-19 stock market crash.

Figure 10: Share of Liquidity Provision During the COVID-19 Crash

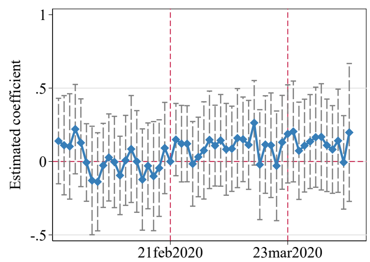


This figure reports statistics describing the behavior of the mandatory and voluntary activities during the 2020 COVID-19 crash. The figure plots the percent share of liquidity provision, i.e. passive trading volume of the respective activity scaled by total trading volume. The red vertical lines indicate the start and the end of the COVID-19 stock market crash.

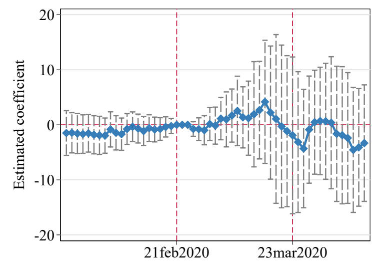
Figure 11: Effects of Obligations, Effects of Incentives, and Overall Program Effects on Liquidity, Volume, and Asset Prices During the COVID-19 Crash



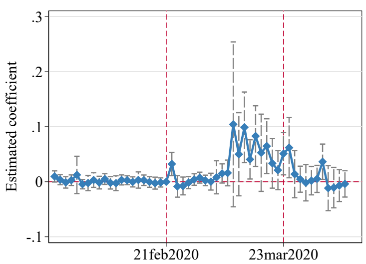
(a) Effect of obligations, Quoted spread



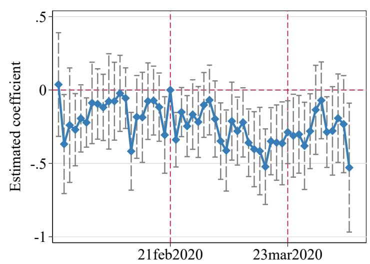
(b) Effect of obligations, Log volume



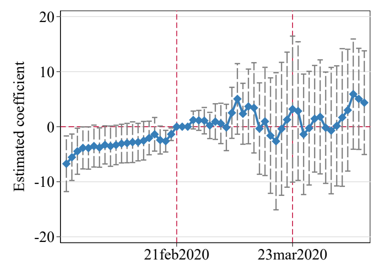
(c) Effect of obligations, CAR



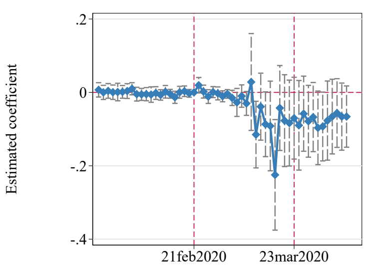
(d) Effect of incentives, Quoted spread



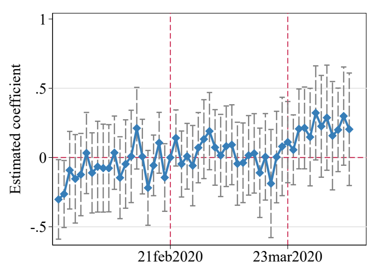
(e) Effect of incentives, Log volume



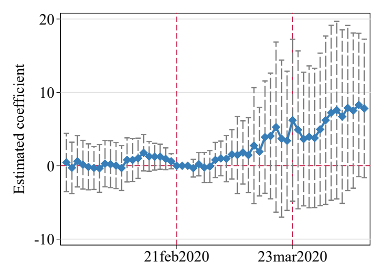
(f) Effect of incentives, CAR



(g) Overall effect, Quoted spread



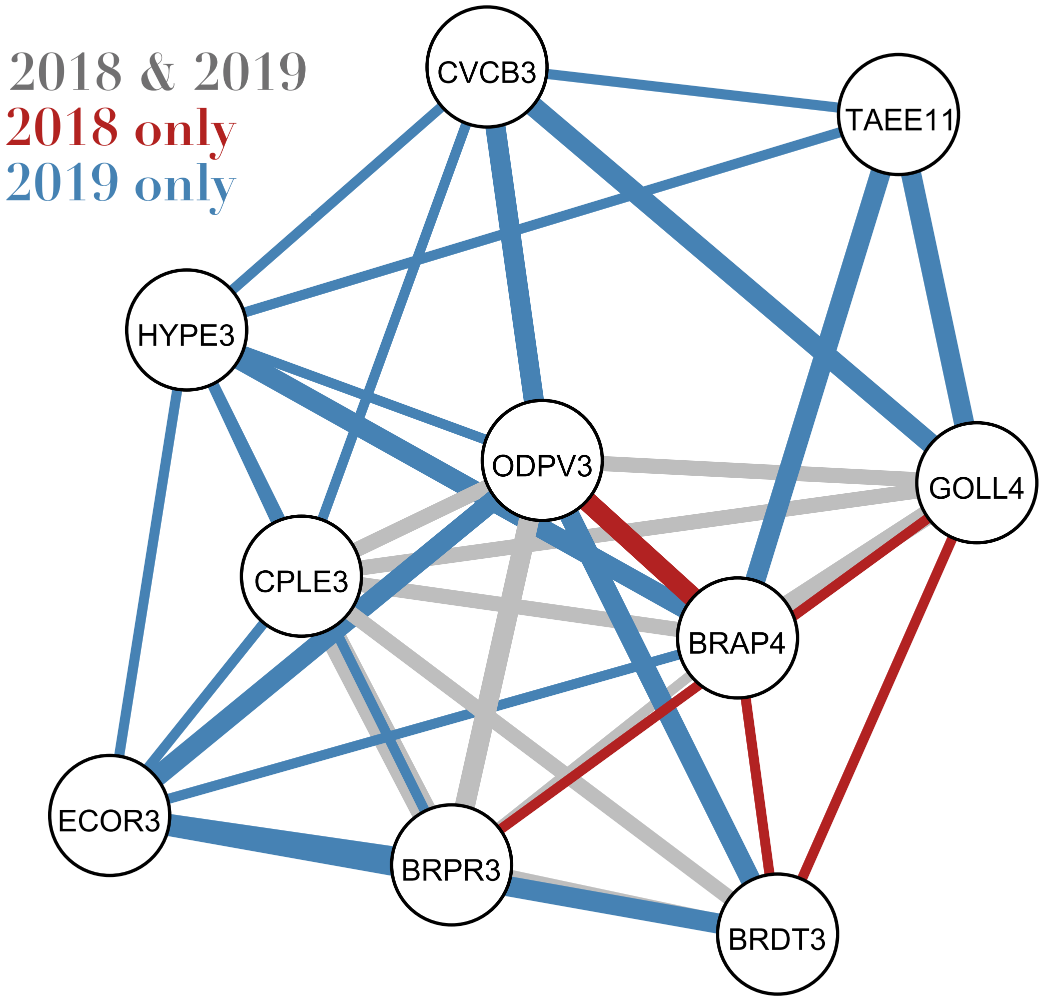
(h) Overall effect, Log volume



(i) Overall effect, CAR

This figure shows overall program effects (a, b, c), effects of tight program obligations (d, e, f), and effects of incentives (g, h, i) during the 2020 stock market crash. We report effects on quoted spreads (a, d, g), log trading volume (b, e, h), and cumulative log returns (c, f, i). The red vertical lines indicate the start and the end of the COVID-19 stock market crash.

Figure 12: The Evolution of the Common Intermediation Network (10 Stock Subsample)



This figure illustrates the natural experiments we exploit. In 2018, the Brazilian stock exchange assigns 2 or 3 (out of 9) market makers to each of 54 (out of around 400) stocks. In 2019, the Brazilian stock exchange assigns 2 to 5 (out of 13) market makers to each of 89 stocks. The nodes in the graph are the ticker symbols of 10 randomly selected program stocks. Nodes are connected if they have a common market maker. Gray edges indicate that the two stocks are connected during both market maker programs. Red edges indicate that stocks were connected during the 2018 program, but got disconnected. Blue edges indicate new connections created by the 2019 program.

Table 1: Stock-Day Level Summary Statistics: Trading and Quoting by Institution

Market Maker	Volume	Trade size	Trades	Quotes	Ratio	% Ag.	% New	% Fill	% Cancel	% Repl.
Panel A: Mandatory Activity										
Bradesco	725	41.1	18	9040	513.0	0.0	39.4	0.1	39.4	21.2
Citadel Securities	823	73.1	11	19082	1694.9	0.0	50.0	0.0	50.0	0.0
Credit Suisse	296	81.5	4	5102	1404.6	0.0	0.4	0.0	0.3	99.3
Green Post Trading	303	57.6	5	7053	1338.2	0.0	0.1	0.0	0.1	99.7
Headlands Technologies	944	50.9	19	15105	814.6	0.0	50.0	0.1	50.0	0.0
Jane Street Capital	1521	55.1	28	8836	320.3	0.0	49.9	0.3	49.8	0.0
Optiver	471	68.1	7	2260	327.1	0.0	20.9	0.1	20.8	58.2
QE Trading	373	61.3	6	5703	938.7	0.0	39.7	0.0	39.7	20.5
Spire X Trading	306	45.9	7	969	145.6	0.0	45.2	0.3	45.0	9.4
Tarpika	620	64.8	10	11997	1253.5	0.0	49.2	0.0	49.2	1.5
Tucana Bay	874	39.5	22	2064	93.3	0.0	49.9	0.4	49.8	0.0
Virtu Financial	570	55.1	10	12453	1202.0	0.0	43.1	0.0	43.1	13.7
XTX Markets	593	63.6	9	2881	309.0	0.0	48.6	0.1	48.5	2.8
Panel B: Voluntary Activity										
Bradesco	22798	5.8	3927	93871	23.9	46.8	47.4	3.5	45.4	3.8
Citadel Securities	30960	7.6	4073	14365	3.5	58.0	43.9	18.1	34.9	3.1
Credit Suisse	20200	4.7	4266	21593	5.1	29.1	44.9	14.4	32.2	8.4
Green Post Trading	11976	7.3	1630	9938	6.1	31.5	38.3	11.7	29.1	20.9
Headlands Technologies	48132	9.8	4916	16814	3.4	21.1	40.5	21.6	33.6	4.4
Jane Street Capital	30657	12.5	2454	8030	3.3	37.5	38.9	27.1	24.6	9.4
Optiver	22679	6.7	3400	25076	7.4	51.9	41.3	8.2	36.5	14.0
QE Trading	13347	7.9	1689	22596	13.4	37.6	28.5	5.2	25.5	40.8
Spire X Trading	12754	7.0	1827	12139	6.6	44.1	42.1	12.2	33.8	12.0
Tarpika	24724	4.6	5388	26065	4.8	33.2	43.4	11.7	33.9	11.0
Tucana Bay	44771	7.8	5734	25575	4.5	59.9	45.8	14.3	38.2	1.7
Virtu Financial	24487	6.4	3837	27034	7.0	44.2	45.7	11.3	38.5	4.5
XTX Markets	26722	6.2	4320	10563	2.4	58.3	42.5	27.0	28.7	1.8

This table provides stock-day level summary statistics by market maker. We report average stock-day trading volume and average trade size in 1000 R$s, the average number of trades and messages, the ratio of quotes to trades, and the % share of volume in which the market maker is the aggressor. We also report the fraction of messages that are new orders, fills, cancels, and replace orders. Panel A reports summary statistics for the mandatory activity, panel B for the voluntary activity. The sample comprises program stocks during the market maker programs.

Table 2: Monthly Stock Level Summary Statistics

	mean	sd	p5	p25	p50	p75	p95
Market value	12756.6	29829.4	140.0	728.4	3663.7	11603.0	48710.7
Price	26.7	33.4	2.4	8.5	18.8	33.5	68.8
Return	3.1	13.7	-16.1	-3.5	2.4	9.2	22.7
Quoted spread	33.6	53.0	4.9	7.5	11.8	31.4	145.2
Effective spread	33.8	53.1	5.0	7.5	11.7	32.0	143.9
Depth (5 levels)	707.2	1533.1	64.1	146.8	281.3	581.0	2931.5
Depth (0.5%)	1379.2	3904.1	26.3	153.9	485.5	1535.0	4638.7
Depth (total)	5214.0	10357.6	138.0	690.1	2832.6	6369.0	17303.6
Volume	49.9	129.8	0.0	0.2	8.9	55.8	181.4
Number of trades	5401.2	8019.3	2.0	38.2	2126.8	8212.4	19812.9
Average trade size	8422.9	33401.6	1329.2	3161.0	5341.8	8592.9	17415.9
Sd(log quoted spread)	48.5	18.4	16.3	35.4	49.9	62.1	75.5
Sd(log effective spread)	37.6	14.5	13.7	26.7	38.6	48.1	60.0
Sd(log depth)	80.0	25.2	45.6	61.2	75.1	98.0	123.2
Sd(log volume)	310.9	68.2	205.6	244.6	322.4	364.6	410.1
Sd(return)	23.5	8.2	14.5	18.3	21.7	26.8	38.0
Observations	3601						

This table reports stock-level summary statistics. We report means, standard deviations, 5th, 25th, 50th, 75th, and 95th percentiles. The variables are stock market value in million R$s, stock price, returns in %, quoted and effective bid-ask spreads in basis points, depth in 1000 R$s, daily volume in million R$s, daily number of trades, average trade size, order flow, order imbalance, percent intraday (5-minute) standard deviations of log quoted and effective spreads, log depth, log volume, and returns. The sample contains the eight-month event window around the respective market maker program at the monthly frequency.

Table 3: Summary Statistics: High-Frequency Stock Pair Level Correlations

	mean	sd	p5	p25	p50	p75	p95
ρ(log quoted spread)	17.3	17.9	-5.0	5.3	13.3	26.4	52.9
ρ(log effective spread)	10.9	9.9	-3.9	5.1	10.6	17.0	26.7
ρ(log depth)	51.3	21.3	12.6	39.1	54.1	66.7	80.6
ρ(log volume)	33.8	30.9	-3.9	7.6	23.1	65.3	83.1
ρ(returns)	7.3	10.7	-6.3	0.5	5.5	12.7	26.7
Observations	169344						

This table reports stock pair level summary statistics. We report means, standard deviations, 5th, 25th, 50th, 75th, and 95th percentiles. The variables are percent intraday (5-minute) correlation coefficients of returns, log quoted and effective spreads, log depth, and log volume. The sample contains the eight-month event window around the respective market maker program at the monthly frequency.

Table 4: Comparison of Treated and Control Stocks?

	(1) 2018	(2) 2019
IBrX 100	0.503***	0.819***
	(0.0967)	(0.192)
1(bilateral DMM)	-0.249***	0.465***
	(0.0591)	(0.106)
1(top stock)	-0.565***	
	(0.102)	
Log market value	0.00711	-0.00674
	(0.0286)	(0.0951)
Log book equity	-0.00873	0.00702
	(0.0194)	(0.0232)
Log PP&E	-0.00680	0.0211
	(0.0137)	(0.0245)
Profitability	-1.155	0.432
	(1.055)	(2.112)
Investment	-3.409	1.842
	(3.214)	(1.697)
Asset growth	-0.353	-0.599
	(0.270)	(0.398)
Log debt	0.0217	-0.0284
	(0.0233)	(0.0469)
Log quoted spread	0.0761	0.00563
	(0.0681)	(0.217)
Log volume	0.0338	-0.0618
	(0.0297)	(0.118)
Sd(log quoted spread)	-0.000571	0.00550
	(0.00152)	(0.00347)
Sd(log volume)	-0.000159	-0.000675
	(0.000409)	(0.00154)
Sd(return)	0.000409	0.0152
	(0.00437)	(0.0171)
R-Squared	0.428	0.412
N	196	87

This table reports results of regressions of a treatment indicator on stock characteristics. Columns 1 and 2 report results for the 2018 and 2019 market maker program, respectively. The sample is the cross-section of treated and control stocks at the beginning of the event window, i.e. 3 months before the treatment. The first regression contains about 200 stocks, the universe of 400 stocks excluding small stocks with a market capitalization below R$100M. The second regression includes all stocks included in the 2019 MM program. ***, **, and * denote significance at the 10%, 5%, and 1% levels.

Table 5: The Effects of Designated Market Makers on Liquidity, Volume, and Asset Prices

Dep. Var	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: The 2018 Market Maker Program						
Log quoted spread	-0.14**	-0.13***	-0.15**	-0.08**	-0.09**	-0.09**
	(0.06)	(0.05)	(0.06)	(0.04)	(0.04)	(0.04)
Log effective spread	-0.16**	-0.15***	-0.16**	-0.09**	-0.10**	-0.10**
	(0.06)	(0.05)	(0.06)	(0.04)	(0.04)	(0.04)
Log depth	0.52***	0.52***	0.53***	0.49***	0.49***	0.49***
	(0.09)	(0.07)	(0.09)	(0.06)	(0.06)	(0.06)
Log volume	0.16*	0.15*	0.16*	0.14**	0.14**	0.14**
	(0.09)	(0.08)	(0.09)	(0.07)	(0.07)	(0.07)
CAR	7.79*	7.32	7.78*	3.81	3.81	3.81
	(4.56)	(4.52)	(4.57)	(3.19)	(3.19)	(3.19)
Panel B: The 2019 Market Maker Program						
Log quoted spread	-0.16***	-0.16***	-0.16***	-0.15***	-0.15***	-0.15***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Log effective spread	-0.18***	-0.18***	-0.18***	-0.17***	-0.17***	-0.17***
	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Log depth	0.51***	0.50***	0.51***	0.52***	0.52***	0.52***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Log volume	0.08	0.09	0.08	0.13	0.13	0.13
	(0.10)	(0.09)	(0.10)	(0.08)	(0.08)	(0.08)
CAR	2.92	2.87	2.87	3.33	3.27	3.27
	(3.49)	(3.50)	(3.51)	(3.51)	(3.52)	(3.52)
Controls		✓				✓
Time FE			✓		✓	✓
Stock FE				✓	✓	✓
Cluster by stock	✓	✓	✓	✓	✓	✓

This table reports estimates of equation 1. The rows report results for different dependent variables: log quoted spreads, log effective spreads, log depth, log volume, and percent cumulative abnormal returns. The columns include different sets of control variables and fixed effects. We report standard errors clustered by stock in parentheses. The sample contains the eight-month event window around the respective market maker program at the monthly frequency. ***, **, and * denote significance at the 10%, 5%, and 1% levels.

Table 6: The Effects of Designated Market Makers on the Volatilities of Liquidity, Volume, and Asset Prices

Dep. Var	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: The 2018 Market Maker Program						
Sd(log quoted spread)	-6.27***	-6.26***	-6.30***	-6.24***	-6.28***	-6.28***
	(1.30)	(1.31)	(1.30)	(1.24)	(1.24)	(1.24)
Sd(log effective spread)	-2.79***	-2.76***	-2.81***	-2.86***	-2.89***	-2.89***
	(1.02)	(1.01)	(1.02)	(0.98)	(0.98)	(0.98)
Sd(log depth)	-8.86***	-8.53***	-8.82***	-9.45***	-9.42***	-9.42***
	(2.24)	(2.14)	(2.25)	(2.05)	(2.05)	(2.05)
Sd(log volume)	-49.00***	-48.52***	-49.00***	-47.79***	-47.81***	-47.81***
	(6.50)	(6.54)	(6.51)	(6.55)	(6.57)	(6.57)
Sd(ret)	-0.80	-0.77	-0.85	0.29	0.22	0.22
	(0.63)	(0.61)	(0.62)	(0.55)	(0.55)	(0.55)
Panel B: The 2019 Market Maker Program						
Sd(log quoted spread)	-6.99***	-7.00***	-7.00***	-7.43***	-7.42***	-7.42***
	(1.69)	(1.69)	(1.68)	(1.55)	(1.54)	(1.54)
Sd(log effective spread)	-3.24**	-3.24**	-3.26**	-3.81***	-3.80***	-3.80***
	(1.31)	(1.31)	(1.30)	(1.20)	(1.19)	(1.19)
Sd(log depth)	-4.19	-4.16	-4.20	-4.01	-4.03	-4.03
	(2.56)	(2.54)	(2.57)	(2.54)	(2.56)	(2.56)
Sd(log volume)	-11.01	-10.97	-11.07	-11.51	-11.56	-11.56
	(8.04)	(8.05)	(8.07)	(8.22)	(8.25)	(8.25)
Sd(ret)	0.37	0.38	0.37	0.37	0.37	0.37
	(0.47)	(0.46)	(0.47)	(0.44)	(0.44)	(0.44)
Controls		✓				✓
Time FE			✓		✓	✓
Stock FE				✓	✓	✓
Cluster by stock	✓	✓	✓	✓	✓	✓

This table reports estimates of equation 1. The rows report results for percent intraday (5-minute) volatilities of different dependent variables: log quoted spreads, log effective spreads, log depth, log volume, and returns. The columns include different sets of control variables and fixed effects. We report standard errors clustered by stock in parentheses. The sample contains the eight-month event window around the respective market maker program at the monthly frequency. ***, **, and * denote significance at the 10%, 5%, and 1% levels.

Table 7: The Separate Effects of Liquidity Provision Obligations and Incentives on Liquidity, Volume, and Asset Prices

Dep. Var	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Effect of Obligations						
Log quoted spread	0.16	0.14	0.16	0.10***	0.10***	0.10***
	(0.13)	(0.11)	(0.13)	(0.03)	(0.03)	(0.03)
Log effective spread	0.16	0.15	0.17	0.11***	0.11***	0.11***
	(0.14)	(0.12)	(0.14)	(0.03)	(0.03)	(0.03)
Log depth	-0.15	-0.10	-0.15	-0.06	-0.06	-0.06
	(0.12)	(0.09)	(0.12)	(0.08)	(0.08)	(0.08)
Log volume	-0.24	-0.21	-0.25	-0.15	-0.15	-0.15
	(0.17)	(0.14)	(0.18)	(0.09)	(0.09)	(0.09)
CAR	-5.95	-5.95	-5.95	-5.95	-5.95	-5.95
	(4.73)	(4.74)	(4.76)	(4.71)	(4.75)	(4.75)
Panel B: Effect of Incentives						
Log quoted spread	-0.17***	-0.17***	-0.17***	-0.16***	-0.16***	-0.16***
	(0.06)	(0.05)	(0.06)	(0.04)	(0.04)	(0.04)
Log effective spread	-0.18**	-0.18***	-0.18***	-0.16***	-0.17***	-0.17***
	(0.07)	(0.05)	(0.07)	(0.04)	(0.04)	(0.04)
Log depth	0.25**	0.23**	0.25**	0.21**	0.22**	0.22**
	(0.11)	(0.10)	(0.11)	(0.09)	(0.09)	(0.09)
Log volume	0.26**	0.26**	0.27**	0.23**	0.24**	0.24**
	(0.13)	(0.11)	(0.13)	(0.10)	(0.10)	(0.10)
CAR	12.75***	12.75***	12.75***	12.75***	12.75***	12.75***
	(3.65)	(3.66)	(3.67)	(3.64)	(3.67)	(3.67)
Controls		✓				✓
Time FE			✓		✓	✓
Stock FE				✓	✓	✓
Cluster by stock	✓	✓	✓	✓	✓	✓

This table reports estimates of equation 1. The rows report results for different dependent variables: log quoted spreads, log effective spreads, log depth, log volume, and cumulative returns. The columns include different sets of control variables and fixed effects. We report standard errors clustered by stock in parentheses. The sample contains the eight-month event window around the respective market maker program at the monthly frequency. ***, **, and * denote significance at the 10%, 5%, and 1% levels.

Table 8: How Do Market Makers Set Quotes?

	Mandatory Activity		Voluntary Activity	
	(1)	(2)	(3)	(4)
OF	14.31***	0.74***	16.21***	1.74***
	(0.17)	(0.06)	(0.14)	(0.05)
OF absorbed	65.53***	8.08***	78.59***	18.74***
	(1.33)	(0.33)	(1.11)	(0.38)
OF (other stocks)	5.97***	-0.20***	7.76***	0.73***
	(0.23)	(0.07)	(0.15)	(0.03)
OF absorbed (other stocks)	19.77***	4.52***	26.51***	3.88***
	(1.57)	(0.46)	(1.06)	(0.22)
Return		0.90***		0.91***
		(0.00)		(0.00)
N events	4,551,149,609	4,551,149,609	6,866,048,833	6,866,048,833
N reactions	85,524,480	85,524,480	46,823,032	46,823,032
MM-stock-days	22,037	22,037	30,736	30,736
MM-days	1,610	1,610	1,629	1,629

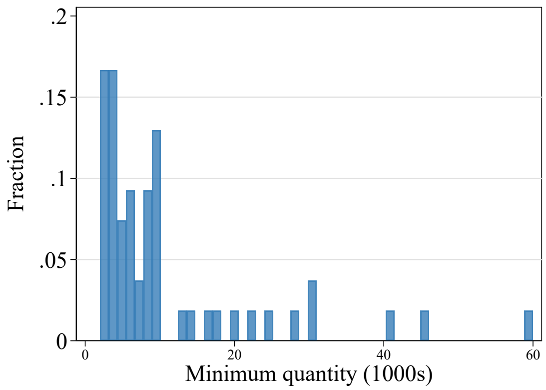
This table reports estimates of equation 6 and shows how market makers revise price quotes in response to order flow, order flow where they provide liquidity, and both variables constructed using all other stocks the respective market maker intermediates. We also control for stock returns. Quote revisions and stock returns are in percent. We estimate equation 6 separately for each market maker x stock x day combination. This is conceptually equivalent to including market maker x stock x day fixed effects. We then compute Fama-MacBeth standard errors robust to within market maker x day correlation from the distribution of the coefficient estimates (Fama and MacBeth, 1973). We report standard errors in parentheses. The sample spans the duration of the market maker programs. ***, **, and * denote significance at the 10%, 5%, and 1% levels.

Table 9: The Effects of Common Intermediation on Co-Movement

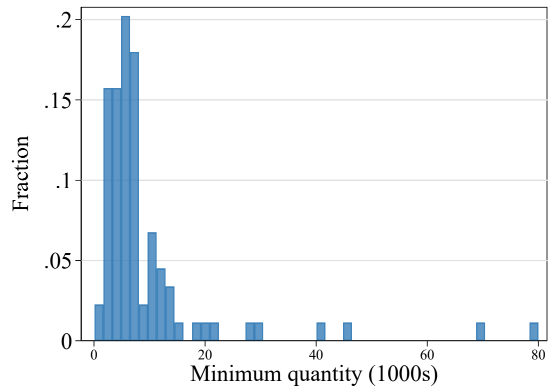
Dep. Var	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: The 2018 Market Maker Program						
ρ(log quoted spread)	1.03**	1.01**	1.04**	1.03**	1.02**	1.01**
	(0.44)	(0.44)	(0.44)	(0.44)	(0.44)	(0.44)
ρ(log effective spread)	1.70***	1.71***	1.83***	1.85***	1.84***	1.86***
	(0.65)	(0.65)	(0.62)	(0.63)	(0.62)	(0.63)
ρ(log depth)	1.63***	1.61***	1.88***	1.81***	1.85***	1.79***
	(0.37)	(0.37)	(0.36)	(0.36)	(0.36)	(0.36)
ρ(log volume)	0.43	0.43	0.54*	0.56*	0.54*	0.56*
	(0.34)	(0.34)	(0.31)	(0.31)	(0.31)	(0.31)
ρ(return)	0.62**	0.60**	0.68***	0.79***	0.66***	0.77***
	(0.26)	(0.25)	(0.23)	(0.23)	(0.23)	(0.23)
Panel B: The 2019 Market Maker Program						
ρ(log quoted spread)	1.51***	1.50***	1.54***	1.56***	1.53***	1.55***
	(0.20)	(0.20)	(0.19)	(0.19)	(0.19)	(0.19)
ρ(log effective spread)	2.77***	2.76***	2.80***	2.82***	2.78***	2.80***
	(0.19)	(0.19)	(0.18)	(0.18)	(0.17)	(0.18)
ρ(log depth)	0.18	0.18	0.24*	0.26*	0.24	0.26*
	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)	(0.15)
ρ(log volume)	0.55***	0.53***	0.63***	0.65***	0.61***	0.64***
	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)
ρ(return)	0.64***	0.61***	0.69***	0.72***	0.66***	0.69***
	(0.10)	(0.11)	(0.10)	(0.10)	(0.10)	(0.10)
Time FE		✓			✓	✓
Stock FE			✓		✓	
Pair FE				✓		✓

This table reports estimates of equation 7. The rows report results for different dependent variables: the percent correlation of intraday (5-minute) log quoted spreads, log effective spreads, log depth, log volume, and returns. The columns include different sets of fixed effects. We report standard errors clustered by stock pair in parentheses. The sample contains the eight-month event window around the respective market maker program at the monthly frequency. ***, **, and * denote significance at the 10%, 5%, and 1% levels.

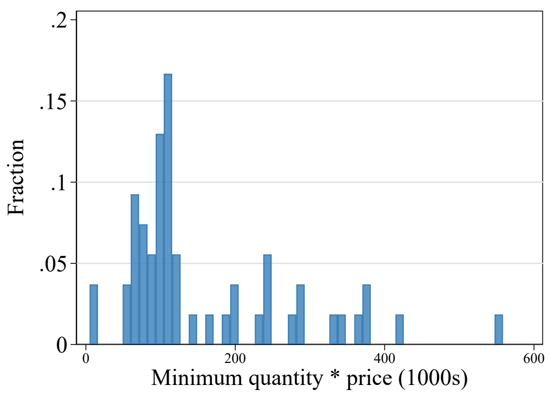
Figure A1: Distribution of Program Parameters



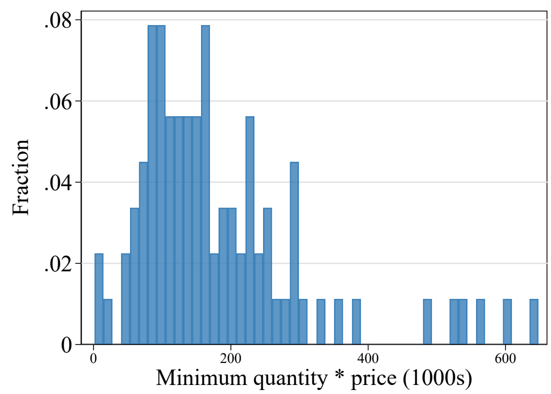
(a) 2018



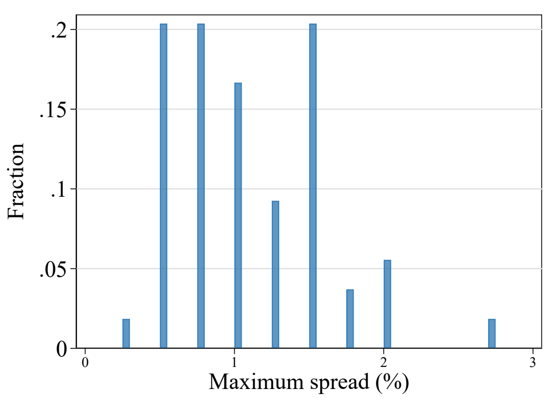
(b) 2019



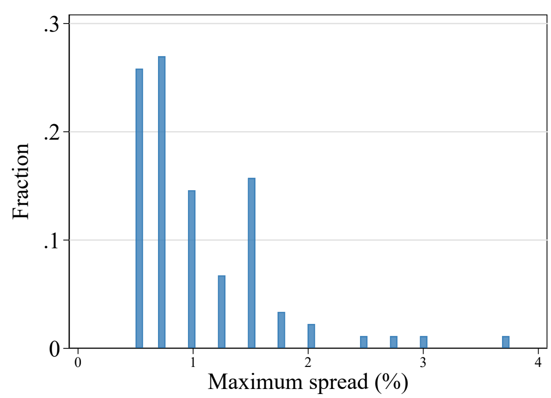
(c) 2018



(d) 2019



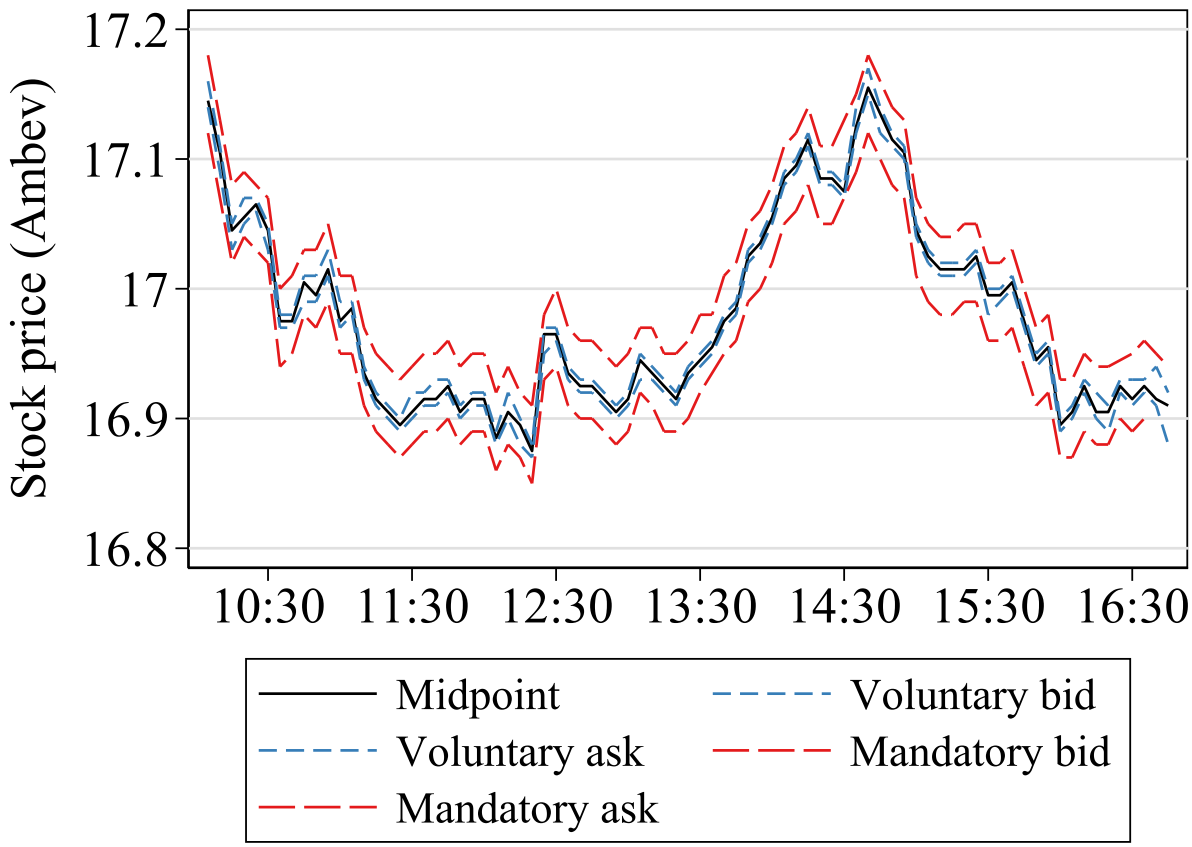
(e) 2018



(f) 2019

This figure shows histograms of program parameters. The panels on the left correspond to the 2018 program, the panels on the right to the 2019 program. The first row summarizes minimum quantities in 1000 shares. The second row shows the corresponding R$ execution risk by multiplying the minimum quantities in 1000 shares with the respective stock prices on the first day of the respective program. The last row shows the distribution of percent maximum spreads.

Figure A2: Illustration of the Mandatory vs. Voluntary Activity: Quoting of Tucana Bay in Ambev on 1st Day of 2018 Program



This figure illustrates the typical quoting behavior of the mandatory vs. voluntary activity using an example. We plot Tucana Bay's quotes for Ambev on the first day of the 2018 program, 10/15/2018. We plot the midpoint in black, Tucana Bay's voluntary bids and asks in blue, and Tucana Bay's mandatory bids and asks in red. The figure shows that, typically, the mandatory activity quotes deep in the book, while the voluntary activity quotes tightly around midpoints.

Table A1: Details of the 2018 Market Maker Program

Ticker	MM 1	MM 2	MM 3	% Spread	Q	% Presence
ABEV3	Headlands Technologies	Tucana Bay	-	.25	25000	80
ALPA4	Headlands Technologies	Tucana Bay	QE Trading	1.5	8000	80
AZUL4	Jane Street Capital	QE Trading	Virtu Financial	1.25	4000	80
BBDC3	Headlands Technologies	Credit Suisse Brasil	QE Trading	.5	4000	80
BBSE3	Credit Suisse Brasil	Tucana Bay	-	.5	9000	80
BPAC11	Headlands Technologies	XTX Markets	QE Trading	1.5	5000	80
BRAP4	XTX Markets	Tucana Bay	Spire X Trading	1	6000	80
BRDT3	Headlands Technologies	Credit Suisse Brasil	XTX Markets	1	10000	80
BRFS3	XTX Markets	Virtu Financial	-	.75	18000	80
BRML3	Credit Suisse Brasil	Tucana Bay	Bradesco	.75	20000	80
BRPR3	Headlands Technologies	Spire X Trading	QE Trading	1.5	10000	80
BRSR6	Headlands Technologies	Credit Suisse Brasil	XTX Markets	1	6000	80
BTOW3	XTX Markets	Spire X Trading	QE Trading	.75	4000	80
CESP6	Spire X Trading	Tucana Bay	QE Trading	1	4000	80
CIEL3	Credit Suisse Brasil	QE Trading	-	1	30000	80
CMIG4	Headlands Technologies	Credit Suisse Brasil	Spire X Trading	.75	28000	80
CPLE3	Headlands Technologies	Tucana Bay	XTX Markets	2	3000	80
CPRE3	Headlands Technologies	Tucana Bay	Spire X Trading	2	3000	80
CSAN3	Headlands Technologies	XTX Markets	QE Trading	.5	3000	80
CSNA3	Jane Street Capital	Spire X Trading	QE Trading	.75	41000	80
ELET3	Headlands Technologies	Credit Suisse Brasil	Virtu Financial	1	14000	80
ELET6	Credit Suisse Brasil	Tucana Bay	XTX Markets	1	6000	80

Table A1: Details of the 2018 Market Maker Program (continued)

Ticker	MM 1	MM 2	MM 3	% Spread	Q	% Presence
EMBR3	Jane Street Capital	QE Trading	Virtu Financial	.5	9000	80
ENGI11	Spire X Trading	Tucana Bay	QE Trading	1.5	3000	80
FIBR3	XTX Markets	Tucana Bay	-	.5	4000	80
GFSA3	Credit Suisse Brasil	Tucana Bay	Spire X Trading	1.5	8000	80
GNDI3	Credit Suisse Brasil	Tucana Bay	XTX Markets	1.5	4000	80
GOAU4	Spire X Trading	QE Trading	-	.75	45000	80
GOLL4	XTX Markets	Tucana Bay	Spire X Trading	.75	7000	80
HAPV3	Credit Suisse Brasil	XTX Markets	QE Trading	1.25	3000	80
HGTX3	Headlands Technologies	Credit Suisse Brasil	XTX Markets	1	6000	80
KLBN11	Headlands Technologies	XTX Markets	QE Trading	.5	5000	80
LAME3	Headlands Technologies	Tucana Bay	Credit Suisse Brasil	1.5	5000	80
MRFG3	Spire X Trading	Tucana Bay	QE Trading	1.25	13000	80
MRVE3	XTX Markets	Tucana Bay	Spire X Trading	.5	8000	80
ODPV3	Spire X Trading	Tucana Bay	QE Trading	1.5	7000	80
PARD3	Spire X Trading	Tucana Bay	QE Trading	1.5	4000	80
PCAR4	Jane Street Capital	Spire X Trading	Virtu Financial	.5	3000	80
POMO4	Headlands Technologies	Credit Suisse Brasil	Spire X Trading	1.75	30000	80
RAIL3	Credit Suisse Brasil	XTX Markets	-	.75	22000	80
RAPT4	Credit Suisse Brasil	Tucana Bay	QE Trading	1.5	16000	80
RENT3	XTX Markets	Tucana Bay	Spire X Trading	.75	8000	80
RNEW11	Headlands Technologies	XTX Markets	Spire X Trading	2	2000	80
SAPR11	Headlands Technologies	Credit Suisse Brasil	XTX Markets	.75	2000	80

Table A1: Details of the 2018 Market Maker Program (continued)

Ticker	MM 1	MM 2	MM 3	% Spread	Q	% Presence
SAPR4	Headlands Technologies	XTX Markets	Spire X Trading	1.25	8000	80
SBSP3	Jane Street Capital	Tucana Bay	Virtu Financial	.5	4000	80
SEER3	Headlands Technologies	XTX Markets	Credit Suisse Brasil	1.5	4000	80
SLCE3	Headlands Technologies	Credit Suisse Brasil	XTX Markets	1.25	2000	80
TPIS3	Headlands Technologies	Tucana Bay	Spire X Trading	2.75	10000	80
UGPA3	Headlands Technologies	Spire X Trading	-	.5	5000	80
USIM5	Headlands Technologies	Spire X Trading	-	.75	60000	80
VVAR11	XTX Markets	Tucana Bay	Spire X Trading	1	9000	80
WEGE3	Credit Suisse Brasil	Spire X Trading	QE Trading	.5	6000	80
WIZS3	Headlands Technologies	Tucana Bay	XTX Markets	1.75	10000	80

This table reports the 2018 market maker program details as provided by B3. The columns report the stock ticker symbol, the designated market makers, the maximum spread in percent, the minimum quantity in number of shares, and the minimum presence during each trading session in percent.

Table A2: Details of the 2019 Market Maker Program

Ticker	MM 1	MM 2	MM 3	MM 4	MM 5	% Spread	Q	% Presence
ALPA4	QE Trading	Credit Suisse	Tucana Bay	Tarpika	Citadel Sec.	1.5	8000	80
AZUL4	QE Trading	Optiver	Virtu Fin.	-	-	.75	4000	80
BBDC3	Headlands Tech.	Credit Suisse	Optiver	-	-	.5	4000	80
BBSE3	Credit Suisse	Tucana Bay	-	-	-	.5	9000	80
BEEF3	QE Trading	Spire X Trading	XTX Markets	Tarpika	Citadel Sec.	1.5	11500	80
BPAC11	QE Trading	XTX Markets	Citadel Sec.	Optiver	-	1.5	5000	80
BRAP4	Headlands Tech.	Optiver	Tucana Bay	-	-	.75	6000	80
BRDT3	Spire X Trading	Credit Suisse	Citadel Sec.	-	-	.75	10000	80
BRFS3	Tucana Bay	Optiver	-	-	-	.5	18000	80
BRML3	Bradesco	Credit Suisse	Tucana Bay	-	-	.75	20000	80
BRPR3	QE Trading	Green Post Tr.	Spire X Trading	Optiver	Citadel Sec.	1.5	10000	80
BRSR6	Spire X Trading	XTX Markets	Optiver	-	-	.75	6000	80
BTOW3	QE Trading	Spire X Trading	Virtu Fin.	-	-	.75	6000	80
CCRO3	Green Post Tr.	Tarpika	-	-	-	.5	10000	80
CESP6	QE Trading	Optiver	Citadel Sec.	-	-	1	4000	80
CIEL3	Spire X Trading	Tarpika	-	-	-	1.5	80000	80
CMIG3	QE Trading	Green Post Tr.	Spire X Trading	Tarpika	Credit Suisse	3.75	6000	80
CMIG4	Green Post Tr.	Optiver	-	-	-	.5	28000	80
CPLE3	QE Trading	Green Post Tr.	Spire X Trading	XTX Markets	Optiver	2	3000	80
CPLE6	XTX Markets	Virtu Fin.	Optiver	-	-	.75	3000	80
CPRE3	Optiver	-	-	-	-	3	1000	80
CRFB3	Citadel Sec.	Tarpika	Green Post Tr.	-	-	1	6500	80
CSAN3	QE Trading	Citadel Sec.	-	-	-	.5	3000	80
CSMG3	Spire X Trading	XTX Markets	Optiver	-	-	.75	3000	80

Table A2: Details of the 2019 Market Maker Program (continued)

Ticker	MM 1	MM 2	MM 3	MM 4	MM 5	% Spread	Q	% Presence
CSNA3	XTX Markets	Optiver	-	-	-	.5	41000	80
CVCB3	Virtu Fin.	Tarpika	XTX Markets	-	-	.75	5500	80
CYRE3	Spire X Trading	Tucana Bay	Tarpika	-	-	.75	6500	80
DTEX3	QE Trading	Spire X Trading	Credit Suisse	Tucana Bay	Citadel Sec.	1	12000	80
ECOR3	Credit Suisse	Optiver	Citadel Sec.	-	-	.5	4000	80
ELET3	QE Trading	Credit Suisse	-	-	-	.75	14000	80
ELET6	Tucana Bay	Tarpika	Citadel Sec.	-	-	.75	6000	80
EMBR3	Tucana Bay	Optiver	Virtu Fin.	-	-	.5	9500	80
ENAT3	QE Trading	XTX Markets	Tucana Bay	Tarpika	Citadel Sec.	1.5	5000	80
ENBR3	Green Post Tr.	XTX Markets	Tarpika	-	-	.75	5000	80
ENGI11	QE Trading	Green Post Tr.	XTX Markets	-	-	.75	3000	80
EZTC3	QE Trading	XTX Markets	Credit Suisse	Optiver	Tarpika	1	5000	80
GFSA3	QE Trading	Green Post Tr.	Spire X Trading	Optiver	Citadel Sec.	1.5	8000	80
GNDI3	Credit Suisse	Tucana Bay	Virtu Fin.	-	-	1	4000	80
GOAU4	Green Post Tr.	Headlands Tech.	Tarpika	-	-	.75	45000	80
GOLL4	XTX Markets	Tucana Bay	Virtu Fin.	-	-	.75	7000	80
HAPV3	QE Trading	Green Post Tr.	Credit Suisse	-	-	1	3000	80
HGTX3	Spire X Trading	XTX Markets	Credit Suisse	-	-	.75	6000	80
HYPE3	Headlands Tech.	Optiver	Tarpika	-	-	1	5000	80
IRBR3	Spire X Trading	XTX Markets	Tarpika	-	-	.75	2000	80
JBSS3	XTX Markets	Citadel Sec.	-	-	-	.5	10000	80
KLBN11	QE Trading	Headlands Tech.	Credit Suisse	-	-	.5	7500	80
LAME3	Green Post Tr.	Spire X Trading	XTX Markets	Credit Suisse	Citadel Sec.	1.5	5000	80
LAME4	Headlands Tech.	Optiver	Tarpika	-	-	.5	7000	80

Table A2: Details of the 2019 Market Maker Program (continued)

Ticker	MM 1	MM 2	MM 3	MM 4	MM 5	% Spread	Q	% Presence
LIGT3	Green Post Tr.	XTX Markets	Tucana Bay	Tarpika	Citadel Sec.	1.25	5000	80
LINX3	Green Post Tr.	Spire X Trading	Citadel Sec.	-	-	1.25	3000	80
LOGG3	QE Trading	Green Post Tr.	Spire X Trading	Optiver	Headlands Tech.	2	6500	80
MDIA3	Spire X Trading	XTX Markets	Credit Suisse	Virtu Fin.	Citadel Sec.	.75	2500	80
MRFG3	QE Trading	Tucana Bay	Virtu Fin.	-	-	1	13000	80
MRVE3	QE Trading	Spire X Trading	Virtu Fin.	-	-	.5	8000	80
MULT3	Headlands Tech.	Tarpika	Optiver	-	-	.75	8000	80
MYPK3	XTX Markets	Credit Suisse	Tucana Bay	Tarpika	Citadel Sec.	1	5000	80
NATU3	Green Post Tr.	Spire X Trading	XTX Markets	-	-	.75	8000	80
ODPV3	QE Trading	XTX Markets	Credit Suisse	Tarpika	Citadel Sec.	1.5	7000	80
PARD3	QE Trading	Green Post Tr.	Spire X Trading	XTX Markets	Optiver	1.5	4000	80
PCAR4	QE Trading	Citadel Sec.	-	-	-	.5	3000	80
POMO4	Green Post Tr.	Tarpika	Headlands Tech.	Tucana Bay	Citadel Sec.	1.75	30000	80
PSSA3	Green Post Tr.	XTX Markets	Tarpika	-	-	.5	4000	80
QUAL3	Green Post Tr.	Tucana Bay	Citadel Sec.	-	-	1.25	8000	80
RAIL3	XTX Markets	Credit Suisse	-	-	-	.5	22000	80
RAPT4	QE Trading	Green Post Tr.	Spire X Trading	Tucana Bay	Tarpika	1.5	16000	80
RENT3	Green Post Tr.	Spire X Trading	-	-	-	.5	8000	80
RNEW11	Green Post Tr.	Optiver	-	-	-	2.5	100	80
SAPR11	Headlands Tech.	Credit Suisse	Optiver	-	-	.75	2000	80
SAPR4	QE Trading	Green Post Tr.	Spire X Trading	XTX Markets	Tucana Bay	1.25	8000	80
SBSP3	Spire X Trading	Credit Suisse	Optiver	-	-	.5	4500	80
SEER3	Spire X Trading	XTX Markets	Credit Suisse	Optiver	Citadel Sec.	1.5	4000	80
SLCE3	Green Post Tr.	Tarpika	Citadel Sec.	-	-	1	3000	80

Table A2: Details of the 2019 Market Maker Program (continued)

Ticker	MM 1	MM 2	MM 3	MM 4	MM 5	% Spread	Q	% Presence
SMLS3	Green Post Tr.	Headlands Tech.	Citadel Sec.	-	-	.75	2000	80
SMTO3	QE Trading	Green Post Tr.	Spire X Trading	Credit Suisse	Citadel Sec.	1	3000	80
SULA11	XTX Markets	Credit Suisse	Citadel Sec.	-	-	1	4000	80
TAEE11	Headlands Tech.	Tucana Bay	Virtu Fin.	-	-	.5	3500	80
TEND3	QE Trading	Green Post Tr.	Spire X Trading	XTX Markets	Optiver	1.5	4000	80
TIET11	Green Post Tr.	Tucana Bay	Optiver	Tarpika	Citadel Sec.	1	8000	80
TIMP3	Headlands Tech.	Tucana Bay	Optiver	-	-	.5	12000	80
TOTS3	Green Post Tr.	XTX Markets	Credit Suisse	Tucana Bay	Citadel Sec.	1.25	4000	80
TPIS3	Green Post Tr.	Optiver	-	-	-	2.75	10000	80
TRPL4	XTX Markets	Tarpika	Optiver	-	-	.5	4000	80
TUPY3	QE Trading	Spire X Trading	Tucana Bay	Tarpika	Citadel Sec.	1.75	5000	80
UGPA3	Spire X Trading	Virtu Fin.	-	-	-	.5	12000	80
USIM5	Green Post Tr.	Headlands Tech.	-	-	-	1.25	70000	80
VLID3	QE Trading	Spire X Trading	Tucana Bay	Optiver	Citadel Sec.	1.5	5000	80
VVAR3	QE Trading	Tucana Bay	Tarpika	-	-	.75	13500	80
WEGE3	QE Trading	Credit Suisse	Optiver	-	-	.5	6000	80
WIZS3	QE Trading	Green Post Tr.	Spire X Trading	XTX Markets	Optiver	1.75	10000	80

This table reports the 2019 market maker program details as provided by B3. The columns report the stock ticker symbol, the designated market makers, the maximum spread in percent, the minimum quantity in number of shares, and the minimum presence during each trading session in percent. The unabbreviated names of the respective designated market makers are Citadel Securities, Green Post Trading, Credit Suisse Brasil, Virtu Financial, and Headlands Technologies.

Table A3: The Strategic Complementarity of Liquidity Provision: The Effects of Designated Market Makers on Other Traders' Liquidity Provision

Dep. Var	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: The 2018 Market Maker Program						
Log quoted spread (non-DMMs)	-0.11*	-0.09**	-0.11*	-0.05	-0.05	-0.05
	(0.06)	(0.04)	(0.06)	(0.04)	(0.04)	(0.04)
Log depth (non-DMMs)	0.20*	0.18**	0.20*	0.08	0.08	0.08
	(0.10)	(0.08)	(0.10)	(0.07)	(0.07)	(0.07)
Panel B: The 2019 Market Maker Program						
Log quoted spread (non-DMMs)	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Log depth (non-DMMs)	0.16**	0.15*	0.16**	0.14*	0.14*	0.14*
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Controls		✓				✓
Time FE			✓		✓	✓
Stock FE				✓	✓	✓
Cluster by stock	✓	✓	✓	✓	✓	✓

This table reports estimates of equation 1. The rows report results for different dependent variables: log quoted spreads ignoring DMM quotes and log depth ignoring DMM quotes. The columns include different sets of control variables and fixed effects. We report standard errors clustered by stock in parentheses. The sample contains the eight-month event window around the respective market maker program at the monthly frequency. ***, **, and * denote significance at the 10%, 5%, and 1% levels.