Liquidity Provision Contracts and Market Quality:

Evidence from the New York Stock Exchange*

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Abstract

We exploit a discontinuity in the New York Stock Exchange (NYSE) Designated Market Maker (DMM) contract to identify causal effects of DMM participation on market quality. We document that contractual features encouraging DMM participation are associated with increased depth, narrower bid-ask spreads, higher rates of price improvement, and improved price efficiency, with most of the improvements attributable to increases in liquidity provision on markets *other* than the NYSE. These results cannot be attributed to the mechanical effects of the contractual changes, and support the interpretation that market making is characterized by strategic complementarity.

I. Introduction

Most trading of equities and futures contracts occurs on electronic limit order markets. A central feature of these markets is that any participant can elect to effectively supply liquidity by posting non-marketable limit orders.[1] Despite the degree of potential competition in the business of liquidity provision, many exchanges employ contracts that commit one or more market participants to supply liquidity in certain circumstances, and additional exchanges are considering the adoption of such agreements.[2] Bessembinder, Hao, and Zheng (2015) present a model where such "Designated Market Maker" (DMM) contracts can improve liquidity and enhance firm value by reducing deadweight costs attributable to asymmetric information, while Venkataraman and Waisburd (2007) show that DMMs can improve risk sharing in a market characterized by a finite number of investors.

Consistent with theory, the literature has documented positive market reactions to the announcement that DMMs will be introduced, and improved market quality after their introduction, for selected stocks on several European markets.[3] However, since these studies focus on firms that endogenously choose to enter DMM contracts, and firms that perceive the largest benefits would presumably select to enter DMM agreements, it is likely that the estimated effects are upward biased relative to those that would pertain to typical firms.

Our paper studies DMMs on the New York Stock Exchange (NYSE), which assigns a DMM to every stock, and contributes to understanding the economics of market making in two ways. First, we provide unbiased estimates of the causal impact of changes in DMM liquidity

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[1] Non-marketable limit orders are those priced so that they enter the limit order book, but do not generate immediate trades that remove existing orders from the book.

[2] For example, the Hong Kong stock exchange is considering the adoption of DMM contracts. https://www.hkex.com.hk/eng/prod/secprod/mms.htm#5.

[3] See Venkataraman and Waisburd (2007), Anand, Tanggaard, and Weaver (2009), Skjeltorp and Odegaard (2015), and Menkveld and Wang (2013).

obligations and incentives on market quality. Second, we provide evidence strongly supporting the reasoning that the business of liquidity provision is characterized by strategic complementarity, in the sense of Bulow, Geanakoplos and Klemperer (1985). In particular, we find improvements in liquidity and market quality for NYSE-listed stocks on markets other than the NYSE at times when the DMM contract provides incentives for the DMM to place more aggressive quotes on the NYSE.

The NYSE DMM program was adopted in 2008, replacing the specialist system that had been in use for decades. The NYSE assigns one firm to act as DMM in every listed stock.[4] In contrast to prior papers that study the endogenous adoption of DMM contracts for selected firms, we exploit a discontinuity in the NYSE DMM contract that applies to all firms to identify causal effects of changes in DMM obligations and incentives on market liquidity and firm value. In particular, the NYSE DMM contract specifies that contractual obligations and compensation for DMMs that change discretely depending on prior-month trading volume. This discontinuity provides the opportunity to identify the causal effect of changes in DMM obligations and incentives on market quality, because volume is determined by market participants in aggregate, not by the DMM, the listed firm, or the exchange.[5]

NYSE Rule 104 specifies DMM obligations and compensation for both "active" and "less active" stocks.[6] The Rule defines active (inactive) stocks as those with consolidated average daily

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[4] A total of 7 firms acted as DMMs on the NYSE during our sample period. The number of listed stocks assigned to individual DMM firms ranges from 56 to 1,185 as of April 2013.
[5] However, we cannot assess the potentially distinct effects of changes in DMM obligations versus changes in DMM compensation, since there is a discrete change in each at the same volume threshold.
[6] NYSE Rule 104 "Dealings and Responsibilities of DMMs" is available at http://nyserules.nyse.com/nyse/rules/nyse-rules/chp_1_3/chp_1_3_7/chp_1_3_7_8/default.asp. The NYSE allocates securities across DMMs in part based on their performance in discharging their DMM obligations. NYSE procedures for allocating securities are delineated in Rule 103B, available at http://nyserules.nyse.com/nyse/rules/nyse-rules/chp_1_3/chp_1_3_7/chp_1_3_7_6/default.asp.

trading volume equal to or greater than (less than) 1 million shares during the prior month. For active securities the obligation is to maintain quotes at the NBBO at least ten percent of the time, while for inactive stocks the quoting obligation is increased to at least fifteen percent of the time. On the compensation side, the DMM receives a rebate of $.0030 per share when supplying liquidity to trades in active stocks, versus a rebate of $.0035 per share when supplying liquidity to trades in less active stocks. Thus, both obligations and incentives for NYSE DMMs are subject to a discrete increase when prior month trading volume is less than one million shares per day. For brevity, we will refer to security/months that meet the "less active" definition as months characterized by an enhanced DMM contract.

We employ a regression discontinuity research design to assess changes in market depth, quoted and effective bid-ask spreads, rates of price improvement, firm value, and price efficiency attributable to enhancement of the DMM contract. A key advantage of the regression discontinuity design is that it focuses on same-firm variation in market outcomes for similar trading volumes just above and below the one-million-share-per-day volume threshold, to isolate the effect of the change in contractual obligations and incentives.

Clark-Joseph, Ye, and Zi (2016) also provide evidence regarding NYSE DMMs, by studying liquidity for NYSE-listed firms traded on non-NYSE markets when the NYSE was forced by a technological malfunction to stop trading for a portion of the July 8, 2015 trading day. They report that bid-ask spreads for NYSE-listed stocks increased significantly during the NYSE trading halt. They also report evidence consistent with the reasoning that the increased spreads were attributable to the removal of the NYSE DMMs from the market, as spreads on average widened more for those stocks where DMMs had a larger pre-closure share of overall trading. However, their evidence is indirect, and does not definitely rule out that the widening of spreads was attributable to attributes of the NYSE other than the DMM obligations per se. For example, the NYSE is the listing exchange for the affected securities, and the majority of price discovery has traditionally taken place at the NYSE (Hasbrouck (1995)). Further, at least some market participants colocate their trading systems in close physical proximity to the NYSE servers, and these locational choices potentially affect market quality when the NYSE ceases trading. The regression discontinuity design we employ assesses directly the effects on liquidity and market quality of exogenous (to the decisions of the DMM or the exchange) changes in the obligations and compensation of the NYSE market makers, without potentially obfuscating effects attributable to the shutdown of the entire NYSE trading systems.

Our results show that liquidity is improved when the DMM contract is enhanced. In particular, quoted bid-ask spreads and effective bid-ask spreads (which allow for trade executions at prices other than the quotes) are both significantly smaller, and rates of price improvement (i.e. trade executions at prices better than the best quotes) are higher when the DMM contract is enhanced. In addition, we demonstrate that market quality is improved, in that quote midpoint changes over short time intervals conform more closely to the random walk benchmark, with the enhanced DMM contract.

We rule out that the striking empirical results obtained here are attributable to some inherent bias in the research design by conducting placebo tests that focus on counterfactual average daily volume breakpoints of 0.5 million and 1.5 million shares, rather than the actual breakpoint of 1.0 million shares. The placebo tests lead to statistically insignificant coefficient estimates associated with all of the market quality outcomes that we consider.

On balance, our results provide strong evidence that exogenous increases in the scope of DMM obligations and compensation are associated with improved liquidity and market quality.

They therefore support the Clark-Joseph, Ye, and Zi (2016) interpretation of their empirical results, and more broadly show that DMM contracts can improve market quality for typical stocks, not just those where firms self-select to employ DMMs.

We investigate further the mechanisms by which stronger DMM market-making obligations are associated with improved market quality by studying trades and quotes for NYSE-listed stocks on markets other than the NYSE, as well as on the NYSE itself. Strikingly, we document lower effective bid-ask spreads, higher rates of price improvement relative to the NBBO, and greater quoted depth for non-NYSE markets that quote and trade NYSE-listed stocks, while each of these measures except effective spreads are essentially unchanged on the NYSE itself. Further, the NYSE actually loses market share to non-NYSE venues at times when the DMM contract is enhanced.

These results provide insights into the nature of economic equilibrium in the market for liquidity provision services. In particular, the results support the reasoning more frequent and aggressive quotations from the NYSE DMM reduce competitors' marginal cost of providing liquidity on the other markets that trade NYSE securities, because liquidity providers there understand that they can more readily unwind unwanted inventory positions against the NYSE DMM's quotations. That is, the results imply that market making is characterized by "strategic complementarity" as the term is defined by Bulow, Geanakoplos and Klemperer (1985). The results also support the O'Hara and Ye (2011) assertion that the apparently fragmented market for the trading of NYSE-listed securities behaves in many ways as a "single virtual market with multiple points of entry."

The effects of DMM obligations on market quality comprise a question of first order importance for those who design and regulate financial markets. While any market participant can choose to provide liquidity on an electronic limit order market, in practice most liquidity is provided by high-frequency trading firms.[7] In the absence of DMM contracts, high frequency firms can cease providing liquidity during times of market uncertainty. For example, Arnuk, Saluzzi, and Leuchtkafer (2011) assert that numerous high frequency firms simply "turned their algo-bots off and disappeared" from the market during the "flash crash" in U.S. equity markets in May, 2010. The evidence provided here contributes to the understanding of how DMM contracts can supplement endogenous liquidity provision to improve the functioning of financial markets, and helps to illuminate the nature of economic equilibrium in the market for liquidity provision services.

II. Designated Market Makers and Strategic Complementarity in Financial Markets

a. Designated Market Makers

Virtually all trading in equities and futures contracts, as well as significant amounts of trading in foreign exchange, has migrated to electronic limit order markets. Any investor can supply liquidity in these markets if they so desire. Nevertheless, officially designated market makers (DMMs) are often observed. Perhaps the best known example of a DMM is the "specialist" employed by the New York Stock Exchange for many decades, until 2008. While the NSYE specialist was broadly tasked with maintaining a "fair and orderly market", the most important explicit specialist obligation came the form of the "price continuity rule", which required that trades be executed at prices close to those of immediately preceding trades.[8] Specialist were traditionally compensated in part through preferential access to the information contained in the book of unexecuted limit orders.

[7] See, for example, Hendershott, Jones, and Menkveld (2011) and Hendershott and Riordan (2013).
[8] See Panayides (2007) and the papers referenced there.

More recently, a number of European stock markets, including those based in Paris, Amsterdam, Stockholm, Olso, and Milan, introduced DMM contracts whereby individual firms could elect to hire a DMM to enhance liquidity in their own shares. These contracts typically call for the firm to pay the DMM a periodic fee in exchange for a requirement that the DMM enter orders sufficient to ensure that the quoted bid-ask spread does not exceed a specified maximum width. DMM contracts of this type were studied by Bessembinder, Hao, and Zheng (2015), Venkataraman and Waisburd (2007), Anand, Tanggaard, and Weaver (2009), Skjeltorp and Odegaard (2015), and Menkveld and Wang (2013). In addition, a number of derivative exchanges identify certain market participants as DMMs.[9]

The current NYSE DMM structure has been in effect since 2008, and is detailed in NYSE Rule 104. Unlike the DMM agreements adopted in several European markets, Rule 104 does not require the DMM to narrow the bid-ask spread, regardless of width. However, the agreement does require the DMM to maintain continuous two-sided quotes at some price, and to post quotes at prices that match the NBBO for a specified portion of the trading day. In addition, Rule 104 includes more qualitative requirements to "assist in the maintenance of a fair and orderly market insofar as reasonably practicable" and to "Assist the Exchange by providing liquidity as needed to provide a reasonable quotation." We focus on quantitative aspects of the NYSE DMM contract, in particular on the discrete shift in the explicit NYSE DMM obligation and in compensation that occur when prior month consolidated trading volume is less than vs. more than 1 million shares, while recognizing that qualitative aspects of performance may also be relevant to the NYSE's decision to retain DMMs.

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[9] For descriptions of some DMM programs, see https://www.cboe.org/general-info/liquidity-provider-info/designated-primary-market-maker-dpm-program-info (Chicago Board Options Exchange), http://www.eurexchange.com/exchange-en/resources/participant-list/market-making-futures (Eurex Futures), and http://business.nasdaq.com/media/NFX-DMM-Program-Tenders_tcm5044-51156.pdf (NFX Futures).

b. Strategic Complementarity

We show here that the enhanced NYSE DMM contract improves market liquidity and price efficiency. This evidence, obtained for a DMM contract that applies to all listed stocks, complements the findings of improved liquidity in the wake of the selective adoption of DMM contracts for some stocks on European Exchanges, as studied by Venkataraman and Waisburd (2007), Anand, Tanggaard, and Weaver (2009), Skjeltorp and Odegaard (2015), and Menkveld and Wang (2013).

Potentially more important, our evidence sheds light on the economics of competition in the business of liquidity supply. The shifts in NYSE DMM obligations and compensation at the 1 million share threshold are modest, yet we document substantial effects on liquidity and price discovery. In a similar vein, Anand, Tanggaard, and Weaver (2009) document substantial improvements in liquidity after the adoption of DMM contracts for certain stocks listed on the Stockholm Exchange, even though the magnitude of the direct compensation to DMM firms, presumably sufficient to offset any costs of providing additional liquidity, averages only about $3,000 per month. We propose that the reason that small changes in liquidity supply attributable to DMM contracts can have substantive effects on market outcomes is that the business of liquidity supply is characterized by "strategic complementarity."

Bulow, Geanakoplos and Klemperer (1985) introduced this term to refer to situations where an increase in an activity by one player increases the marginal benefit of that activity to other players, leading them to increase the activity as well. Strategic complementarity is potentially of first-order importance in financial markets, because it implies the existence of "amplification" effects, where the impact of a given exogenous shock is magnified by strategic interactions between players.

Amplification resulting from strategic interactions has been identified in a number of studies. Chen, Goldstein, and Jiang (2010) note that mutual fund outflows impose costs that are borne by investors who remain in the fund, implying that the marginal benefit of immediate exit increases when other investors exit. They show that this strategic complementarity manifests itself in stronger outflows in reaction to negative performance news at equity mutual funds that hold less liquid assets. Related, Goldstein, Jiang, and Ng (JFE, 2017) document an asymmetry whereby corporate bond mutual fund flows are more sensitive to negative than to positive performance news. The resulting "first seller" advantage implies that bond fund flows may amplify the effects of negative bond performance.

Barlevy and Veronesi (2000) present a model where asset prices depend both on information regarding fundamentals and on random liquidity shocks. They show that the acquisition of information regarding fundamental value by some traders can induce higher informational investment by others, particularly during times of negative shocks to fundamental values, when informed investors drive prices downwards and uninformed investors wish to learn whether the shock is fundamental or liquidity-driven. Goldstein and Yang (2015) develop a model where agents' receive signals regarding different aspects of fundamental value. They show that more aggressive information-based trading by those who receive one signal can reduce uncertainty regarding other aspects of information, thereby inducing additional information acquisition and more aggressive trading, and amplifying the effect of changes in information. Related, Cella, Ellul, and Giannetti (2013) show that, during times of market turmoil, "short horizon" investors sell more aggressively than others. They thus amplify the effect of negative market wide shocks by demanding liquidity when it is scarce.

Although amplification attributable to strategic interactions has been documented in prior studies, and market illiquidity contributes to strategic interactions in some cases, to our knowledge no prior study has assessed whether the business of liquidity provision is itself subject to strategic complementarity. We provide direct evidence on this issue by studying liquidity supply in NYSE stocks by agents both on and off the NYSE.

Stocks listed on the NYSE (as well as Nasdaq) are traded not just on the listing exchange, but on as many as nine other Exchanges and in dozens of off-exchange venues, including so-called “Dark Pools” and individual brokerage firms that “internalize” orders. The TAQ database upon which we rely records quotations and transactions from each exchange.[10] We assess whether the enhanced DMM contract alters the competitive strategies and outcomes for liquidity suppliers other than the DMM by studying quotations entered and trades executed for NYSE-listed stocks both off and on the NYSE.

Simply observing that liquidity on the NYSE is positively correlated with liquidity off the NYSE would not be sufficient to draw implications regarding potential strategic complementarity, as this result could simply reflect common variation in the costs of providing liquidity. However, since our regression discontinuity design focuses on contractually-induced shifts in liquidity supply that apply only to the NYSE DMM, we can directly test the strategic complementarity hypothesis by examining off-NYSE outcomes.

Our results show that the liquidity provision is indeed characterized by strategic complementarity, as the more binding DMM obligation on the NYSE results in higher rates of price improvement and lower effective bid-ask spreads *off* the NYSE. We conjecture that more

[10] Off-exchange trades are reported in the TAQ data as TRF (Trade Reporting Facility) transactions.

frequent and aggressive quotations from the NYSE DMM reduce competitors' marginal cost of providing liquidity, because non-NYSE liquidity providers understand that they can more readily unwind unwanted inventory positions against the NYSE DMM's quotations.

More broadly, the evidence of strategic complementarity in liquidity provision helps to explain the notion of illiquidity spirals, whereby a negative shock affecting some suppliers of liquidity cascades to reduce liquidity supply by competitors as well. Further, strategic complementarity in liquidity supply provides an explanation, distinct from the informational or risk sharing motives previously identified, for why a contract that has a modest direct effect on only a single market participant can result is a substantial enhancement of overall market quality.

III. The Regression Discontinuity Research Design

To identify the impact of the NYSE DMM contract on market quality, we use a regression discontinuity research design focused on the discrete shift in DMM obligations and compensation at one million shares average daily trading volume. The regression discontinuity design (RDD) is a quasi-experimental approach with the defining characteristic that the probability of receiving treatment changes discontinuously as a function of one or more underlying variables (Hahn, Todd, and van der Klaauw (2001), Cameron and Trivedi (2005)). RDD methods have been widely adopted in Economics and Finance research in recent years.[11]

In the research setting for this study, less than one million shares average daily trading volume in a calendar month corresponds to the treatment of the enhanced DMM contract, in that the DMM is required to maintain quotes at the NBBO for at least 15% of the time and receives a higher liquidity-supply rebate. Firm-months with trading volume of just more than one million

[11] See Kwan, Masulis, and McInish (2015) and Crane, Sébastien Michenaud, and Weston (2016), as a pair of examples among many.

shares provide the control, as the DMM is required to maintain quotes at NBBO only 10% of the day and receives a smaller rebate. Since the function that maps the distance between the average daily trading volume of a stock and the threshold into the treatment effect is discontinuous, our research design fits the regression discontinuity paradigm.

Our treatment variable is an indicator variable for the enhanced contract is defined as

$$DMM_{i,t} = \begin{cases} 1 \;\; if \; Vol_{i,t-1} - VT \; < 0 \\ 0 \;\; if \;\; Vol_{i,t-1} - \; VT > 0, \end{cases} \qquad (1)$$

where i and t index firm and year-month observations, $Vol_{i,t-1}$ is the monthly average consolidated daily trading volume in previous month, and VT is the treatment volume threshold which is at one million shares. Therefore, when the average daily trading volume of a stock in the previous month crosses this specified threshold, the DMM obligation and compensation changes in the current month. The enhanced DMM obligation and compensation stay in effect until the average daily trading volume in a month again crosses the threshold.

Following Imbens and Lemieux (2008), we estimate the following panel regression model:

$$y_{i,t} = \alpha + \beta_0 DMM_{i,t} + \beta_1 * (ln(Vol_{i,t-1}) - \ln(VT)) + \beta_2 * (ln(Vol_{i,t-1}) - \ln(VT)) \times DMM_{i,t}$$
$$+\eta_i + \nu_t + \varepsilon_{i,t}, \qquad (2)$$

where y_{it} is a measure of market quality or price efficiency, $DMM_{i,t}$ is the indicator variable that equals one if the DMM for stock i has a stronger minimum quoting time obligation, and zero otherwise, $Vol_{i,t-1}$ is the average consolidated daily trading volume in the previous month, VT is the threshold of one million shares in average consolidated daily trading volume for a calendar month, η_i is an indicator variable for firm i to allow for firm fixed effects, ν_t is an indicator variable for year-month t to allow for calendar fixed effects, and $\varepsilon_{i,t}$ is the error term. The parameter of interest is β_0, which measures the impact of the enhanced DMM contract. Given the inclusion of the firm fixed effect, identification of β_0 comes only from those firms that experience a shift of average daily trading volume across the one million shares threshold.

The nonlinear relation in equation (1) allows us to identify the treatment effect. That is, even if $\varepsilon_{i,t}$ is correlated with the difference, $\ln(Vol_{i,t-1}) - \ln(VC)$, estimates of β_0 are unbiased as long as $\varepsilon_{i,t}$ does not exhibit precisely the same discontinuity as $DMM_{i,t}$ (Lee and Lemieux (2010)). The intuition behind an RDD is that observations below and above the cutoff can be compared directly to draw inference on the effect of the treatment.

The design is valid if the stock's average daily trading volume in a month can be considered as good as randomly assigned below or above the threshold. A crucial feature of the RDD is that if individuals are unable to precisely manipulate the assignment variable then the variation in treatment near the threshold is randomized as though from a randomized experiment. Further, the key assumption that outcomes just above or below the cutoff occur randomly is empirically testable, as described by McCrary (2008). If the density of the assignment variable for each individual is continuous, then the marginal density of the assignment variable over the population should be continuous as well. In contrast, a jump in the density of the assignment variable at the threshold would provide evidence of endogenous selection, and would invalidate the appropriateness of the RD design.

In terms of our study, if DMMs or firms could manipulate the assignment variable by altering the consolidated (across markets trading NYSE-listed stocks) volume of trading, the RDD tests would not lead to valid inference. Figure 1 displays average monthly trading volume (rounded to 10,000) shares for sample stocks, and displays no obvious abnormalities in the vicinity of the 1 million share cutoff. To verify formally that the RDD provides for valid inference in our application, we implement the density discontinuity test of McCrary (2008) to check whether the density of the aggregated trading volume is continuous at the threshold. The results do not indicate any discontinuity at the threshold, implying that the RDD design is valid. In addition, we conduct placebo tests by implementing the RDD design for counter-factual volume cutoffs of 0.5 million and 1.5 million shares per day. None of the placebo tests indicates significant effects at the counterfactual volume cutoffs.

To identify the effects of the enhanced DMM contract, we estimate equation (2) on firm-day observations with trading volume close to the point of discontinuity. A key research design issue when implementing the RDD design is the selection of a "bandwidth", i.e. the range of volume around the one-million-share threshold used to estimate model parameters. The smaller the bandwidth the more accurate is the implicit assumption that firms are randomly assigned to either side of the one-million threshold. However, statistical power is reduced with a narrower bandwidth due to the smaller sample size. We assess the optimal bandwidth using the algorithm presented by Imbens and Kalyanaraman (2012).[12]

Our sample is drawn from the Trade-and-Quote (TAQ) database, and pertains to the period September 2009 to December 2013. NYSE Rule 104, amended effective October 2008, sets forth DMM obligations. Effective August 31, 2009, the Exchange amended Rule 104(a)(1) to increase the amount of time that a DMM unit must maintain a bid and offer at the inside from 10% to 15% for Less Active Securities and from 5% to 10% for More Active Securities[13]. The stated rationale was to improve market quality by increasing liquidity at the NBBO. We commence our sample period immediately thereafter, on September 1, 2009. The sample includes all NYSE-listed

[12] Imbens and Kalyanaraman (2012) propose a fully data-driven, asymptotically optimal bandwidth choice to achieve asymptotic optimality in the bias-variance trade-off.

[13] See Securities Exchange Act Release No. 60595 (August 31, 2009), 74 FR 46261 (September 8, 2009) (SR-NYSE-2009-91) (Notice of Filing) ("DMM quoting requirement filing") https://www.sec.gov/rules/sro/nyse/2009/34-60595.pdf.

common stocks for which the average consolidated daily trading volume is both less than and greater than the 1 million share threshold for at least one sample month. A total of 756 stocks meet this criterion.

Table 1 provides descriptive statistics for the sample. As these statistics depend on the bandwidth, we provide results for several bandwidths (the no bandwidth columns include all trading days). The tradeoffs involved in bandwidth selection can be readily observed. With no bandwidth restriction, the sample includes 628,766 firm-days, while by comparison a narrow bandwidth of 25,000 shares reduces the sample size to 16,074 firm-days. On the other hand, firms are much more closely matched in terms of characteristics that may be relevant to liquidity and market quality with the narrower bandwidth. In the absence of any bandwidth restriction the sample average market capitalization (shares outstanding times share price) for months with the less restrictive market-making obligation greatly exceeds ($4.95 billion vs. 2.93 billion) the mean for months with the more restrictive market-making obligation. In contrast, the match is much closer ($5.02 billion vs. $4.43 billion) with the 25,000 share bandwidth.

We compute both quoted and effective bid-ask spreads. The quoted spread is simply the difference between the best ask quote and the best bid quote, and measures the transaction cost for a round trip trade executed at the quotes. To allow for the fact that some trades occur at prices better or worse than the quotations, we also compute effective spreads as twice the signed difference between the trade price and the midpoint of the best bid and ask quotes at the time of the trade.[14] We express each spread measure in basis points, relative to the midpoint of the bid and ask prices at the time of the trade.

[14] For customer buys, the difference is the trade price less then quote midpoint, while for customer sells the difference is the quote midpoint less the trade price. Trades are assigned as customer buys or customer sells using the algorithm of Lee and Ready (1991), modified to compare trade prices to contemporaneous rather than lagged quotes.

Results with the narrow (25,000 share) bandwidth reported on Table 1 indicate that sample average quoted bid-ask spreads for stock-days with trading close to 1 million shares average about 10.5 to 11.5 basis points. Effective spreads are narrower (8.3 to 9.2 basis points), reflecting inside-the-quote executions. We also compute market depth, i.e. the average quantity of shares and dollar amount (price times quantity) of unexecuted orders at the best bid and offer quotes. Results on Table 1 indicate that, with the narrow bandwidth, depth averages about 1,500 to 1,800 shares, or $320,000.

IV. Empirical Results for the Overall Market

Following the suggestion of Lee and Lemieux (2010, Section 4.1), as well as Kwan, Masulis, and McInish (2015) and Crane, Sébastien, Michenaud, and Weston (2016), we graphically display in Figure 2 the empirical relation between each dependent variable and trading volume (having grouped the data for display purposes into fifty evenly displayed bins on each side of the threshold). On Tables 2 to 8 we report the results of estimating expression (2) for an array of market quality measures, based on market-wide outcomes. Tables 9 and 10 report the results of placebo tests where we estimate expression (2) for volume cutoffs other than the contractually-referenced 1 million share threshold. Finally, Tables 11 to 14 report the results of estimating (2) separately for NYSE vs. non-NYSE market quality variables. The key statistical tests reported on these Tables concern the coefficient estimate on DMM_{it}, which estimates the discontinuity in the regression estimates at the 1 million share threshold.

a. Bid-Ask Spreads

Table 2 reports results obtained when expression (2) is estimated with quoted and effective spreads as the dependent variable. Results are reported with bandwidths of 100,000 shares, 50,000 shares (the optimal bandwidth, according to the Imbens and Kalyanaraman (2012) test), and 25,000 shares.

Focusing on the results for the optimal bandwidth (middle columns of Table 2), the estimates indicate that the quoted bid-ask spread is reduced by 0.94 basis points when the designated market maker has the stronger obligation. By comparison, the average quoted spread in the vicinity of the one-million-share threshold (Table 1) is about ten to eleven basis points. The results on Table 2 also indicate lower effective bid-ask spreads with the stronger DMM obligation. The estimated reduction at the threshold is 0.87 basis points, compared to a sample average effective spread near the threshold of eight to nine basis points.

Clark-Joseph, Ye, and Zi (2016) previously showed that quoted spreads for NYSE stocks increased when the NYSE was forced to stop trading, and attributed the result to the removal of NYSE DMMs from the market. Our results support their interpretation, by showing directly that a reduced DMM market-making obligation is associated with wider quoted spreads.

The estimates of the bid-ask spread reductions reported on Table 2 imply substantial reductions in dollar amounts paid as transaction costs. The average daily trading volume for firms in the 50,000 share bandwidth sample during the months when stronger DMM obligation is in force is 974 thousand shares (Table 1). Given an average share price of $38.45, an effective spread reduction of 0.866 basis points implies a transaction cost reduction with the more stringent DMM obligation of about $817,000 per firm year.[15] Further, the estimated spread reductions are larger than the increase in the DMM rebate when the contract is enhanced. The increased rebate of $0.0005 is only about 0.13 basis points relative to an average event share price of $38.45. This

[15] $974,000 x 38.45 x 0.0000866 x 252 (trading days per year) = $817,000.

implies that average spread reduction of nearly one basis point is not simply attributable to competitive pass-through of the increased liquidity provision rebate.

Comparing the results for the optimal bandwidth discussed above with the results for the wider and narrower bandwidths presented in the left and right columns respectively in Table 2 shows the tradeoff between precision of estimation (significance level) and bias. With the smaller bandwidth and fewer observations, standard errors are larger. However, the smaller bandwidth also implies somewhat larger point estimates for the reduction in spreads when the DMM contract is enhanced. On balance, the results reported on Table 2 indicate that customers enjoy lower average trade execution costs for NYSE stocks when the NYSE DMM is required to provide more liquidity and receives higher rebates.

b. Market Depth

Table 3 reports results obtained when expression (2) is estimated with depth, measured both in shares and in dollars, as the dependent variable. Results are reported with bandwidths of 300,000 shares, 150,000 shares (the optimal bandwidth, according to the Imbens and Kalyanaraman (2012) test), and 70,000 shares. The estimated coefficient on DMM_{it} is positive and significant for the 70,000 share and optimal bandwidths. The estimated increase in depth is larger for the smallest bandwidth as compared to the optimal bandwidth, suggesting that the estimates obtained with the optimal bandwidth may be downward biased. In any case, our finding of greater market depth with the enhanced DMM contract contrasts with the Clark-Joseph, Ye, and Zi (2016) result that depth was not significantly changed when the NYSE ceased trading. That is, the results reported here indicate that a stronger NYSE DMM obligation is indeed associated with greater market depth, in addition to narrower bid-ask spreads. This result is not unanticipated, since the more binding obligation requires the DMM to contribute size to the NBBO quotes more frequently. Whether the result arises *solely* from the DMM obligation to quote at the NBBO more frequently cannot be ascertained based on the Table 3 results, because we cannot measure how often the requirement is binding. We provide additional evidence on this question when we examine depth on and off the NYSE in Section VI below.

c. Additional Control Variables

The finding documented here that liquidity is enhanced when the NYSE DMM contract is enhanced is more striking in light of the widely documented fact that liquidity tends to improve for more actively traded securities, while the DMM obligation binds when trading activity is lower. Specification (2) controls for the direct effects of trading activity by the inclusion of trading activity as an explanatory variable. However, the market microstructure literature has documented (e.g. Stoll (1978), Benston and Hagerman (1974), O'Hara (1995), and Demsetz (1968)) that additional variables, including share price and return volatility, have pervasive explanatory power for market liquidity.

To ensure that our key results are robust to variation in share price or return volatility that may accompany changes in volume, we report on Table 4 results obtained when spread and depth measures are the dependent variable, and inverse price and realized return volatility are included as additional explanatory variables in expression (2). Consistent with the prior literature, the results indicate that bid-ask spreads in basis points decline with share price (increase with inverse share price), and that depth in shares decreases with share price (increases with inverse share price). Also consistent with the prior literature, liquidity supply is reduced (spreads widen and depth declines) when return volatility is greater.

More important, the estimates on Table 4 show that the key conclusions obtained here, that quoted and effective spreads are significantly lower, and that depth measured in shares or dollars is significantly larger, when the DMM contract is enhanced continue to hold when additional explanatory variables are included in the regression.

d. Rates of Price Improvement

The fact that effective bid-ask spreads are narrower when the NYSE DMM contract is enhanced could result directly from the finding that quoted bid-ask spreads are narrower then. However, effective spreads are also potentially affected by trade executions at prices inside or outside of the best quotes. In fact, 19.4% of all transactions in our sample are executed at prices within (i.e. customer buys at prices lower than the best ask or sells at prices better than the best bid) the best quotes. We next assess whether the rate of price improvement, that is the percentage of trades executed at prices better than the NBBO quotes, is affected by the NYSE DMM obligation.

On Table 5 we report results of estimating expression (1) when the dependent variable is the rate of price improvement. The resulting coefficient estimate on the DMM indicator variable is positive and statistically significant for both the optimal bandwidth of 0.07 million shares and with a narrower bandwidth. That is, the results indicate that the enhanced DMM contract is associated with a higher rate of trade executions at prices better than the NBBO quotes. The NYSE DMM obligation involves matching, but does not require improvements on, the NBBO quotes. This finding is therefore important, because it shows that the improved market quality documented when the DMM contract is enhanced cannot arise solely as a mechanical outcome of the requirement to supply more liquidity, but instead indicates that the more frequent required presence of the DMM alters order submissions and the equilibrium in the market for liquidity provision.

e. Trading Volume

Improved market liquidity should, other things equal, attract additional trading activity. We next assess whether the enhanced DMM contract is associated with higher levels of trading. Since the enhancement of the DMM contract is triggered by low prior-month volume, the analysis focuses on the question of whether current month volume for stocks with low prior-month volume is greater than would be anticipated, after allowing for the continuous amount of prior month volume, return volatility, and share price.

Results obtained when estimating expression (2) for volume in shares are reported in Table 6, while Table 7 reports results for dollar volume. The coefficient estimates on DMM_{it} are uniformly positive and significant, for both share and dollar volume, for the optimal bandwidth as well as for narrower and broader bandwidths. The point estimates for both share and dollar volume are greater when the bandwidth is narrower, increasing for example from 0.0125 with a bandwidth of 0.27 million shares to 0.0326 with a bandwidth of 0.07 million shares when explaining the log of share volume. The results therefore imply increased trading activity as a result of enhancement of the DMM contract.

f. Price Efficiency

Finally, we assess the effect of an enhanced DMM contract on the efficiency of stock market prices. An efficient stock price is the present value of all expected future dividends to the share, when expectations are formed rationally based on all available information. Since expectations cannot be observed, we follow numerous prior authors (e.g. Barnea, 1974, Lo and

MacKinlay, 1988, Boehmer and Kelley, 2009) in assessing short run market efficiency by studying variance ratios. Price efficiency need not imply random walk behavior in prices, except under restrictive assumptions including a constant expected rate of return. Nevertheless, since the effects of changes in expected returns are mainly manifest at long time horizons, random walk behavior is widely taken as a reasonable market efficiency benchmark over short time horizons. In particular, we compute the variance of daily and weekly returns for each stock, and then assess the ratio of the weekly stock return variance to five time the daily stock return variance. If stock prices follow a random walk then this variance ratio should not differ systematically from a benchmark of one.

In Table 8 we report the results of estimating expression (2) when the dependent variable for each firm is the absolute value of the difference between the computed variance ratio and the efficient market benchmark of one. Results are reported for bandwidths of 500,000 shares, 250,000 shares (the optimal bandwidth per the Imbens and Kalyanaraman (2012) test), and 140,000 shares, with and without the inclusion of return volatility and inverse price as control variables.

The key result that can be observed in Table 8 is that the estimated coefficient on DMM_{it} is negative and statistically significant for each bandwidth, with and without the inclusion of control variables. The estimated reduction is largest (approximately 7.1%) when the bandwidth is narrowest, but is also substantial (approximately 4.3%) with the optimal bandwidth. That is, daily stock prices conform more closely to the random walk benchmark when the DMM contract is enhanced, supporting the reasoning that the price efficiency of the market is improved.

V. Placebo Tests

In the preceding sections we show that firm/months where the DMM market maker contract is enhanced are associated with narrower bid ask spreads, higher rates of price improvement, greater market depth, and more efficient prices. These results are perhaps surprising, in light of the fact that the DMM's explicit obligations associated with the enhanced contract appear to be rather minimal, involving only the requirement to maintain orders at prices that match the BBO quotes for an additional five percent of the time, and the increased rebates associated with the enhanced contract are relatively small, averaging only about 0.13 basis points relative to the share price. While the RDD research design we employ has desirable properties, and is capable of providing unbiased estimates of the causal effect of the DMM obligation under assumptions that appear to be satisfied, we cannot rule out that some unrecognized or omitted market feature causes the RDD design to identify spurious results.

To shed some light on the possibility that the results reported here could be spurious for unknown reasons, we repeat all tests using volume thresholds of 0.5 million shares per day in the prior month and 1.5 million shares per day in the prior month to define the DMM_{it} variable. These volume thresholds are in the general vicinity of the one million per share level that actually triggers the change in the DMM obligation, but do not trigger such changes. Results for quoted spreads, effective spreads, rates of price improvement, market depth in shares, market depth in dollars, abnormal stock returns, and the deviation of variance ratios from one are reported on Tables 9 and 10, based 0.5 million and 1.5 million share thresholds, respectively. Results in each case are based on the optimal bandwidth as specified by the Imbens and Kalyanaraman (2012) test.

The results in Tables 9 and 10 can be summarized succinctly. In no case is the coefficient estimate on the DMM_{it} indicator variable statistically significant when the indicator is defined based on counterfactual share volume cutoffs of 0.5 or 1.5 million shares per day. That is, none of the effects on liquidity and market quality documented here for the actual DMM obligation threshold of 1.0 million shares per day are observed for alternative thresholds. These results strongly support the interpretation that the improvements in market quality and improved price efficiency documented here for stock months where the DMM contract is enhanced are indeed attributable to the increased DMM obligations.

VI. On versus off NYSE Outcomes

A finding that market liquidity is improved at times when a contractual obligation to enhance liquidity as well as compensation for doing so becomes stronger could be viewed as uninformative, if the improved liquidity simply reflects the direct effects of the fulfillment of the enhanced obligations or the competitive pass-through of the enhanced compensation. However, the results here are informative, because the findings go far beyond any plausible mechanical effects. NYSE Rule 104 requires only that the DMM match the best bid or offer for a portion of the trading day, and does not require the DMM to narrow the bid-ask spread or to execute trades at prices better than the quotes. Further, the reductions in spreads that are observed are substantially larger than the enhanced rebates for liquidity supply. Thus, the DMM contract itself cannot mechanically explain the findings that quoted and effective spreads are narrowed, that the rate of price improvement is increased, or that price efficiency is enhanced when the DMM obligation is more binding.

Bulow, Geanakoplos and Klemperer (1985) introduce the notion of "strategic complements." In particular, Bulow, Geanakoplos and Klemperer refer to strategic complementarity in a situation where more "aggressive" play by one market participant leads to increased marginal profits (i.e. decreased marginal costs) for competing firms, causing them to respond by playing more aggressively as well. This mechanism is plausible in the case of DMM commitments, since other firms or individuals who also supply liquidity in the same stocks can be more certain that they will be able to offload unwanted inventory positions against the DMM's quotations. Strategic complementarity in financial markets may be of particular importance, because it would imply the existence of spill-over effects, where a shock to liquidity supplied by some participants would be associated with same-direction changes in liquidity supply by other market participants.

To investigate this possibility, we estimate expression (1) separately for market quality estimates measured separately on and off the NYSE, when the dependent variable is the rate of price improvement, the effective bid-ask spread, and market depth.[16] Figure 3 and 4 displays regression discontinuity plots constructed in the same manner as Figure 2, while Tables 11, 12, and 13, report the resulting coefficient estimates.

Focusing first on rates of price improvement, the results reported on Table 11 indicate a positive coefficient and statistically significant (t-statistics exceed 4.2) estimate on the DMM_t indicator variable for trades executed *off* the NYSE. In contrast, the coefficient estimate for trades executed on the NYSE is negative and insignificant. The results reported on Table 12 indicate significant reductions in effective bid-ask spreads at the discontinuity threshold both for trades executed off the NYSE and for trades executed on the NYSE, with the former slightly larger in absolute magnitude. The results reported on Table 13 show positive and significant coefficient

[16] We separate the depth at both the national best bid and national best offer into NYSE and non-NYSE components by maintaining a running count of the outstanding quantities at the best prices. We average on-NYSE and off-NYSE across the ask and bid sides as of the time of each quote update, and then compute the monthly average of each based on the elapsed time before the next quote that alters the NBBO depth.

estimates when explaining depth measured both in shares and in dollars from non-NYSE quotes, but insignificant coefficient estimates when explaining depth computed from NYSE quotes.

These results are potentially important, because they show that the enhanced NYSE DMM contract is associated with improved liquidity *off* the NYSE. Focusing on the price improvement outcome in particular, the "trade through" rule, mandated by U.S. Securities and Exchange Commission Regulation NMS in 2007 specifies that trades cannot be executed at prices inferior to the best quotation available on any electronically-accessible exchange, but does not require price improvement relative to the best quotes. And, NYSE Rule 104 itself never requires the DMM to quote at a price that improves on the NBBO quote. The improved rate of price discovery off the NYSE therefore reflects a change in equilibrium outcomes in the market for liquidity supply rather than any direct effect of the contract change. Similarly, since any direct effect of an enhanced obligation on the part of NYSE DMMs to quote at the NBBO should manifest itself in greater depth in the NYSE quotes, rather than an increase in off-NYSE depth, the results for market depth also indicate a spillover effect in liquidity supply.

Finally, we estimate expression (1) while using the NYSE share of overall market trading in sample stocks as the dependent variable. On Table 14 we report the results obtained when market share is measured based on the number of trades, number of shares traded, and dollar value of shares traded. In each case, and with or without the inclusion of volatility and share price as control variables, we find that the NYSE market share is significantly *lower* when the DMM contract is enhanced. This result also implies the existence of strategic interactions in liquidity supply across markets, because any direct effects of the DMM obligation should manifest themselves in greater depth and/or improved quotes on the NYSE, which would be anticipated to attract additional marketable orders, *ceteris paribus*.[17]

The finding that effective spreads are narrowed, depth is increased, and price improvement rates are increased off the NYSE when the NYSE DMM contract is enhanced provides strong, if indirect, evidence that the behavior of other market participants and the resulting market equilibrium is altered by the knowledge that the NYSE DMM will be present more frequently. This result is broadly consistent with the findings of Anand and Venkataraman (2016), who show that electronic liquidity providers on the Toronto Stock Exchange tend to increase their provision of liquidity at times when other market makers are also more active, because they are more confident that they can offload unwanted positions in the more active market. The fact that effective spreads are reduced both on and off the NYSE when the NYSE DMM contract is enhanced in particular supports the interpretation that the business of liquidity provision is characterized by strategic complementarity, as the term is used by Bulow, Geanakoplos and Klemperer (1985).

This result implies positive spillover effects in liquidity supply, and is potentially important to those who develop theoretical models of equilibrium in securities markets. The result also helps to understand why a DMM contract that applies to only a single market participant and that would appear to have only minor direct effects on the DMM's quotation behavior can have a more substantive effect on equilibrium liquidity supply. Finally, the result helps to explain illiquidity spirals, as a negative shock (e.g., due to deterioration in funding conditions or the value of

[17] Note that since market shares sum to one by construction, more aggressive quotations both on and off the NYSE must result in either no change in market shares or a decrease in share for either the NYSE or off-NYSE markets. That fact that the NYSE share declines when the DMM contract is enhanced is suggestive that off-NYSE liquidity providers and their customers benefit more from greater NYSE liquidity provision than vice versa.

collateral) to some participants' ability to supply liquidity can reduce liquidity supply by their competitors as well.

VII. Conclusions

A key question facing those who design or regulate securities markets is whether the electronic limit order book can attract sufficient liquidity endogenously, i.e., in the absence of any specific measures to encourage liquidity provision. Although a number of stock markets have adopted designated market makers (DMMs) for at least some stocks, our collective understanding of the importance and desirability of DMM contracts remains quite incomplete.

We contribute to the understanding of these issues by studying DMMs on the New York Stock Exchange. Since the NYSE designates a DMM for every stock, possible selection bias in the securities with DMMs is not a concern with our research design. We exploit the fact that NYSE Rule 104 specifies a discontinuity in both DMM obligations and compensation. In particular, they are (i) required to maintain orders at the NBBO more frequently and (ii) receive larger rebates for supplying liquidity for stocks where the prior month average daily volume was less than a threshold level of one million shares.

In particular, we use a Regression Discontinuity research design to estimate the causal effect of more stringent DMM obligations on liquidity, share valuation, and price efficiency. The RDD design can provide unbiased estimates of the causal effect of a change in DMM obligations and incentives. At the same time, the Regression Discontinuity approach by design provides estimates that are local, applying at the point of discontinuity, which in this case is 1 million shares of average daily trading volume. It should also be recognized that the method identifies the effects of changes in the DMM contract at the point of discontinuity, and cannot necessarily be extrapolated estimate the effects of implementing or canceling a DMM contract.

Our results indicate the enhanced DMM contract in effect when prior month volume is less than 1 million shares are associated with improved liquidity, in the form of lower average quoted and effective bid-ask spreads, as well as higher rates of price improvement and higher trading volume. These results therefore support Clark-Joseph, Ye, and Zi (2016) in their interpretation that the widening of quoted spreads observed when the NYSE abruptly ceased trading on July 8, 2015, was indeed attributable at least in part to the fact that the NYSE DMMs were removed from the market. However, our evidence is more specific, in that we can link market quality directly to changes in the DMM obligation, without the potentially confounding effects of removing the entire NYSE trading structure from the market. In addition to documenting that the DMM contract affects liquidity, we show that stock prices conform more closely to the random walk benchmark when the DMM contract is enhanced.

In addition to using the RDD design to document improved market quality when the DMM contract is enhanced based on the actual 1 million shares trading volume threshold, we show that the RDD method does not indicate any statistically significant results when we implement placebo tests based on counterfactual share volume thresholds of 0.5 million shares or 1.5 million shares. This evidence strongly supports the reasoning that the RDD method has identified causal effects of the NYSE DMM contract on market quality and firm value.

While the results reported here are informative, they are also in some ways puzzling. The NYSE DMM contract calls only for the DMM to maintain orders that match the best bid and offer for a relatively small percentage of each trading day. The contract does not require that the DMM narrow bid-ask spreads by entering orders at prices superior to the NBBO quotes. Further, the enhanced rebates for supplying liquidity in low volume stocks amounts to only about 0.13 basis points relative to share prices. As a consequence, the observed magnitudes of the improvements in bid ask spreads and rates of price improvement, the increased trading activity, and the improved price efficiency associated with the more stringent DMM obligations are unlikely to simply arise mechanically. One possibility, as suggested by Corwin and Coughenour (2008) is that DMMs have limited attention, and that the more binding DMM constraint motivates them to focus their attention on stocks with the more binding obligation. However, this perspective cannot provide a complete explanation, as we find that rates of price improvement are increased, market depth is increased, and average effective spreads are decreased when the NYSE DMM contract is enhanced *even for trades executed off the NYSE.*

These results provide strong, if indirect, evidence that the knowledge that NYSE DMMs will be present more frequently affects other traders' order submission strategies and equilibrium in the market for liquidity. In particular, the results support the reasoning that market making equilibrium is characterized by strategic complementarity in the sense of Bulow, Geanakoplos and Klemperer (1985), where more aggressive play by one supplier (the DMM) results in decreased marginal costs for competitors. This result would arise if competitors are more certain that they can unwind unwanted inventory positions when the DMM obligation is more binding. The existence of strategic complementarity implies positive spillover effects in the business of liquidity supply. Such positive spillovers are important for theoreticians seeking to develop models of security market equilibrium, and also help to understand both the existence of illiquidity spirals and the fact that seemingly small DMM obligations can have substantive effects on equilibrium liquidity. Developing models that allow for such spillovers to gain an improved understanding of how the presence of contractually-required DMM orders alters other traders' behavior and equilibrium outcomes comprises an important challenge for future research.

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Figure 1: Distribution of Trading Volume

This figure displays the frequency distribution of the consolidated average daily trading volume around one million shares during calendar month t for the sample stocks. Each observation is assigned to a 10,000 share category for display purposes. The sample includes all stocks that at least have one change in DMM obligation during the period of Oct. 2009 to Dec. 2013.

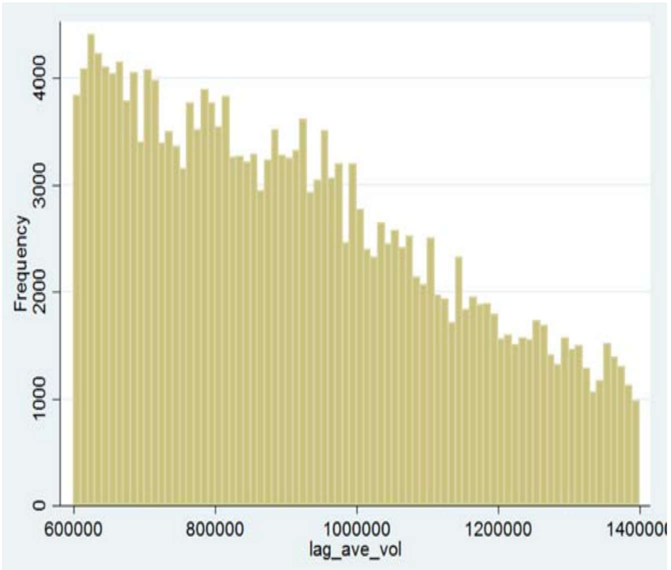

Figure 2: Regression Discontinuity Plots

These figures display the functional form and a fitted regression curve of the market quality measures for the group of stocks that crosses the trading volume threshold for changes in DMM obligations during the time period from Sep. 2009 to Dec. 2013. The Y axis displays market quality measures. The X axis represents a firm's aggregated average daily trading volume in calendar month t-1. The vertical line is the cutoff point, one million shares. Firms on the left (right) side are treatment (control) groups with less than (equal to or more than) one million shares average daily trading volume in month t-1 and are associated with stronger (weaker) DMM obligation in month t. The regression discontinuity plots represent local sample means using 50 non-overlapping evenly-spaced bins on both sides of the threshold following the methodology described in Calonico et al. (2014). The line represents a first-order polynomial regression curve.

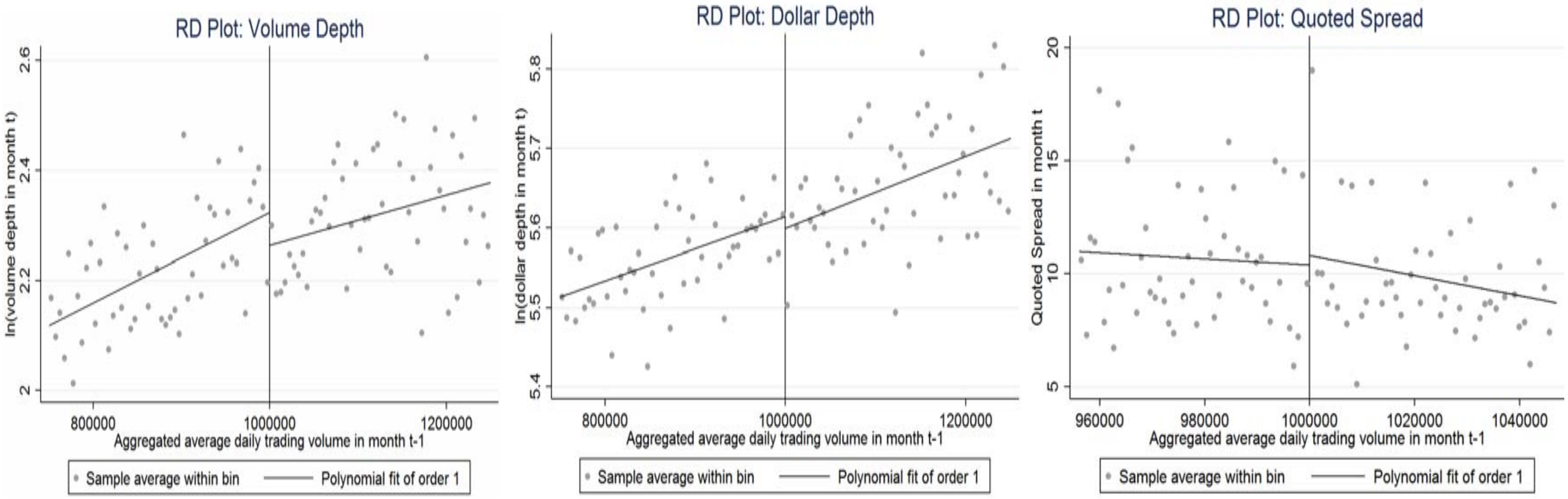

Figure 2: Regression Discontinuity Plots (cont.)

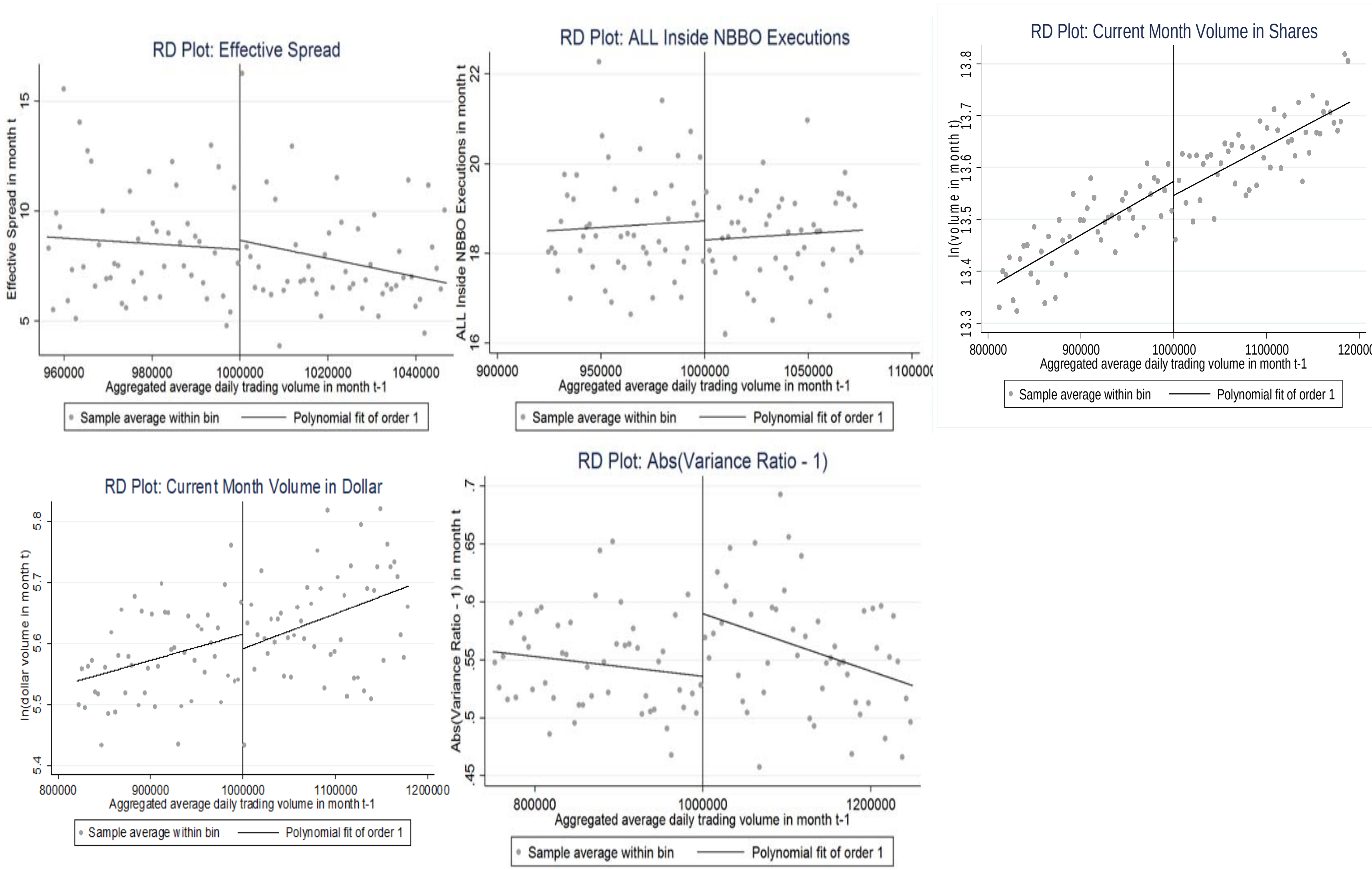

Figure 3: Regression Discontinuity Plots for On-NYSE and OFF-NYSE Transactions

These figures display the functional form and a fitted regression curve of the percentage of NBBO executions and effective spread for On-NYSE and OFF-NYSE Transactions for the group of stocks that crosses the trading volume threshold for changing DMM obligations during the time period from Sep. 2009 to Dec. 2013. The X axis represents a firm's aggregated average daily trading volume in calendar month t-1. The vertical line is the cutoff point, one million shares. Firms on the left (right) side are treatment (control) groups with less than (equal to or more than) one million shares average daily trading volume in month t-1 and are associated with stronger (weaker) DMM obligation in month t. The regression discontinuity plots represent local sample means using 50 none-overlapping evenly-spaced bins on both sides of the threshold following the methodology described in Calonico et al. (2014). The fitted lines represent the first-order polynomial regression curves.

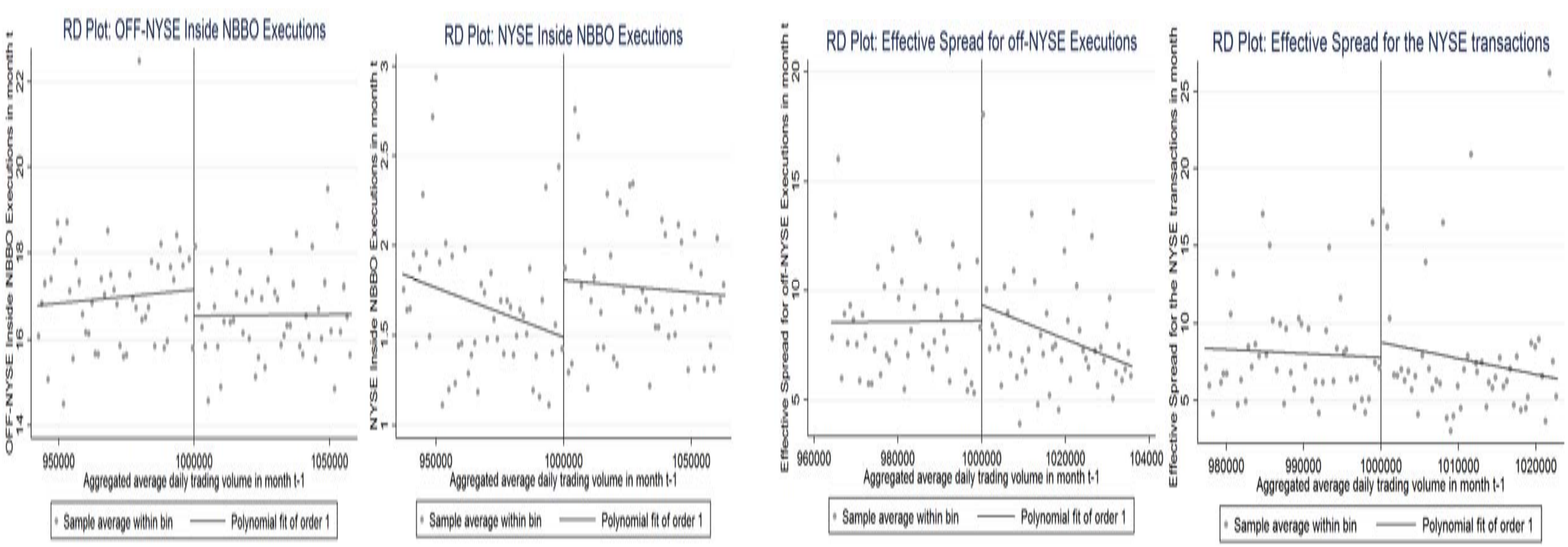

Figure 4: Regression Discontinuity Plots for On-NYSE and OFF-NYSE Depths

These figures display the functional form and a fitted regression curve of the volume depth and dollar depth at the NBBO from NYSE and none-NYSE of the group of stocks that crosses the trading volume threshold for changing DMM obligations during the time period from Sep. 2009 to Dec. 2013. The X axis represents a firm's aggregated average daily trading volume in calendar month t-1. The vertical line is the cutoff point, one million shares. Firms on the left (right) side are treatment (control) groups with less than (equal to or more than) one million shares average daily trading volume in month t-1 and are associated with stronger (weaker) DMM obligation in month t. The regression discontinuity plots represent local sample means using 50 none-overlapping evenly-spaced bins on both sides of the threshold following the methodology described in Calonico et al. (2014a). The fitted lines represent the first-order polynomial regression curves.

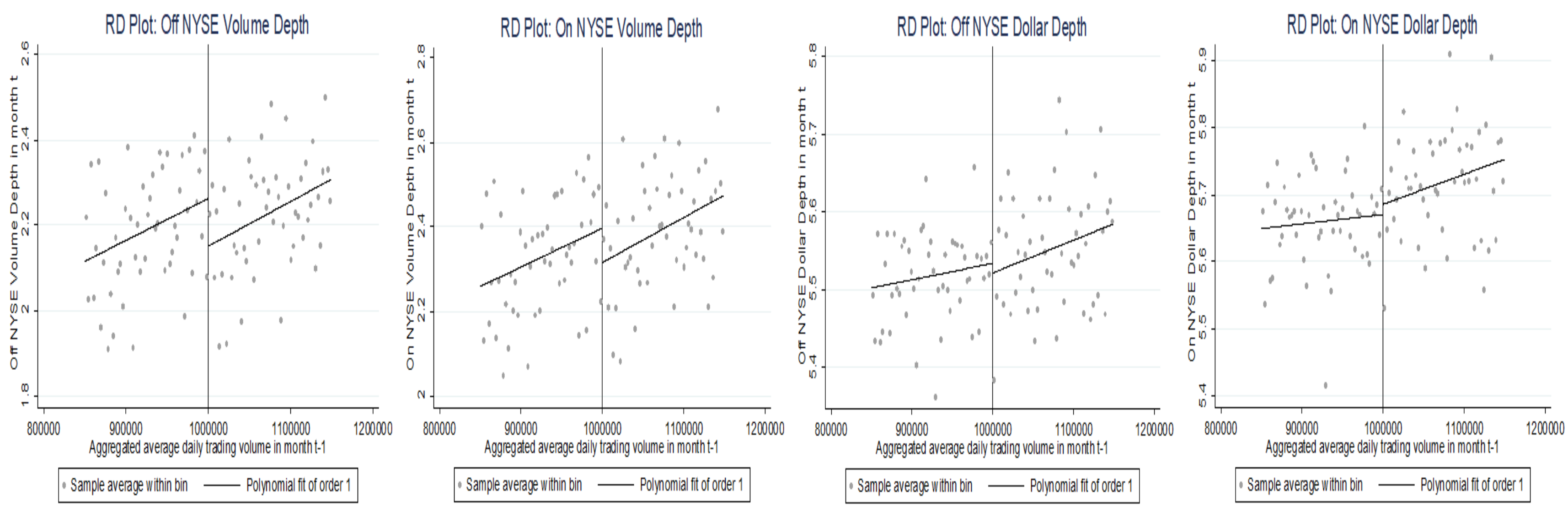

Table 1: Sample Summary Statistics

This table reports descriptive statistics for all stocks (bandwidth = none) that have at least one shift from consolidated average daily trading volume during a calendar month below one million shares to above one million shares or vice versa between Sep. 2009 and Dec. 2013. This table also reports descriptive statistics for the subsets of stocks with bandwidths of 0.5, 0.1, 0.05, and 0.025 million shares. For each bandwidth, we report the number of firms, firm-months, and firm-days. Within each bandwidth, we report the descriptive statistics for the treatment group with stronger DMM obligation and the control group with weaker DMM obligation, respectively. Consolidated average daily trading volume is in thousands of shares; market capital is in million dollars; price of the stock is in dollars; turnover and stock daily return volatility are in percentage; quoted spread, and effective spread are in basis points; volume depth is in shares; dollar depth is in thousands of dollar.

Bandwidth (million shares)	none		0.5		0.1		0.05		0.025	
Number of firms	756		738		606		512		399	
Number of firm-months	30,819		16,228		3,196		1,585		726	
Number of firm-days	628,766		336,850		66,409		33,019		16,074	
Stronger DMM obligation	1	0	1	0	1	0	1	0	1	0
consolidated average daily trading volume (1000s)	537	1,845	730	1,222	949	1,049	974	1,025	988	1,012
Market Capitalization ($mil)	2,933	4,946	3,892	5,003	4,584	5,030	4,637	5,013	4,425	5,020
Share Price ($)	33.55	34.39	39.80	37.91	38.71	39.61	38.45	39.93	36.84	39.47
Turnover (%)	0.98	1.73	1.11	1.36	1.21	1.23	1.20	1.20	1.23	1.15
Return Standard Deviation (%)	2.33	2.41	2.20	2.24	2.27	2.17	2.27	2.17	2.40	2.15
Quoted Spread (basis points)	19.25	10.34	11.77	10.06	10.71	10.13	10.84	10.18	11.45	10.44
Effective Spread (basis points)	14.97	8.47	9.29	8.10	8.59	8.07	8.65	8.10	9.16	8.34
Volume Depth（shares）	1,331	2,659	1,369	1,956	1,642	1,606	1,724	1,491	1,814	1,509
Dollar Depth(1000$)	23.61	41.11	28.32	35.81	31.64	33.25	31.88	32.45	32.03	32.26

Table 2: Regression discontinuity tests: Bid-Ask Spreads

This table reports the results of estimating the regression discontinuity specification (2) for quoted and effective bid-ask spreads, for stocks that cross the trading volume threshold during the time period from Sep. 2009 to Dec. 2013. We estimate the following panel regression model:

$$y_{i,t} = \alpha + \beta_0 DMM_{i,t} + \beta_1\big(\ln(Vol_{i,t-1}) - \ln(VC)\big) + \beta_2\big(\ln(Vol_{i,t-1}) - \ln(VC)\big)DMM_{i,t} + \eta_i + \nu_t + \varepsilon_{i,t}$$

where $y_{i,t}$ is percentage quoted spread and effective spread. $Vol_{i,t-1}$ is the consolidated average daily trading volume during calendar month t-1 for stock i in shares, $DMM_{i,t}$ is an indicator that takes the value of 1 if $Vol_{i,t-1}$ is less than one million shares and a value of 0 if $Vol_{i,t-1}$ is equal to or greater than the one million shares, $Vol_{i,t-1}$ is reduced by VC (one-million-share threshold) to have the threshold at zero. Spreads are in basis points. Estimation uses a panel regression with firm fixed effects, η_i, year-month fixed effects, ν_t, and robust standard errors are clustered by firm. We report results with three different bandwidths, including the optimal one is based on Calonico et al. (2014). T-statistics are shown below the coefficient estimates. ***, **, and * indicate a significance level of 1%, 5%, and 10%, respectively.

	Bandwidth (0.1 million shares)		Optimal Bandwidth (0.05 million shares)		Bandwidth (0.025 million shares)	
	Quoted Spread	Effective Spread	Quoted Spread	Effective Spread	Quoted Spread	Effective Spread
DMM	0.00678	-0.0576	-0.941**	-0.866**	-1.276*	-1.276**
	(0.02)	(-0.19)	(-2.15)	(-2.09)	(-1.91)	(-1.99)
ln(Vol)-ln(VC)	-3.427	-4.190	-10.64	-12.40*	-76.87*	-81.37**
	(-0.61)	(-0.88)	(-1.09)	(-1.32)	(-1.83)	(-2.22)
(ln(Vol)-ln(VC))DMM	1.032	1.413	-4.968	2.122	79.40	94.46**
	(0.15)	(0.25)	(-0.42)	(0.19)	(1.46)	(2.04)
FE	Yes	Yes	Yes	Yes	Yes	Yes
N	55,834	55,834	27,970	27,970	13,431	13,431
adj. R-sq.	0.727	0.696	0.709	0.624	0.785	0.685

Table 3: Regression discontinuity tests: Depth

This table reports the results of estimating the regression discontinuity specification (2) for depth at the BBO, for stocks that cross the trading volume threshold during the time period from Sep. 2009 to Dec. 2013. We estimate the following panel regression model:

$$y_{i,t} = \alpha + \beta_0 DMM_{i,t} + \beta_1\left(\ln(Vol_{i,t-1}) - \ln(VC)\right) + \beta_2\left(\ln(Vol_{i,t-1}) - \ln(VC)\right)DMM_{i,t} + \eta_i + \nu_t + \varepsilon_{i,t}$$

Where $y_{i,t}$ is ln(volume depth), and ln(dollar depth). $Vol_{i,t-1}$ is the consolidated average daily trading volume during calendar month t-1 for stock i in shares, $DMM_{i,t}$ is an indicator that takes the value of 1 if $Vol_{i,t-1}$ is less than the one million shares and a value of 0 if $Vol_{i,t-1}$ is equal to or greater than one million shares, $Vol_{i,t-1}$ is reduced by VC (one-million-share threshold) to have the threshold at zero. Volume depth is in number of round lots, and dollar depth is in hundreds of dollar. Estimation is done using a panel regression with firm fixed effects, η_i, year-month fixed effects, ν_t, and the robust standard errors are clustered by firm. We report results with three different bandwidths, where the optimal one is based on Calonico et al. (2014). T-statistics are shown below the coefficient estimates. ***, **, and * indicate a significance level of 1%, 5%, and 10%, respectively.

	Bandwidth (0.30 million shares)		Optimal Bandwidth (0.15 million shares)		Bandwidth (0.07 million shares)	
	ln(Volume Depth)	ln(Dollar Depth)	ln(Volume Depth)	ln(Dollar Depth)	ln(Volume Depth)	ln(Dollar Depth)
DMM	-0.0007	-0.0016	0.0113**	0.0103**	0.0208**	0.0355***
	(-0.20)	(-0.44)	(2.18)	(2.08)	(2.61)	(4.63)
ln(Vol)-ln(VC)	0.321***	0.166***	0.316***	0.175***	0.806***	0.630***
	(15.68)	(8.58)	(6.39)	(3.73)	(5.56)	(4.53)
(ln(Vol)-ln(VC))DMM	-0.122***	0.0872**	0.0958	0.163**	-.253	-0.0228
	(-5.19)	(3.93)	(1.55)	(2.78)	(-1.30)	(-0.12)
FE	Yes	Yes	Yes	Yes	Yes	Yes
N	160,780	160,780	82,518	82,518	38,905	38,905
adj. R-sq.	0.823	0.671	0.843	0.689	0.853	0.699

Table 4: Regression discontinuity tests with additional controls: Spread and Depth

This table reports the results of estimating the regression discontinuity specification (2) for different spread measures, for stocks that cross the trading volume threshold during the time period from Sep. 2009 to Dec. 2013. We estimate the following panel regression model:

$$y_{i,t} = \alpha + \beta_0 DMM_{i,t} + \beta_1\big(\ln(Vol_{i,t-1}) - \ln(VC)\big) + \beta_2\big(\ln(Vol_{i,t-1}) - \ln(VC)\big)DMM_{i,t} + \gamma\, X_{i,t-1} + \eta_i + \nu_t + \varepsilon_{i,t}$$

Where $y_{i,t}$ is percentage quoted spread, effective spread, ln(volume depth), and ln(dollar depth). $Vol_{i,t-1}$ is the consolidated average daily trading volume during calendar month t-1 for stock i in shares, $DMM_{i,t}$ is an indicator that takes the value of 1 if $Vol_{i,t-1}$ is less than one million shares and a value of 0 if $Vol_{i,t-1}$ is equal to or greater than one million shares, $Vol_{i,t-1}$ is reduced by VC (one-million-share threshold) to have the threshold at zero. Spreads are in basis points, and volume depth is in number of round lots, and dollar depth is in hundreds of dollar. $X_{i,t-1}$ represents a set of controlling variables, including intraday realized volatility and inverse price. Estimation is done using a panel regression with firm fixed effects, η_i, year-month fixed effects, ν_t, and the robust standard errors are clustered by firm. We report results with the optimal bandwidth based on Calonico et al. (2014). T-statistics are shown below the coefficient estimates. ***, **, and * indicate a significance level of 1%, 5%, and 10%, respectively.

	Optimal Bandwidth (0.05 million shares)		Optimal Bandwidth (0.15 million shares)	
	Quoted Spread	Effective Spread	ln(Volume Depth)	ln(Dollar Depth)
DMM	-0.807**	-0.736**	0.0127**	0.0114**
	(-2.23)	(-2.07)	(2.46)	(2.32)
ln(Vol)-ln(VC)	-11.88	-13.60	0.281***	0.217***
	(-1.27)	(-1.47)	(5.74)	(4.66)
(ln(Vol)-ln(VC))DMM	1.833	8.714	0.154**	0.112*
	(0.14)	(0.75)	(2.53)	(1.93)
Realized Volatility	0.0110**	0.0107**	-0.0005***	-0.0006***
	(2.07)	(2.26)	(-8.41)	(-9.28)
Inv. Price	41.97***	40.70***	0.861***	-0.797***
	(3.12)	(3.85)	(38.19)	(-37.21)
FE	Yes	Yes	Yes	Yes
N	27,970	27,970	82,518	82,518
adj. R-sq.	0.714	0.630	0.846	0.695

Table 5: Regression discontinuity tests without/with additional controls: Rate of Price Improvement

This table reports the results from the analysis using the regression discontinuity specification (2) with the rate of price improvement as dependent variable on stocks that cross the trading volume threshold during the time period from Sep. 2009 to Dec. 2013. We estimate the following panel regression model:

$$y_{i,t} = \alpha + \beta_0 DMM_{i,t} + \beta_1\big(\ln(Vol_{i,t-1}) - \ln(VT)\big) + \beta_2\big(\ln(Vol_{i,t-1}) - \ln(VT)\big)DMM_{i,t} + \gamma\, X_{i,t-1} + \eta_i + \nu_t + \varepsilon_{i,t}$$

where $y_{i,t}$ is the percentage of transactions executed within the NBBO quotes for stock i in calendar month t, $Vol_{i,t-1}$ is the consolidated average daily trading volume during calendar month t-1 for stock i in shares, $DMM_{i,t}$ is an indicator that takes the value of 1 if a stock is associated with a stronger DMM obligation, i.e., its $Vol_{i,t-1}$ is less than the one million shares, and a value of 0 if a stock is associated with a weaker DMM obligation, i.e., its $Vol_{i,t-1}$ is equal to or greater than one million shares, $Vol_{i,t-1}$ is reduced by VT (one-million-share threshold) to have the threshold at zero, and $X_{i,t-1}$ represents a set of controlling variables, including intraday realized volatility and inverse price. Estimation is done using a panel regression with firm fixed effects, η_i, year-month fixed effects, ν_t, and the robust standard errors are clustered by firm. We report results based on all executions within NBBO with three different bandwidths, where the optimal one is based on Calonico et al. (2014). T-statistics are shown below the coefficient estimates. ***, **, and * indicate a significance level of 1%, 5%, and 10%, respectively.

	Execution within NBBO					
	Bandwidth (0.14 million shares)		Optimal Bandwidth (0.07 million shares)		Bandwidth (0.035 million shares)	
DMM	0.0689	0.0827	0.327***	0.324***	0.358***	0.388***
	(1.22)	(1.46)	(3.88)	(3.85)	(2.76)	(2.99)
ln(Vol)-ln(VT)	-1.122**	-1.184**	3.354**	2.536*	5.724	6.869
	(-2.00)	(-2.11)	(2.20)	(1.67)	(1.24)	(1.49)
(ln(Vol)-ln(VT))DMM	-1.539**	-1.451**	-2.269	-1.275	-5.059	-6.011
	(-2.16)	(-2.04)	(-1.07)	(-0.60)	(-0.73)	(-0.87)
Realized Volatility		0.0668***		0.0768***		0.0537***
		(8.99)		(6.87)		(2.87)
Inv. Price		-7.393***		-10.37***		-11.20***
		(-16.41)		(-15.93)		(-9.75)
FE	Yes	Yes	Yes	Yes	Yes	Yes
N	99,598	99,598	50,378	50,378	25,720	25,720
adj. R-sq.	0.573	0.574	0.592	0.594	0.610	0.612

Table 6: Regression discontinuity tests without/with additional controls: Volume in Shares

This table reports the results from the analysis using the regression discontinuity specification (2) with the daily volume in shares as dependent variable on stocks that cross the trading volume threshold at least once during the time period from Sep. 2009 to Dec. 2013. We estimate the following panel regression model:

$$y_{i,t} = \alpha + \beta_0 DMM_{i,t} + \beta_1\left(\ln(Vol_{i,t-1}) - \ln(VT)\right) + \beta_2\left(\ln(Vol_{i,t-1}) - \ln(VT)\right)DMM_{i,t} + \gamma\, X_{i,t-1} + \eta_i + \nu_t + \varepsilon_{i,t}$$

where $y_{i,t}$ is the natural logarithm of daily volume in shares for stock i in calendar month t, $Vol_{i,t-1}$ is the consolidated average daily trading volume during calendar month t-1 for stock i in shares, $DMM_{i,t}$ is an indicator that takes the value of 1 if a stock is associated with a stronger DMM obligation, i.e., its $Vol_{i,t-1}$ is less than the one million shares, and a value of 0 if a stock is associated with a weaker DMM obligation, i.e., its $Vol_{i,t-1}$ is equal to or greater than one million shares, $Vol_{i,t-1}$ is reduced by VT (one-million-share threshold) to have the threshold at zero, and $X_{i,t-1}$ represents a set of controlling variables, including intraday realized volatility and inverse price. Estimation is done using a panel regression with firm fixed effects, η_i, year-month fixed effects, ν_t, and the robust standard errors are clustered by firm. We report results based on all executions within NBBO with three different bandwidths, where the optimal one is based on Calonico et al. (2014). T-statistics are shown below the coefficient estimates. ***, **, and * indicate a significance level of 1%, 5%, and 10%, respectively.

	Ln(Daily Trading Volume in Shares)					
	Bandwidth (0.27 million shares)		Optimal Bandwidth (0.135 million shares)		Bandwidth (0.07 million shares)	
DMM	0.0127**	0.0125**	0.0314***	0.0297***	0.0338***	0.0326***
	(2.42)	(2.38)	(3.96)	(3.97)	(2.93)	(2.82)
ln(Vol)-ln(VT)	0.614**	0.615***	0.727***	0.685***	1.045***	1.054***
	(21.33)	(21.36)	(8.69)	(9.65)	(4.98)	(5.02)
(ln(Vol)-ln(VT))DMM	-0.134***	-0.136***	-0.193*	-0.137	-0.754***	-0.789***
	(-4.06)	(-4.14)	(-1.85)	(-1.55)	(-2.68)	(-2.79)
Realized Volatility		0.0002***		0.0004***		0.0003**
		(2.90)		(3.82)		(2.48)
Inv. Price		-0.113***		-0.105***		-0.0649
		(-5.44)		(-3.21)		(-0.87)
FE	Yes	Yes	Yes	Yes	Yes	Yes
N	160,780	160,780	82,518	82,518	38,905	38,905
adj. R-sq.	0.213	0.214	0.184	0.181	0.206	0.206

Table 7: Regression discontinuity tests without/with additional controls: Volume in Dollar

This table reports the results from the analysis using the regression discontinuity specification (2) with the daily volume in dollar as dependent variable on stocks that cross the trading volume threshold at least once during the time period from Sep. 2009 to Dec. 2013. We estimate the following panel regression model:

$$y_{i,t} = \alpha + \beta_0 DMM_{i,t} + \beta_1\big(\ln(Vol_{i,t-1}) - \ln(VT)\big) + \beta_2\big(\ln(Vol_{i,t-1}) - \ln(VT)\big)DMM_{i,t} + \gamma\, X_{i,t-1} + \eta_i + \nu_t + \varepsilon_{i,t}$$

where $y_{i,t}$ is the natural logarithm of daily volume in dollar for stock i in calendar month t, $Vol_{i,t-1}$ is the consolidated average daily trading volume during calendar month t-1 for stock i in shares, $DMM_{i,t}$ is an indicator that takes the value of 1 if a stock is associated with a stronger DMM obligation, i.e., its $Vol_{i,t-1}$ is less than the one million shares, and a value of 0 if a stock is associated with a weaker DMM obligation, i.e., its $Vol_{i,t-1}$ is equal to or greater than one million shares, $Vol_{i,t-1}$ is reduced by VT (one-million-share threshold) to have the threshold at zero, and $X_{i,t-1}$ represents a set of controlling variables, including intraday realized volatility and inverse price. Estimation is done using a panel regression with firm fixed effects, η_i, year-month fixed effects, ν_t, and the robust standard errors are clustered by firm. We report results based on all executions within NBBO with three different bandwidths, where the optimal one is based on Calonico et al. (2014). T-statistics are shown below the coefficient estimates. ***, **, and * indicate a significance level of 1%, 5%, and 10%, respectively.

	Ln(Daily Trading Volume in Dollar)					
	Bandwidth (0.27 million shares)		Optimal Bandwidth (0.135 million shares)		Bandwidth (0.07 million shares)	
DMM	0.0123**	0.0126**	0.0298***	0.0288***	0.0495***	0.0361***
	(2.12)	(2.22)	(3.66)	(3.59)	(3.98)	(2.95)
ln(Vol)-ln(VT)	0.463***	0.480***	0.541***	0.621***	0.875***	1.128***
	(14.56)	(15.37)	(6.98)	(8.14)	(3.87)	(5.06)
(ln(Vol)-ln(VT))DMM	0.0771**	0.0453	-0.0541	-0.175*	-0.487	-1.201***
	(2.12)	(1.27)	(-0.56)	(-1.84)	(-1.61)	(-4.01)
Realized Volatility		0.0001		0.0003***		0.0002
		(1.13)		(3.09)		(1.57)
Inv. Price		-1.744***		-1.814***		-2.765***
		(-77.70)		(-51.68)		(-35.04)
FE	Yes	Yes	Yes	Yes	Yes	Yes
N	160,780	160,780	82,518	82,518	38,905	38,905
adj. R-sq.	0.761	0.770	0.770	0.777	0.787	0.794

Table 8: Regression discontinuity tests without/with additional controls: Price Efficiency

This table reports the results of estimating the regression discontinuity specification (2) for the price efficiency measure, for stocks that cross the trading volume threshold during the time period from Sep. 2009 to Dec. 2013. We estimate the following panel regression model:

$$y_{i,t} = \alpha + \beta_0 DMM_{i,t} + \beta_1\big(\ln(Vol_{i,t-1}) - \ln(VC)\big) + \beta_2\big(\ln(Vol_{i,t-1}) - \ln(VC)\big)DMM_{i,t} + \gamma\, X_{i,t-1} + \eta_i + \nu_t + \varepsilon_{i,t}$$

where $y_{i,t}$ is the absolute value of the difference between one and the variance ratio of weekly return to five times of the daily return for stock i in calendar month t. $Vol_{i,t-1}$ is the consolidated average daily trading volume during calendar month t-1 for stock i in shares. $DMM_{i,t}$ is an indicator that takes the value of 1 if a stock is associated with strong DMM obligation, i.e., its $Vol_{i,t-1}$ is less than the one million shares, and a value of 0 if a stock is associated with weaker DMM obligation, i.e., its $Vol_{i,t-1}$ is equal to or greater than one million shares. $Vol_{i,t-1}$ is reduced by VC (one-million-share threshold) to have the threshold at zero. $X_{i,t-1}$ represents a set of controlling variables, including intraday realized volatility and inverse price. Estimation is done using a panel regression with firm fixed effects, η_i, year-month fixed effects, ν_t, and the robust standard errors are clustered by firm. We report results with three different bandwidths, where the optimal one is based on Calonico et al. (2014). T-statistics are shown below the coefficient estimates. ***, **, and * indicate a significance level of 1%, 5%, and 10%, respectively.

	Abs |VR-1|					
	Bandwidth (0.5 million shares)		Optimal Bandwidth (0.25 million shares)		Bandwidth (0.14 million shares)	
DMM	-0.0286*	-0.0286*	-0.0433**	-0.0433**	-0.0717**	-0.0711**
	(-1.89)	(-1.89)	(-2.00)	(-2.00)	(-2.36)	(-2.34)
ln(Vol)-ln(VC)	-0.0988*	-0.0988*	-0.206*	-0.207*	-0.204	-0.203
	(-1.69)	(-1.69)	(-1.69)	(-1.69)	(-0.69)	(-0.68)
(ln(Vol)-ln(VC))DMM	0.125**	0.125**	0.187	0.187	-0.211	-0.206
	(2.03)	(2.03)	(1.25)	(1.26)	(-0.57)	(-0.55)
Realized Volatility		-0.00001		-0.00004**		-0.00007
		(-0.17)		(-2.20)		(-0.11)
Inv. Price		0.00145		0.00796		-0.0512
		(0.22)		(0.70)		(-0.146)
FE	Yes	Yes	Yes	Yes	Yes	Yes
N	17517	17517	8544	8544	4653	4653
adj. R-sq.	0.032	0.032	0.032	0.032	0.050	0.050

Table 9: Placebo Regression discontinuity tests at 0.5 million share threshold

This table reports the results of estimating the regression discontinuity specification (2) for DGTW average characteristic adjusted return, for stocks that cross a 0.5 million share placebo threshold during the time period from Sep. 2009 to Dec. 2013. We estimate the following panel regression model:

$$y_{i,t} = \alpha + \beta_0 DMM_{i,t} + \beta_1\big(\ln(Vol_{i,t-1}) - \ln(VT)\big) + \beta_2\big(\ln(Vol_{i,t-1}) - \ln(VT)\big)DMM_{i,t} + \gamma\, X_{i,t-1} + \eta_i + \nu_t + \mathcal{E}_{i,t}$$

Where $y_{i,t}$ is percentage quoted spread, effective spread, realized spread, price impact, ln(volume depth), ln(dollar depth), and percentage inside NBBO execution for stock i in day t., or DGTW characteristic adjusted monthly return and the absolute value of the difference between one and the variance ratio of weekly return to five times of the daily return for stock i in calendar month t. $Vol_{i,t-1}$ is the consolidated average daily trading volume during calendar month *t*-1 for stock *i* in million shares, $DMM_{i,t}$ is an indicator that takes the value of 1 if $Vol_{i,t-1}$ is less than 0.5 million shares and a value of 0 if $Vol_{i,t-1}$ is equal to or greater than 0.5 million shares, $Vol_{i,t-1}$ is reduced by *VT* (0.5 million share threshold) to have the threshold at zero. Spreads are in basis points. Volume depth is number of round lots, and dollar depth is in hundreds of dollar. DGTW adjusted returns are in percentage. Estimation is done using a panel regression with firm fixed effects, η_i, year-month fixed effects, ν_t, and the robust standard errors are clustered by firm. We report results with the optimal bandwidths based on Calonico et al. (2014). The optimal bandwidths (in shares) are listed under each dependent variable. T-statistics are shown below the coefficient estimates. ***, **, and * indicate a significance level of 1%, 5%, and 10%, respectively.

Dependent Variable	Quoted Spread (0.04 million)	Effective Spread (0.04 million)	ln(Volume Depth) (0.02 million)	ln(Dollar Depth) (0.02 million)	Abs |VR-1| (0.15 million)	Inside NBBO (0.05million)
DMM	-0.461	-0.357	-0.00644	-0.0158	-0.00098	-0.126
	(-0.57)	(-0.56)	(-0.49)	(-1.32)	(-0.05)	(-0.26)
ln(Vol)-ln(VT)	-16.97	-13.03	0.802*	0.349	-0.00166	-5.184
	(-1.53)	(-1.49)	(1.82)	(0.87)	(-0.02)	(0.77)
(ln(Vol)-	20.27	15.05	1.008*	-0.318	-0.679	-11.84
ln(VT))DMM	(1.19)	(1.12)	(1.72)	(-0.59)	(-0.59)	(-1.30)
FE	Yes	Yes	Yes	Yes	Yes	Yes
N	42,118	42,118	21,442	21,442	9,945	54,137
adj. R-sq.	0.741	0.676	0.816	0.722	0.039	0.044

Table 10: Placebo Regression discontinuity tests at a 1.5 million share threshold

This table reports the results of estimating the regression discontinuity specification (2) for DGTW average characteristic adjusted return, for stocks that cross a 1.5 million share placebo threshold during the time period from Sep. 2009 to Dec. 2013. We estimate the following panel regression model:

$$y_{i,t} = \alpha + \beta_0 DMM_{i,t} + \beta_1\big(\ln(Vol_{i,t-1}) - \ln(VT)\big) + \beta_2\big(\ln(Vol_{i,t-1}) - \ln(VT)\big)DMM_{i,t} + \gamma\, X_{i,t-1} + \eta_i + \nu_t + \varepsilon_{i,t}$$

Where $y_{i,t}$ is percentage quoted spread, effective spread, ln(volume depth), ln(dollar depth), and percentage inside NBBO execution for stock i in day t., or DGTW characteristic adjusted monthly return and the absolute value of the difference between one and the variance ratio of weekly return to five times of the daily return for stock i in calendar month t. $Vol_{i,t-1}$ is the consolidated average daily trading volume during calendar month *t*-1 for stock *i* in shares, $DMM_{i,t}$ is an indicator that takes the value of 1 if $Vol_{i,t-1}$ is less than 1.5 million shares and a value of 0 if $Vol_{i,t-1}$ is equal to or greater than the 1.5 million shares, $Vol_{i,t-1}$ is reduced by VT (1.5 million share threshold) to have the threshold at zero. Spreads are in basis points. Volume depth is in number of round lots, and dollar depth is in hundreds of dollar. DGTW adjusted returns are in percentage. We estimate a panel regression with firm fixed effects, η_i, year-month fixed effects, ν_t, and robust standard errors clustered by firm. We report results with the optimal bandwidths based on Calonico et al. (2014). The optimal bandwidths (in shares) are listed under each dependent variable. T-statistics are shown below the coefficient estimates. ***, **, and * indicate a significance level of 1%, 5%, and 10%, respectively.

Dependent Variable	Quoted Spread (0.13 million)	Effective Spread (0.13 million)	ln(Volume Depth) (0.05 million)	ln(Dollar Depth) (0.05 million)	Abs |VR-1| (0.44 million)	Inside NBBO (0.20million)
DMM	-0.202	-0.163	-0.0189	-0.00619	-0.0107	0.577
	(-0.49)	(-0.47)	(-1.45)	(-1.26)	(-0.49)	(1.21)
ln(Vol)-ln(VC)	-4.422	-3.812	-1.872***	0.169***	-0.0274	-4.784
	(-0.79)	(-0.83)	(-3.89)	(3.56)	(-0.21)	(-0.79)
(ln(Vol)-	8.972	8.070	3.071***	-0.0245	-0.0209	2.321
ln(VC))DMM	(1.30)	(1.42)	(4.84)	(-0.42)	(-0.14)	(0.30)
FE	Yes	Yes	Yes	Yes	Yes	Yes
N	45,773	45,773	18,999	18,999	7,742	51,094
adj. R-sq.	0.742	0.702	0.880	0.688	0.036	0.059

Table 11: Regression discontinuity tests for on-NYSE and off-NYSE transactions: Rate of Price Improvement

This table reports the results from the analysis using the regression discontinuity specification (2) with the rate of price improvement as dependent variable on stocks that cross the trading volume threshold during the time period from Sep. 2009 to Dec. 2013. We estimate the following panel regression model:

$$y_{i,t} = \alpha + \beta_0 DMM_{i,t} + \beta_1\big(\ln(Vol_{i,t-1}) - \ln(VT)\big) + \beta_2\big(\ln(Vol_{i,t-1}) - \ln(VT)\big)DMM_{i,t} + \gamma\, X_{i,t-1} + \eta_i + \nu_t + \varepsilon_{i,t}$$

where $y_{i,t}$ is the percentage of transactions happening within NBBO on-NYSE (or off-NYSE) for stock i in calendar month t, $Vol_{i,t-1}$ is the consolidated average daily trading volume during calendar month t-1 for stock i in shares, $DMM_{i,t}$ is an indicator that takes the value of 1 if a stock is associated with a stronger DMM obligation, i.e., its $Vol_{i,t-1}$ is less than the one million shares, and a value of 0 if a stock is associated with a weaker DMM obligation, i.e., its $Vol_{i,t-1}$ is equal to or greater than one million shares, $Vol_{i,t-1}$ is reduced by VT (one-million-share threshold) to have the threshold at zero, and $X_{i,t-1}$ represents a set of controlling variables, including intraday realized volatility and inverse price. Estimation is done using a panel regression with firm fixed effects, η_i, year-month fixed effects, ν_t, and the robust standard errors are clustered by firm. We report results with the optimal bandwidth based on Calonico et al. (2014). T-statistics are shown below the coefficient estimates. ***, **, and * indicate a significance level of 1%, 5%, and 10%, respectively.

	Optimal Bandwidth (0.07 million shares)			
	Off-NYSE Execution within NBBO		On-NYSE Execution within NBBO	
DMM	0.343***	0.335***	-0.0173	0.0126
	(4.31)	(4.22)	(-0.77)	(-0.56)
ln(Vol)-ln(VC)	3.476**	2.844**	-0.139	-0.323
	(2.42)	(1.98)	(-0.34)	(-0.80)
(ln(Vol)-ln(VC))DMM	-1.394	-0.756	-0.928	-0.581
	(-0.70)	(-0.38)	(-1.64)	(-0.60)
Realized Volatility		0.0765***		0.0768***
		(7.26)		(6.87)
Inv. Price		-7.487***		-10.37***
		(-12.19)		(-15.93)
FE	Yes	Yes	Yes	Yes
N	50,378	50,378	50,378	50,378
adj. R-sq.	0.579	0.580	0.592	0.594

Table 12: Regression discontinuity tests for on-NYSE and off-NYSE transactions: Effective Spread

This table reports the results from the analysis using the regression discontinuity specification (2) with the effective spread as dependent variable on stocks that cross the trading volume threshold during the time period from Sep. 2009 to Dec. 2013. We estimate the following panel regression model:

$$y_{i,t} = \alpha + \beta_0 DMM_{i,t} + \beta_1\big(\ln(Vol_{i,t-1}) - \ln(VT)\big) + \beta_2\big(\ln(Vol_{i,t-1}) - \ln(VT)\big)DMM_{i,t} + \gamma\, X_{i,t-1} + \eta_i + \nu_t + \varepsilon_{i,t}$$

where $y_{i,t}$ is the effective spread of transactions that occur on-NYSE (or off-NYSE) for stock i in calendar month t, $Vol_{i,t-1}$ is the consolidated average daily trading volume during calendar month t-1 for stock i in shares, $DMM_{i,t}$ is an indicator that takes the value of 1 if a stock is associated with a stronger DMM obligation, i.e., its $Vol_{i,t-1}$ is less than the one million shares, and a value of 0 if a stock is associated with a weaker DMM obligation, i.e., its $Vol_{i,t-1}$ is equal to or greater than one million shares, $Vol_{i,t-1}$ is reduced by *VT* (one-million-share threshold) to have the threshold at zero, and $X_{i,t-1}$ represents a set of controlling variables, including intraday realized volatility and inverse price. Estimation is done using a panel regression with firm fixed effects, η_i, year-month fixed effects, ν_t, and the robust standard errors are clustered by firm. We report results with the optimal bandwidth based on Calonico et al. (2014). T-statistics are shown below the coefficient estimates. ***, **, and * indicate a significance level of 1%, 5%, and 10%, respectively.

	Optimal Bandwidth (0.05 million shares)			
	Effective Spread for Off-NYSE Executions		Effective Spread for On-NYSE Executions	
DMM	-0.900**	-0.768**	-0.787*	-0.636*
	(-2.15)	(-2.13)	(-1.77)	(-1.83)
ln(Vol)-ln(VC)	-14.23	-15.45	-8.415	-9.706
	(-1.48)	(-1.63)	(-0.92)	(-1.11)
(ln(Vol)-ln(VC))DMM	5.217	11.88	-5.837	1.560
	(0.46)	(1.00)	(-0.56)	(0.15)
Realized Volatility		0.0111**		0.0104***
		(2.22)		(2.89)
Inv. Price		41.28***		44.87***
		(4.01)		(3.63)
FE	Yes	Yes	Yes	Yes
N	27,970	27,970	27,970	27,970
adj. R-sq.	0.616	0.622	0.836	0.844

Table 13: Regression discontinuity tests for on-NYSE and off-NYSE depths

This table reports the results from the analysis using the regression discontinuity specification (2) with the volume depth and dollar depth at NBBOs as dependent variables on stocks that cross the trading volume threshold during the time period from Sep. 2009 to Dec. 2013. We estimate the following panel regression model:

$$y_{i,t} = \alpha + \beta_0 DMM_{i,t} + \beta_1\big(\ln(Vol_{i,t-1}) - \ln(VT)\big) + \beta_2\big(\ln(Vol_{i,t-1}) - \ln(VT)\big)DMM_{i,t} + \gamma\, X_{i,t-1} + \eta_i + \nu_t + \varepsilon_{i,t}$$

where $y_{i,t}$ is the on-NYSE (or off-NYSE) volume depth, and dollar depth at NBBOs for stock i in calendar month t, $Vol_{i,t-1}$ is the consolidated average daily trading volume during calendar month t-1 for stock i in shares, $DMM_{i,t}$ is an indicator that takes the value of 1 if a stock is associated with a stronger DMM obligation, i.e., its $Vol_{i,t-1}$ is less than the one million shares, and a value of 0 if a stock is associated with a weaker DMM obligation, i.e., its $Vol_{i,t-1}$ is equal to or greater than one million shares, $Vol_{i,t-1}$ is reduced by VT (one-million-share threshold) to have the threshold at zero, and $X_{i,t-1}$ represents a set of controlling variables, including intraday realized volatility and inverse price. Estimation is done using a panel regression with firm fixed effects, η_i, year-month fixed effects, ν_t, and the robust standard errors are clustered by firm. We report results with the optimal bandwidth based on Calonico et al. (2014). T-statistics are shown below the coefficient estimates. ***, **, and * indicate a significance level of 1%, 5%, and 10%, respectively.

	Optimal Bandwidth (0.15 million shares)							
	Volume Depth at NBBO (Off-NYSE)		Volume Depth at NBBO (On-NYSE)		Dollar Depth at NBBO (Off-NYSE)		Dollar Depth at NBBO (On-NYSE)	
DMM	0.0117**	0.128**	-0.0011	0.0003	0.0146***	0.0158***	0.005	0.006
	(2.14)	(2.36)	(-0.20)	(0.05)	(2.89)	(3.17)	(0.92)	(1.23)
ln(Vol)-ln(VC)	0.301***	0.266***	0.259***	0.246***	0.188***	0.235***	0.151***	0.215***
	(5.78)	(5.14)	(4.91)	(4.67)	(4.14)	(5.21)	(3.28)	(4.74)
(ln(Vol)-ln(VC))DMM	0.0911	0.148**	0.149	0.177	0.144**	0.0875	0.217***	0.138**
	(1.40)	(2.30)	(2.26)	(2.70)	(2.55)	(1.56)	(3.79)	(2.44)
Realized Volatility		-0.0005***		-0.0006***		-0.0006***		-0.0007***
		(-7.66)		(-9.26)		(-9.11)		(-11.17)
Inv. Price		0.860***		0.416***		-0.805***		-1.118***
		(4.01)		(3.63)		(-5.13)		(8.47)
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	82,466	82,466	82,466	82,466	86985	86985	86985	86985
adj. R-sq.	0.824	0.827	0.799	0.799	0.650	0.655	0.680	0.683

Table 14: Regression discontinuity tests for NYSE Market Shares

This table reports the results from the analysis using the regression discontinuity specification (2) with the NYSE market share as the dependent variable on stocks that cross the trading volume threshold during the time period from Sep. 2009 to Dec. 2013. We estimate the following panel regression model:

$$y_{i,t} = \alpha + \beta_0 DMM_{i,t} + \beta_1\big(\ln(Vol_{i,t-1}) - \ln(VT)\big) + \beta_2\big(\ln(Vol_{i,t-1}) - \ln(VT)\big)DMM_{i,t} + \gamma\, X_{i,t-1} + \eta_i + \nu_t + \varepsilon_{i,t}$$

where $y_{i,t}$ is the NYSE market share in percent, measured by number of trades, share volume, and dollar volume for stock i in calendar month t, $Vol_{i,t-1}$ is the consolidated average daily trading volume during calendar month t-1 for stock i in shares, $DMM_{i,t}$ is an indicator that takes the value of 1 if a stock is associated with a stronger DMM obligation, i.e., its $Vol_{i,t-1}$ is less than the one million shares, and a value of 0 if a stock is associated with a weaker DMM obligation, i.e., its $Vol_{i,t-1}$ is equal to or greater than one million shares, $Vol_{i,t-1}$ is reduced by *VT* (one-million-share threshold) to have the threshold at zero, and $X_{i,t-1}$ represents a set of controlling variables, including intraday realized volatility and inverse price. Estimation is done using a panel regression with firm fixed effects, η_i, year-month fixed effects, ν_t, and the robust standard errors are clustered by firm. We report results with the optimal bandwidth based on Calonico et al. (2014). T-statistics are shown below the coefficient estimates. ***, **, and * indicate a significance level of 1%, 5%, and 10%, respectively.

	NYSE market shares in Number of Transactions		NYSE market shares in Total Share Volume		NYSE market shares in Total Dollar Volume	
DMM	-0.270**	-0.278**	-0.307***	-0.295**	-0.306**	-0.295**
	(-2.43)	(-2.50)	(-2.21)	(-2.13)	(-2.21)	(-2.12)
ln(Vol)-ln(VT)	-4.214**	-4.016**	-0.912	-0.849	-0.928	-0.865
	(-2.08)	(-1.99)	(-0.36)	(-0.34)	(-0.37)	(-0.34)
(ln(Vol)-ln(VT))DMM	-2.588	-3.116	-5.356	-5.326	-5.335	-5.306
	(-0.95)	(-1.15)	(-1.58)	(-1.57)	(-1.58)	(-1.56)
Realized Volatility		-0.0008		-0.006***		-0.006***
		(-0.70)		(-4.08)		(-4.08)
Inv. Price		-2.279***		-1.321		-1.326
		(-3.18)		(-1.48)		(-1.48)
FE	Yes	Yes	Yes	Yes	Yes	Yes
N	38,905	38,905	38,905	38,905	38,905	38,905
adj. R-sq.	0.550	0.550	0.497	0.497	0.497	0.497