Liquidity Provision Contracts and Market Quality:

Evidence from the New York Stock Exchange*

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Abstract

We exploit a discontinuity in the contractual obligations of Designated Market Maker (DMM) firms on the New York Stock Exchange (NYSE) to identify the causal effect of more binding DMM obligations on market quality. We show that more stringent market-making requirements are associated with increased depth, narrower bid-ask spreads, increased firm value, and improved price efficiency. These results cannot be attributed to the mechanical effects of more binding DMM obligations, and contribute to the growing body of evidence that the functioning of limit order markets can be improved by contracts that commit one or more participants to provide liquidity.

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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 absence of any barrier to entry to the business of liquidity provision, many exchanges employ contracts that require 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 upon the announcement that DMMs will be introduced for selected stocks on several European markets.[3]

We contribute to the understanding of how DMM contracts can affect firm value and market quality by studying DMMs on the New York Stock Exchange (NYSE). The NYSE DMM program was adopted in 2008, replacing the specialist system that had been used for many decades. The NYSE selects 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 obligation that applies to all firms to identify exogenous effects

[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).
[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.

of contractual DMM obligations on market quality and firm value. In particular, the NYSE contract requires DMMs to maintain competitive bids and offers for a fraction of the trading day that depends on prior-month trading volume. For those securities that have a consolidated average daily volume of less than one million shares in the prior calendar month, the DMM must maintain a bid or an offer at the national best bid or offer (NBBO) for at least 15% of the trading day. For securities that have a consolidated average daily volume greater than one million shares per calendar month, the DMM must maintain a bid or an offer at the NBBO for at least 10% of the trading day.

The discontinuity in the DMM obligation at one-million-share average daily trading volume provides the opportunity to identify the causal effect of the DMM obligation on market quality, because the extent of the obligation is determined by market outcomes, and is not chosen by the listed firm or the exchange. 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 changes in the DMM's contractual obligation. 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.

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 collocate 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 of exogenous (to the decisions of the DMM or the exchange) changes in the obligations 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 obligations are more binding.[5] 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 lower, and rates of price improvement (i.e. trade executions at prices better than the best quotes) are higher when the DMM obligations are more binding. Further, we document positive abnormal returns for the affected stocks in months when DMM obligations are more binding. In addition, we demonstrate that market quality is improved, in that quote midpoint changes conform more closely to the random walk benchmark, when the DMM obligations are more binding.

[5] Of course, we cannot be sure that the obligations are binding in the sense that the DMM would have quoted less often in the absence of the obligation. The obligation is binding only in the sense that the DMM does not have the option to quote less frequently.

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.

Our results provide strong evidence that exogenous changes in the magnitude of DMM obligations 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 and improve share values.

NYSE Rule 104 specifies that the DMM should "assist in the maintenance of a fair and orderly market insofar as reasonably practicable."[6] However, in terms of tangible responsibilities, Rule 104 requires only that its DMMs maintain orders at prices that match the best bid and offer prices for a specified portion of each day. The Rule does not require the DMM to narrow the bid-ask spread by improving on the best quotes or to execute trades within the best quotes. Nor does the rule specify a minimum quantity of shares that the DMM must post.[7] As a consequence, the narrowing of bid-ask spreads, increases in market depth, increased rates of price improvement and improved price efficiency associated with the stronger DMM obligations cannot be direct or mechanical results of the stronger obligations.

[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.

[7] The NYSE DMM obligation is therefore less binding than the DMM obligations considered by list references, which require the DMM to narrow the bid ask spread in certain circumstances.

We investigate further the mechanisms by which stronger DMM market-making obligations are associated with improved market quality by studying outcomes for trades completed on and off the NYSE. Strikingly, we document higher rates of price improvement and lower effective bid-ask spreads when the DMM obligation is more binding for trades executed off the NSYE, but not for trades executed on the NYSE. The results imply that the more stringent NYSE DMM obligation induces other market participants to provide more liquidity (in the form of greater depth and improved prices) off of the NYSE. O'Hara and Ye (2011) provide evidence indicating 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". Our results support this interpretation, since they show that more aggressive DMM quotes on the NYSE lead to more aggressive order submissions off the NYSE as well. These results are important because they provide guidance for those who develop models of equilibrium outcomes in securities markets. In particular, they show that the contractual requirement that the DMM market maker be present even for a portion of the trading day alters the order submission strategies of other market participants, and the resulting market equilibrium.

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.[8] 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

[8] See, for example, Hendershott, Jones, and Menkveld (2011) and Hendershott and Riordan (2013).

algo-bots off and disappeared" from the market during the "flash crash" in U.S. equity markets in May, 2010.[9] The evidence provided here contributes to the understanding of how DMM contracts can supplement endogenous liquidity provision to improve the functioning of financial markets.

II. The Regression Discontinuity Research Design

To identify the impact of the strength of the NYSE DMM requirement on market quality, we use a regression discontinuity research design focused on the discrete shift in the DMM obligation 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.[10]

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 a more binding DMM obligation, in that the DMM is required to maintain quotes at the NBBO for at least 15% of the time. Firm-months with trading volume of just more than one million shares provide the control, as the DMM is required to maintain quotes at NBBO for at least 10% of the day. 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.

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[9] However, Kirilenko, Kyle, Samadi, and Tuzan (2017) conclude that, while high-frequency typically trade in the same direction as price changes, their behavior did not change meaningfully during the "flash crash" in U.S. equity markets during 2010.

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

Our treatment variable is an indicator variable for the stronger obligation, is defined as

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

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* = one million shares is the treatment volume threshold. Therefore, when the average daily trading volume of a stock in the previous month crosses this specified threshold, the DMM obligation changes in the current month. The new DMM obligation stays 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:

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

where y_{it} is a measure of market quality, firm value, 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 DMM requirement to maintain a market presence at the NBBO for a longer time period. 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. As Lee and Lemieux (2010) emphasize, this effective randomization differentiates the RD from instrumental variables or matching sample methods, whose implicit assumptions may be difficult to justify.

Further, the key assumption required to validate the RDD approach, 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. 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 precisely 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. To verify that the RDD provides for valid inference in our application, we implement the density discontinuity test of McCrary (2008), to verify that 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 stronger DMM obligations, 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). [11]

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[12]. 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 common stocks for which the average consolidated daily trading

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

[12] 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,

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.[13] We express each spread measure in basis points, relative to the midpoint of the bid and ask prices at the time of the trade.

[13] 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).

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.

III. Empirical Results.

Following the suggestion of Lee and Lemieux (2010, Section 4.1), and both Kwan, Masulis, and McInish (2015) and Crane, Sébastien Michenaud, and Weston (2016), we graphically display in Figure 1 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 7 we report the results of estimating expression (2). 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. 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 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.

Although the estimates of the bid-ask spread reductions reported on Table 2 are small when stated in basis points, the implied dollar amounts are substantial. 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.[14]

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

[14] $974,000 x 38.45 x 0.0000866 x 252 (trading days per year) = $817,000.

bandwidth also implies somewhat larger point estimates for the reduction in spreads when the DMM obligation is more binding. 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.

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 more binding DMM obligation 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 anticipated, since the more binding obligation requires the DMM to contribute size to the NBBO quotes more frequently.

c. Additional Control Variables

The finding documented here that liquidity is enhanced when the NYSE DMM obligation is more binding is more striking in light of the fact that 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), (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 obligation is more binding 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 obligation is more binding 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 a more binding DMM obligation 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 obligation is more binding cannot arise 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. Share Values

Amihud and Mendelson (1980) show that investors will require lower rates of return, implying higher valuations, for securities with narrower bid-ask spreads, other things equal.

Bessembinder, Hao, and Zheng (2015) show that DMM contracts have potential to improve share values in particular when asymmetric information costs are more prominent.

We next assess whether more binding DMM obligations are associated with improvements in share prices. The ideal experiment would focus on changes in investors' forecasts of future liquidity, which in turn would depend in part on changes in their probabilistic assessments of the likelihood that the DMM obligations would bind in each future month. Unfortunately, investors' forecasts of future liquidity cannot be observed.

We instead estimate expression (2) using the firm's characteristic-adjusted return as dependent variable.[15] If observing that $DMM_{it} = 1$ (i.e. the DMM obligation is more binding in the current month) causes investors to forecast improved liquidity for future months as well then this specification has power to detect a possible relation between liquidity improvements attributable to more binding DMM obligations and stock values.

Results are reported in Table 6 for bandwidths of 480,000 shares, 240,000 shares (the optimal bandwidth per the Imbens and Kalyanaraman (2012) test), and 120,000 shares, with and without the inclusion of inverse share price and market volatility as control variables. The key result that can be observed on Table 6 is that the estimated abnormal stock return is positive both for the optimal bandwidth and for the 120,000 share bandwidth, with and without the inclusion of the control variables. The estimated average increases in share value are economically modest, ranging from 1.6 basis points (optimal bandwidth with no control variables) to 3.0 basis points (120,000 share bandwidth and no control variables), but are statistically significant. The

[15] We adjust returns using the method of Daniel, Grinblatt, Titman, and Wermers (1997). The adjusted monthly return for stock i in calendar month t, is defined as the raw monthly return minus the average return of all CRSP firms in the same size, market-book, and one year momentum quintile. The quintiles are defined with respect to the entire universe in that month, and portfolios are refreshed every calendar month.

current month DMM_{it} variable is at best a noisy proxy for expected future liquidity, implying that the associated coefficient estimate is likely to be biased toward zero. The modest positive coefficient estimates reported on Table 6 should therefore be viewed as a lower-bound estimate of the actual valuation effect of the more stringent DMM obligation.

In addition to reporting results for the narrow (120,000 share) and optimal (240,000) share bandwidths, each of which indicate positive abnormal returns when the more stringent DMM obligation applies, we report results for a wide bandwidth (480,000 shares around the 1 million share threshold), and results obtained when t-1 volume is more than 480,000 shares away from the one-million-share threshold. In contrast for results obtained when t-1 volume is close to the threshold, neither of these specifications indicates any significant abnormal return in the months when the more stringent DMM obligation is in effect. This non-result is consistent with the reasoning that the abnormal returns do not accrue in months where the more stringent DMM obligation is in effect but investors could readily forecast at earlier dates that this would be the case. That is, the positive abnormal returns accrue only when the $DMM_{it} = 1$ outcome was ex ante uncertain.

f. Price Efficiency

Finally, we assess the effect of a more binding DMM obligation 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. 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.[16]

In Table 7 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 on Table 7 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 obligation is more binding, supporting the reasoning that the price efficiency of the market is improved.

IV. Placebo Tests

In the preceding sections we show that firm/months where the DMM market maker faces a more binding obligation are associated with narrower bid ask spreads, higher rates of price improvement, greater market depth, abnormal stock returns, and more efficient prices. These results are perhaps surprising, in light of the fact that the DMM's explicit obligations appear to

[16] 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.

be rather minimal, involving only the requirement to maintain orders at prices that match the BBO quotes for a minority of each trading day. 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, it is not impossible 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 8 and 9, 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 8 and 9 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 obligation is more binding are indeed attributable to the increased DMM obligations.

V. On versus off NYSE Outcomes

A finding that market liquidity is improved at times when a contractual obligation to enhance liquidity becomes binding could be viewed as uninformative, if the improved liquidity simply reflects the direct effect of the fulfillment of the obligation under the contract. However, the results here are informative, because the findings go far beyond any plausible mechanical effect. 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. 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.

To investigate further, we consider outcomes for trades executed on the NYSE and for trades executed off the NYSE. The former will include trades executed against quotes entered by the DMM pursuant to their contractual obligations, while the latter will not.[17] In our sample of NYSE-listed stocks, 21.4% of trades and 25.0% of dollar volume is executed on the NYSE, with the remainder executed on competing venues, including Nasdaq, Bats, Direct Edge, etc.

In particular, we estimate expression (1) separately for trades executed on and off the NYSE, when the dependent variable is the rate of price improvement and when it is the effective bid-ask spread. Figure 2 displays regression discontinuity plots constructed in the same manner as Figure 1, while Tables 10 and 11 report the resulting coefficient estimates.

Focusing first on rates of price improvement, the results reported on Table 10 indicate a positive coefficient and statistically significant (t-statistics exceed 4.2) estimate on the DMM_t

[17] We cannot rule out that an off-NYSE trade could involve an order posted by an NYSE DMM on another venue, but even if so the trade would not arise from the DMM's obligation to post quotes.

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 11 indicate negative and significant coefficient estimates for the DMM_t indicator variable both for trades executed off the NYSE and for trades executed on the NYSE, with the former slightly larger in absolute magnitude.

These results are potentially important, because they show that more stringent NYSE DMM requirements are associated with more favorable trade executions for NYSE-listed stocks, even for executions off the NYSE. The "trade through" rule, mandated by U.S. Securities and Exchange Commission Regulation NMS on 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.

Finally, we estimate expression (1) while using the NYSE share of overall market trading in sample stocks as the dependent variable. On Table 12 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 obligation is more binding. This result is unexpected since any direct effects of the DMM obligation should manifest themselves in greater depth on the NYSE, which would be anticipated to attract additional marketable orders, *ceteris paribus*.

The findings that effective spreads are narrowed and price improvement rates are increased off the NYSE, and that the off-NYSE market share improves when the NYSE DMM obligation is more stringent provide 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. In particular, it must be the case that the more stringent NYSE DMM obligation induces other market participants to provide more liquidity (in the form of greater depth and improved prices) off of the NYSE. 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, possibly because they are more confident that they can offload unwanted positions in the more active market. This result is potentially important to those who develop theoretical models of equilibrium in securities markets.

VI. 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 DMM obligations, whereby they are required to maintain orders at the NBBO more frequently 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.

Our results indicate that more stringent DMM obligations 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. 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 obligation affects liquidity, we show that excess stock returns are positive during periods when the DMM obligations are more binding, and we find that stock prices conform more closely to the random walk benchmark when the DMM obligations are more binding. That is, stronger DMM obligations are associated with higher stock valuations and more efficient pricing, as well as improved liquidity.

In addition to using the RDD design to document improved share values and market quality when the DMM obligation variable is 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 obligation 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. As a consequence, the improvement in bid ask spreads and rates of price improvement, the increased share prices, and the improved price efficiency associated with the more stringent DMM obligations cannot 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 and average effective spreads are decreased when the NYSE DMM obligation is more binding *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. O'Hara and Ye (2011) provide evidence indicating 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". Our results support this interpretation, since they show that more aggressive DMM quotes on the NYSE lead to more aggressive order submissions off the NYSE as well. These findings are important for theoreticians seeking to develop models of security market equilibrium. Developing such models and gaining 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: 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. (2014a). The line represents a first-order polynomial regression curve.

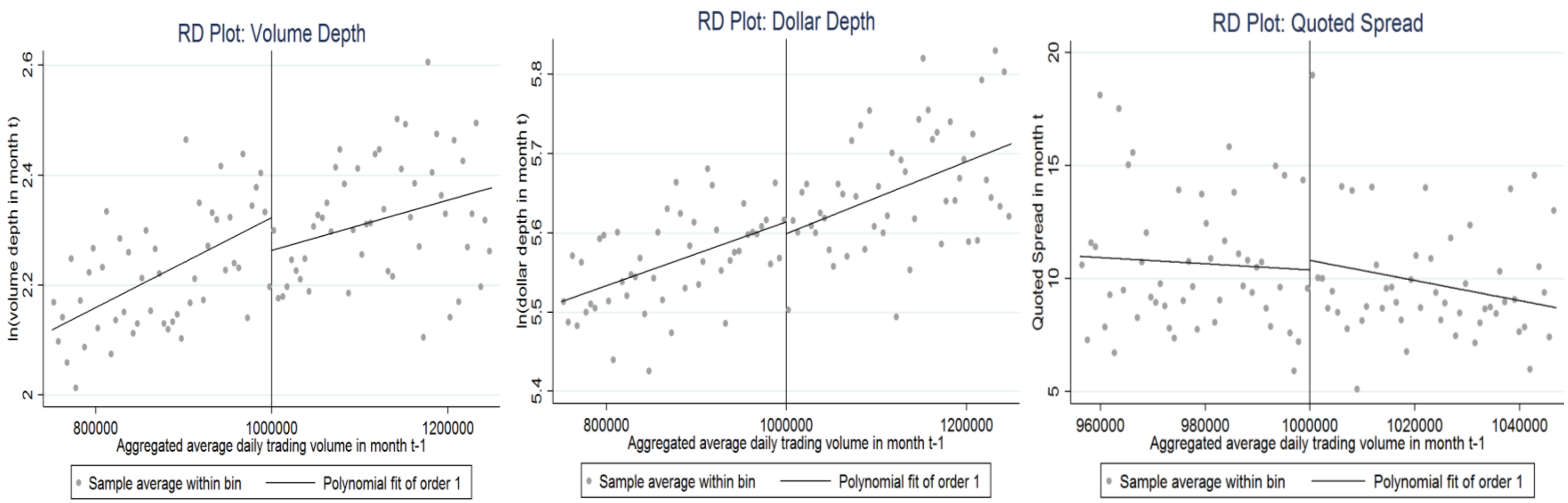

Figure 1: Regression Discontinuity Plots (cont.)

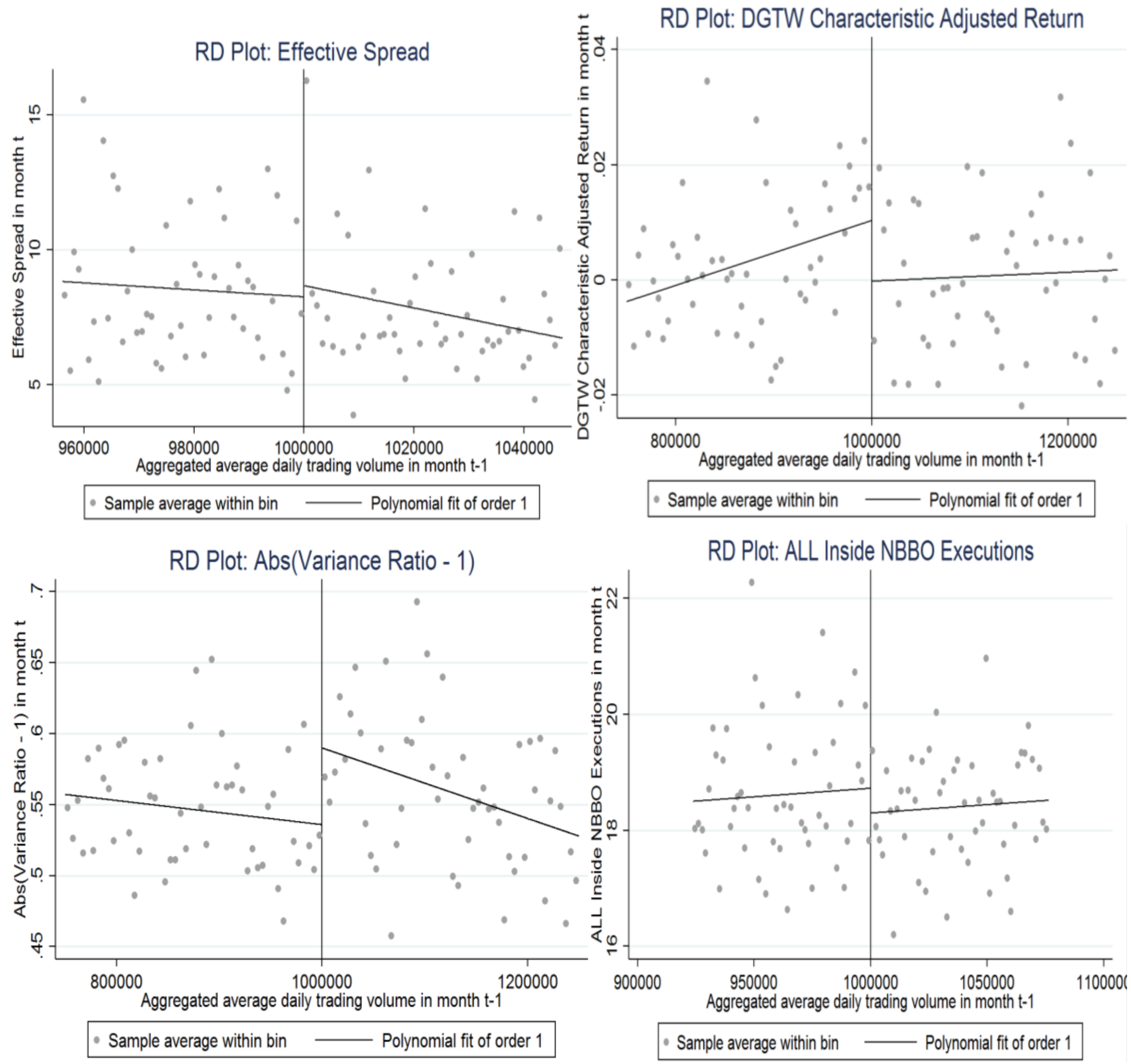

Figure 2: Regression Discontinuity Plots for On-NYSE and OFF-NYSE Transactions

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. (2014a). The fitted lines represent the first-order polynomial regression curves.

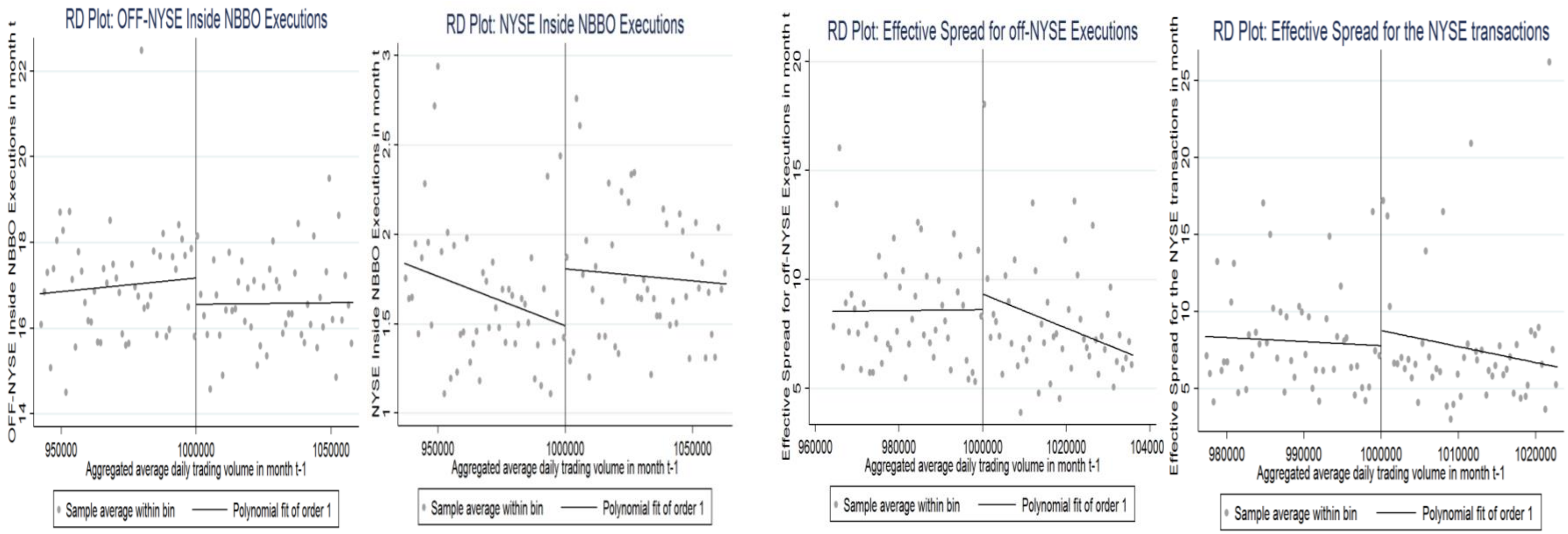

Table 1: Sample Summary Statistics

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 Imbens and Kalyanaraman (2012). 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:

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

Where $y_{i,t}$ is 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 Imbens and Kalyanaraman (2012). 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 (-0.20)	-0.0016 (-0.44)	0.0113** (2.18)	0.0103** (2.08)	0.0208** (2.61)	0.0355*** (4.63)
ln(Vol)-ln(VC)	0.321*** (15.68)	0.166*** (8.58)	0.316*** (6.39)	0.175*** (3.73)	0.806*** (5.56)	0.630*** (4.53)
(ln(Vol)-ln(VC))DMM	-0.122*** (-5.19)	0.0872** (3.93)	0.0958 (1.55)	0.163** (2.78)	-.253 (-1.30)	-0.0228 (-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:

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

Where $y_{i,t}$ is percentage quoted spread, effective spread, 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 Imbens and Kalyanaraman (2012). 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:

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

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 Imbens and Kalyanaraman (2012). T-statistics are shown below the coefficient estimates. ***, **, and * indicate a significance level of 1%, 5%, and 10%, respectively.

	All 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: Stock Return

This table reports the results of estimating the regression discontinuity specification (2) for DGTW average characteristic adjusted return, 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 DGTW characteristic adjusted monthly return for stock i in calendar month t, defined as raw monthly return minus the average return of all CRSP firms in the same size, market-book, and one year momentum quintile. The quintiles are defined with respect to the entire universe in that month and DGTW portfolios are refreshed every calendar month. DGTW adjusted returns are in percentage. $Vol_{i,t-1}$ 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 one million shares, and a value of 0 if a stock is associated with weaker DMM obligation. $Vol_{i,t-1}$ is reduced by VC (one-million-share threshold) to have the threshold at zero. $X_{i,t-1}$ represents the controlling variables, including intraday realized volatility and inverse price. Only firm-month observations on month t and month t-1 are included. 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 four different bandwidths, where the optimal one is based on Imbens and Kalyanaraman (2012).T-statistics are shown below the coefficient estimates. ***, **, and * indicate a significance level of 1%, 5%, and 10%, respectively.

	DGTW Characteristic Adjusted Return							
	Bandwidth (0.48 million shares)		Optimal Bandwidth (0.24 million shares)		Bandwidth (0.12 million shares)		Far Outside the Optimal Bandwidth (>0.48 million shares)	
DMM	-0.000119	0.00433	0.0164**	0.0165**	0.0309**	0.0284**	0.0970	0.00803
	(-0.02)	(0.69)	(2.21)	(2.22)	(2.48)	(2.28)	(0.94)	(0.11)
ln(Vol)-ln(VC)	-0.0507*	-0.0392	0.0136	0.00733	0.0267	-0.0377	0.0209	-0.0379
	(-1.96)	(-1.57)	(0.35)	(0.19)	(0.19)	(-0.28)	(0.20)	(-0.51)
(ln(Vol)-ln(VC))DMM	0.0555	0.0642*	0.0746	0.0825*	0.324*	0.379**	-0.0332	0.00851
	(1.48)	(1.91)	(1.48)	(1.66)	(1.67)	(2.07)	(-0.26)	(0.08)
Realized Volatility		0.00014***		-0.00015		-0.00021		-0.000196
		(0.36)		(-0.53)		(-0.31)		(-0.17)
Inv. Price		0.498***		0.265***		0.419***		0.338**
		(5.74)		(4.82)		(3.85)		(2.00)
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	6,781	6,781	4,643	4,643	2,634	2,634	1,149	1,149
adj. R-sq.	0.049	0.158	0.039	0.075	0.097	0.172	-0.143	0.040

Table 7: 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 Imbens and Kalyanaraman (2012). 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 8: 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 Imbens and Kalyanaraman (2012). 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.

	With Placebo cut at 0.5 million shares						
	Quoted Spread (0.04 million)	Effective Spread (0.04 million)	ln(Volume Depth) (0.02 million)	ln(Dollar Depth) (0.02 million)	DGTW Return (0.14 million)	Abs |VR-1| (0.15 million)	Inside NBBO (0.05million)
DMM	-0.461	-0.357	-0.00644	-0.0158	0.00289	-0.00098	-0.126
	(-0.57)	(-0.56)	(-0.49)	(-1.32)	(0.40)	(-0.05)	(-0.26)
ln(Vol)-ln(VT)	-16.97	-13.03	0.802*	0.349	0.0341	-0.00166	-5.184
	(-1.53)	(-1.49)	(1.82)	(0.87)	(0.78)	(-0.02)	(0.77)
(ln(Vol)-	20.27	15.05	1.008*	-0.318	-0.136**	-0.679	-11.84
ln(VT))DMM	(1.19)	(1.12)	(1.72)	(-0.59)	(-2.19)	(-0.59)	(-1.30)
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	42,118	42,118	21,442	21,442	5,550	9,945	54,137
adj. R-sq.	0.741	0.676	0.816	0.722	0.068	0.039	0.044

Table 9: 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:

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

Where $y_{i,t}$ is 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 Imbens and Kalyanaraman (2012). 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.

	With Placebo cut at 1.5 million shares						
	Quoted Spread (0.13 million)	Effective Spread (0.13 million)	ln(Volume Depth) (0.05 million)	ln(Dollar Depth) (0.05 million)	DGTW Return (0.58 million)	Abs |VR-1| (0.44 million)	Inside NBBO (0.20million)
DMM	-0.202	-0.163	-0.0189	-0.00619	-0.00620	-0.0107	0.577
	(-0.49)	(-0.47)	(-1.45)	(-1.26)	(-0.98)	(-0.49)	(1.21)
ln(Vol)-ln(VC)	-4.422	-3.812	-1.872***	0.169***	0.0166	-0.0274	-4.784
	(-0.79)	(-0.83)	(-3.89)	(3.56)	(0.59)	(-0.21)	(-0.79)
(ln(Vol)-ln(VC))DMM	8.972	8.070	3.071***	-0.0245	-0.0844**	-0.0209	2.321
	(1.30)	(1.42)	(4.84)	(-0.42)	(-2.25)	(-0.14)	(0.30)
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	45,773	45,773	18,999	18,999	5,783	7,742	51,094
adj. R-sq.	0.742	0.702	0.880	0.688	0.065	0.036	0.059

Table 10: 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 Imbens and Kalyanaraman (2012). 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 11: 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:

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

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 Imbens and Kalyanaraman (2012). 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

Table 12: 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 Imbens and Kalyanaraman (2012). 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