The Effect of Designated Market Makers on Market Volatility: Evidence from a Natural Experiment

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Abstract

We study the effect of designated market makers(DMMs) on market quality by exploiting a natural experiment in the Korean Stock Exchange market. We find that DMMs not only improve the liquidity of securities, but that they also increase the return volatility. We find evidence that the increases in volatility from DMM activities coincide with higher prices as well as heavier trading volumes of funds, compared to other investor types in the market. This suggests that the volatility increase is likely due to "churning" from delegated portfolio management attracted to DMMs, implying that the positive effects of DMMs on volatility is not necessarily evidence of deterioration of market quality. Finally, our work sheds light on whether DMMs can be effective as the main supplier of liquidity in financial markets with financial transaction taxes.

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1 Introduction

Many stock markets around the world utilize designated market makers(DMM) to improve market quality. The prevailing wisdom is that DMMs provide liquidity and reduce volatility. For example, the New York Stock Exchange (2019) claims that DMMs are core liquidity providers for the NYSE and reduce price volatility. Weaver (2012), in a review for the UK Government's Foresight Project, states that reduced volatility is a benefit of DMMs. However, while the positive effect of market makers on market liquidity have been well established, the effect of DMMs on market volatility are not well documented.

In this paper, we study the effect of designated market makers on market quality and find that DMMs not only improve the liquidity of securities but, contrary to popular belief, also increase their volatility. This increase in volatility from DMM activities is both economically and statistically significant, and is consistently estimated in securities with both low and high market cap and securities with both high and low levels of liquidity ex-ante. In contrast, volatility increases from DMM activity is highly concentrated in securities with high volatility levels ex-ante, while the effect is significantly smaller for securities with low levels of volatility ex-ante.

Because our findings regarding volatility seem at odds with the conventional wisdom and, to the best of our knowledge, new to the literature, we further investigate the potential causes for this phenomenon. We hypothesize three possible explanations for the increase in volatility from DMM activity. First, we posit that volatility increases could be due to an increase in irrational or liquidity trading stemming from DMM presence. Secondly, designated market makers could induce noise trading in the form of *"churning"* by delegated portfolio managers to increase stock volatility. Thirdly, it is possible that market prices were previously slow in adapting to the changes in the fundamental value of the security, and that the introduction of DMMs have allowed for faster price discovery.

We test each hypothesis and provide evidence suggesting that increased volatility from DMMs is due to increased churning. We show that both privately and publicly offered funds increase trading as a proportion of total trading volume when DMMs are introduced, although only the increase for publicly offered funds are statistically significant. Private equity funds, however, increase their presence in ex-ante volatile securities but not for securities with low ex-ante volatility, which coincides with our finding that the positive effects of DMMs on volatility are concentrated in ex-ante high volatility stocks. Moreover, we also find that the DMM activities increase prices of securities, but that this effect is greatly mitigated in the case of lower volatility stocks, which is consistent with previous findings that show institutional demand can increase prices (Shleifer, 1986, Harris and Gurel, 1986, Carhart et al., 2002, Coval and Stafford, 2007, and Lou ,2012) and that noise trading via churning can be welfare improving (Dow and Gorton, 1997).

In contrast, the predictions of the other two hypotheses do not appear to find support from the data. The fact that prices increase with DMMs and that these increases coincide with volatility increases are less favorable to the possibility of irrational noise trading being the main reason behind volatility increases. The increase in the volatility of prices via irrational traders would decrease the value of the security as previous studies suggest,[1] so that one would have expected to find prices to move in the opposite direction of volatility. Furthermore, we find that the fraction of individual traders in a

[1]See, for example, De Long et al. (1990).

security, a plausible proxy for irrational noise trading, decreases with DMMs, further making this possibility remote. Finally, although the fact that price increases correlate with volatility increases is also consistent with the explanation that DMM allow for faster price adjustment, we find little evidence that DMMs improve price discovery when we test this conjecture directly.

In addition, we show that the degree of competition among market makers do not alter our results. Previous research has shown that competition among market makers and endogenous liquidity providers can affect the behavior of DMMs.[2] Then, one may worry that the presence of financial transaction taxes(FTT) in the Korean stock market may have reduced the competition from other liquidity providers and have influenced our results. However, we find that while competition among DMMs tend to improve the price and liquidity of a security, the presence of competition does not alter our findings regarding volatility.

All in all, our results show that designated market makers generally improve market quality. The fact that DMMs also induce volatility increases is not necessarily a sign of deterioration of market quality, as we find that this is likely due to expanded participation of delegated portfolio managers. As Dow and Gorton (1997) suggest, increased churning can be welfare enhancing for all parties participating in the stock market and such noise trading may be viewed as a public good.

We study the effects of designated market makers in the Korean Stock Exchange market. The unique circumstances around market maker designation in Korea allows us to identify the effects of DMMs in a cleaner way than was possible in most other settings. We study the effect of DMMs by comparing the performance improvements of stocks after DMM designation to those without DMMs. Our cause is aided by the fact that the Korea

[2]For example, see Dennert (1993), Rust and Hall (2003), Anand and Venkataraman (2016), Ait-Sahalia and Saglam (2017) and Bellia et al. (2019).

Exchange(KRX), who oversees the DMM policy, utilizes a discrete eligibility rule for securities. In 2019, the KRX utilized two measures, the effective spread and the turnover rate, to determine the eligibility of a security to have a market maker designated. The discrete nature of the cut-off allows us to utilize a regression discontinuity design to estimate the causal effect of market making activities on various measures of market quality.

While many studies find that DMMs improve liquidity,[3] the effect of DMMs on stock or market volatility is under-explored. In their analysis of the Stockholm Stock Exchange, Anand et al.(2009) find that designated liquidity providers lower intra-day return volatility. Menkveld and Wang (2013), find that volatility is unaffected by the introduction of DMMs to Euronext Amsterdam. Venkataraman and Waisburd (2007) find that firms with designated dealers show less variability in returns. However, establishing causality between designated liquidity providers and market quality is empirically challenging in their research settings, as the listed firms contract voluntarily with the liquidity providers and choose whether or not to adopt market makers.

Endogenous selection bias is especially worrisome with regard to DMMs, as previous studies have found that market makers prefer higher volatility of stocks. Anand and Venkataraman (2016) finds that a higher level of volatility increases the participation of liquidity providers and, in turn, their profits. Anand et al.(2009) find that higher information asymmetry associated with high volatility increases the likelihood of designated liquidity provision. Ait-Sahalia and Saglam (2017) find liquidity provision from DMMs to be inverse U-shaped as a function of price volatility in their model of high-frequency market makers. In our setting, DMMs are determined exogenously by the

[3]Some recent examples include Bessembinder et al. (2019) and Bellia et al.(2019), as well as Mayhew (2002), Anand et al.(2009), Menkveld and Wang (2013), and Venkataraman and Waisburd (2007).

eligibility criterion set by the KRX, so that the DMM securities and non-DMM securities are comparable in many aspects around the cutoffs.

This paper is also linked to the literature on portfolio managers' churning behaviors. The theoretical literature on delegated portfolio management has found that agency problems may induce noise trading in the form of churning. Allen and Gorton (1993) show that agency frictions incentivize churning, which in turn can cause asset prices to deviate from the fundamental value and cause speculative bubbles. However, Dow and Gorton (1997) demonstrate that noise trading by portfolio managers can be Pareto-improving in equilibrium by increasing hedging and profits of informed managers. Furthermore, Dow and Gorton provide insight as to why funds may prefer securities with DMM participation. They show that an adequate amount of hedging demand is needed to cover the cost of delegated portfolio management, which in our setting DMMs may enhance.

Guerrieri and Kondor (2012) provide a direct link between delegated management and asset price volatility. They find that managers' career concerns can generate a reputational premium dependent on the default probability. As default risk changes stochastically over time, the reputational premium amplifies asset price volatility relative to an economy with no such mechanism. Bhattacharyya and Nanda (2013) argue that fund managers increase the price of securities by buying securities they already hold, biasing their prices upward and increasing trading activity.

Finally, our work also sheds light on whether DMMs can be effective as the main supplier of liquidity in financial markets with financial transaction taxes. While FTTs gained traction as a method of allocating responsibility to the financial sector and mitigating the risks of high frequency trading, concerns about market quality have prevented widespread adoption.[4] The

[4]For example, France and Italy each implemented FTTs in 2012 and 2013 respectively citing such reasons. The European Union is having on-going discussions regarding the

adoption of tax-exempted designated market makers along with the adoption of FTTs has been discussed as a potential remedy to market quality concerns. However, the current research on market makers have yet to consider their effects in markets with FTTs. In this paper we show that designated market makers can be utilized to improve market quality in markets with financial transaction taxes as speculated, and thus open the possibility of implementing FTTs to mitigate risks of financial crises and risks from excessive high-frequency trading.

The rest of this paper is organized as follows. Section 2 provides the institutional background of designated market makers in the Korean stock market. In Section 3, we discuss why a regression discontinuity design can be used to explore the effects of designated market makers. The data and empirical results are presented in Section 4. In Section 5, we show the validity of our identification assumptions and that our results are robust across various specifications. Section 6 concludes.

2 Institutional Background

In March of 2016, designated market makers were introduced to the Korean stock markets in an attempt to increase liquidity and lower trading costs. They were introduced in both the KOSPI Market (the main stock exchange market) and the KOSDAQ market simultaneously.[5] Designated market mak-

implementation of a EU wide tax but such discussions have stalled recently as member countries have voiced worries about its effect on market quality.

[5]The KOSDAQ market is a specialized market listing information technology, bio technology and culture technology firms as well as other venture firms, similar to the NASDAQ market of the US. For the remainder of this paper, we restrict our attention to securities in the KOSPI market. We do not include securities in the KOSDAQ market in our analysis (and description) because many are small and have very low trading volume on a large number of days. In addition, most securities in the KOSDAQ market do not have futures

ers are required to maintain orders on both sides of the ledger, within 4 to 6 ticks depending on the security. Their orders must be for at least 2,000,000 to 10,000,000 won on each side, again depending on the security.[6]

To facilitate participation and increase the efficacy of market makers, the Korean government introduced legislation allowing designated market makers to be exempt from financial transaction taxes for transactions initiated to fulfill their market marker obligations. Minus the exemption, all participants were required to pay a financial transaction tax of 0.3% upon sale of securities up until June 2019, which was then reduced to 0.25% in April 2019 and 0.23% in 2021.

Initially, only securities with high bid-ask spreads and low trading volume were eligible for market maker designation, rendering the incentives of dealers too low to participate. As a result, only 2 dealers and 40 securities were assigned designated market makers in 2016. To increase participation and effectiveness, the Korea Exchange (KRX), who operate the stock market in Korea, has continuously broadened the set of securities eligible for market maker designation.[7]

Each year, the KRX first announces eligible securities as well as the obligations and incentives of designated market makers, which can differ by security. Dealers who wish to participate then enlist their services to the Korea Exchange, who then select which dealers participate as designated market makers. Eligible securities are divided into two categories labeled "competitive" and "monopolistic". Competitive securities are relatively large and

contracts that can be traded publicly which many DMMs are known to use for hedging purposes. Our concern is that these characteristics may make the properties of securities in the KOSDAQ market different from those in the main KOSPI market.

[6]As of October 10th 2020, the dollar to won ratio is 1 to 1143.5.

[7]The Korea Exchange must negotiate with the Ministry of Economy and Finance in determining the breadth of market maker designation to secure market maker exemption of financial transaction taxes.

liquid and are assigned to all the market makers that wish to deal in the security. The monopolistic securities, on the other hand, are assigned to only one designated market maker, thus the moniker monopolistic. These securities are assigned via a draft in which each market maker picks, in draft order, a security for which it wishes to provide liquidity. There are as many rounds as needed, so that each designated market maker may select as many securities as they desire. Note that, since not all securities are mandatorily assigned, some eligible securities may not be assigned a designated market maker.

For 2019, the Korea Exchange deemed a security eligible for market maker designation if the turnover rate was below median or the effective spread was above median during the evaluation period lasting from July 2017 to June 2018. This was a change from the previous year when they used trading volume instead of the turnover rate to determine eligibility. The change in measure from trading volume to turnover rate significantly increased the number of eligible securities and many stocks with relatively high trading volume and market cap were granted eligibility. The number of eligible securities increased from 82 in 2018 to 574 in 2019.

The sudden increase in the number of securities eligible for market maker designation in 2019, provides us with an ideal environment to study the effect of designated market makers on market quality. We utilize a regression discontinuity design around the liquidity cutoffs to estimate the causal effect of designated market makers on market quality. As long as securities just above and below the cutoffs are (on average) comparable, then we are able to identify the causal effect of market making on various dimensions of market quality. In the following section, we describe our research design in greater detail.

3 Empirical Design

3.1 Data

We use daily data of individual stocks from July to December of 2018 and July to December of 2019 provided to us by the Korea Exchange. Our dataset includes daily information on the price (last price), the high and low price of each day, the transaction volume, the last bid-ask spread of each day, the execution rate, and price continuity. We also utilize the list of designated market makers, the securities they are matched to, and the start and end dates of the contract for the designated market maker match to each security.

We limit our analysis to securities that did not have a designated market maker during any point of 2018. In addition to daily transaction volume, price, and return, we use various measures of market liquidity and volatility to conduct our analysis.

We use three measures of market liquidity: the last bid-ask spread of the day, the execution rate, and the liquidity ratio. Each represents a different dimension of liquidity. First, the bid-ask spread measures the cost of trading for a hypothetical round trip trade in which the liquidity demander buys at the current offer price and simultaneously sells at the current bid price. Chung and Zhang (2014) find that the bid-ask spread from closing bid and offer prices available does a better job of capturing percent effective spreads in the U.S. data than any other proxy they test. Fong et al.(2017) find that for both monthly and daily frequencies that closing percent quoted spread strongly dominates all other percent-cost proxies for global research.

- **Bid-Ask spread** (last bid-ask spread of the day):

$$\text{BA}_{it} = 2 * 100 * \frac{ask_{it} - bid_{it}}{ask_{it} + bid_{it}} \tag{1}$$

where ask_{it} and bid_{it} are respectively the asking price and the bid price offered for stock i at close of market on day t.

Second, the execution rate measures the quantity and time dimension of liquidity. It examines the outcome of submitted orders over a day. Higher execution rates imply more liquidity.

- **Execution Rate**:

$$\mathrm{ER}_{it} = 2 * 100 * \frac{\text{Shares traded}_{it}}{\text{Orders submitted}_{it} - \text{Orders canceled}_{it}} \tag{2}$$

where orders are measured as numbers of shares.

Third, the liquidity ratio measures the depth and resiliency of trade. It is the inverse of the Amihud (2002) illiquidity measure, which measures the expected gross return on the stock needed to compensate for the price movement induced by trading. Fong et al.(2017) find that of the cost-per-volume proxies they consider using daily data, the liquidity measure of Amihud(2002) performs best.

- **Liquidity Ratio**:

$$\mathrm{LR}_{it} = \frac{\text{Total transaction value}_{it}}{|R_{it}|} \tag{3}$$

where R_{it} is the daily return of stock i.

We also use two volatility measures for our analysis, the absolute return and the daily price amplitude. Absolute return is one of the simplest and most commonly used ways to measure volatility. We use the absolute return instead of squared return (a common estimator of the daily variance) since it is less sensitive to outliers.

- **Absolute Return:**

$$AR_{it} = |R_{it}|\sqrt{\pi/2} \tag{4}$$

The daily price amplitude provides volatility information from the intraday price path, without the need of high frequency data. It is similar to the High-Low estimator for volatility of Parkinson (1980), but we find that the daily price amplitude is less sensitive to outliers in our setting.

- **Daily Price Amplitude**

$$DPA_{it} = 2 * 100 * \frac{PH_{it} - PL_{it}}{PH_{it} + PL_{it}} \tag{5}$$

where PH_{it} is the highest price and PL_{it} is the lowest price for stock i on day t.

As the daily price amplitude captures the within day volatility and the absolute return captures the day-to-day movements in return, these two measures capture volatility based on different time scales.

For our analysis, we drop any securities for which we do not observe 248 trading days, the total number of trading days between July and December of 2018 and also between July and December of 2019. In addition, we drop securities with changes to their face value and securities with missing values for any of the variables that we utilize. We mitigate the effect of outliers using the following procedure. First, we compute the monthly mean value of select variables from the daily data.[8] Then we calculate the average and standard deviation of these values across securities in each given month. For each month, we drop securities with monthly mean values not included in the range $[\bar{x} - 3 \times \hat{\sigma}, \bar{x} + 3 \times \hat{\sigma}]$, where $\bar{x}$ is the average value across securities and $\hat{\sigma}$ is the standard deviation of a given month. In total, 654 securities are included in our final sample.[9]

In Table 1, we compare the average daily value and the standard deviation of our measures during July to December of 2018 and July to December of

[8] We use market cap, daily turnover rate, liquidity ratio, execution rate, bid-ask spread, daily price amplitude, and absolute return for this purpose.

[9] As of December 31, 2019, the total number of securities enrolled in KOSPI is 799.

2019. The average price of securities in our sample decreased between the second half of 2018 and 2019. Furthermore, all indicators suggest that the volatility decreased, as evidenced by the decrease in the absolute return and DPA. The cross-sectional dispersion of prices and returns were also smaller in 2019. On the other hand, transaction volume and liquidity measures show no significant differences across time.

[**Table 1 around here**]

3.2 Research Design

In this section, we discuss how we establish causality between market making activities and market performance. Generally speaking, the KRX designate DMMs to less liquid securities, and thus, securities with DMMs and those without DMMs may exhibit different ex-ante qualities associated liquidity level. This would imply that a simple comparison of the two groups is not likely to produce a causal effect of market making activities.

Hence, we exploit the discrete eligibility rule that the KRX imposes when it designates market makers for each security. Specifically, in 2019, the KRX utilized two variables, the effective spread rate and the turnover rate, in determining whether a security is eligible to have a market maker designated for the calendar year. If either the security's average effective spread or the turnover rate was worse than median among all the listed securities between July 2017 to June 2018, the security was eligible for the market maker selection process. If the security's effective spread rate was low *and* its turnover rate high during that time window, then it was classified as "high-liquidity" and ineligible for the market maker designation.

[**Figure 1 around here**]

In Figure 1 we plot each security by their average turnover rate and effective spread during the evaluation period of July 2017 to June 2018. The X-axis shows the turnover rate in terms of log differences from the median value multiplied by negative one and the Y-axis plots the average effective spread rate again as differences from the median value. Each red dot represents a security for which a market maker was designated, and each '×' represents a security without a designated market maker. Note that the securities positioned in the third quadrant of Figure 1 are ineligible. While most of the other securities are assigned a DMM, some eligible securities in the first and second quadrants are not matched with a DMM even though they are eligible.[10] All in all, out of the 654 securities in our sample, we find that 252 securities were not designated with market makers.

The discrete nature of the eligibility rule allows us to utilize a regression discontinuity design to estimate the causal effect of market making activities on stock market performances. In essence, we compare securities with and without DMMs in a narrow band around the cutoffs. However, this approach is complicated by the fact that our cut-off rule is two dimensional. Therefore, we construct variable x_i as a function of the two cut-off variables, the turnover rate and the effective spread, to utilize as the running variable determining the eligibility of security i. The variable is defined as follows:

$$x_i \equiv \max\{log\Big(\frac{0.4378}{turnover_i}\Big), log\Big(\frac{spread_i}{2.11}\Big)\} \tag{6}$$

where 0.4378 and 2.11 are the median turnover rate and the median effective spread respectively.

If $x_i > 0$ then the security is eligible for market maker designation, and if $x_i < 0$ it is ineligible. The log function is used to compare the two variables'

[10] As previously explained, eligibility does not guarantee that the security will necessarily be designated a market maker. Some eligible securities will not be assigned a market maker because no participating dealer shows interest in being matched with the security.

effective "distances" from their respective cut-offs, and the max function determines the variable of which distance is more critical than the other. If both $log\left(\frac{0.4378}{turnover_i}\right)$ and $log\left(\frac{spread_i}{2.11}\right)$ are positive, the security has low liquidity levels in terms of both measures. As long as one of the two is negative, the security is eligible for market maker designation, and the value of x_i is positive. Only when both of $log\left(\frac{0.4378}{turnover_i}\right)$ and $log\left(\frac{spread_i}{2.11}\right)$ are negative would the security be ineligible, in which case $x_i < 0$. In this way, our running variable x_i represents the effective distance to cutoff for each security.

[**Figure 2 around here**]

In Figure 2 we show the probability of treatment (i.e. market maker designation) below and above the cutoff of zero. Figure 2 shows that there is not only a large discrete jump in the probability of treatment at the cutoff, but the probability of treatment around the cutoff is close to one for securities just above the cutoff point.

Nevertheless, because some eligible securities are not treated, we utilize a fuzzy regression discontinuity design for our main analysis. Let $D_i \in \{0, 1\}$ take the value of 0 if security i is not eligible for designation and 1 if eligible. We estimate,

$$y_i = \alpha + \beta treat_i + f_1(x_i) + D_i \cdot f_2(x_i) + \epsilon_i \tag{7}$$

where $treat_i$ is a dummy variable that takes the value of 0 if security i is not designated a market maker and 1 if one is designated. Following Hahn et al.(2001), we use D_i as the IV for $treat_i$. y_i is the variable of interest. We estimate these equations for the transaction volume, price, our three liquidity measures, and our two volatility measures. Functions f_1 and f_2 are continuous functions of x_i. In our main specification we use a first degree polynomial function for f_1 and f_2.

4 Empirical Results

4.1 The Effect of DMM on Market Quality

We begin by presenting a graphical illustration of our results in Figure 3. It shows the distribution of each market quality measure around the cutoff where market makers are designated. For price, execution rate, DPA and absolute return the discontinuity around the cutoffs are stark. For example, the level of discontinuity around the cutoff for the execution rate exceeds 0.06 percentage points. Similarly, the jump in the DPA is over 0.4 percentage points. On the other hand, the jumps around the cutoffs are relatively small for transaction volumes, the bid-ask spread and the liquidity ratio.

[**Figure 3 around here**]

We now turn to the formal regression discontinuity regression analysis. We estimate equation (7) within a bandwidth of 0.3 around the cutoff $x = 0$. We utilize a first degree polynomial of the running variable.[11] Figure 4 illustrates the securities included in our analysis around the cutoffs. The solid dots represent securities included in our estimation and the hollowed dots represent those not included.

We estimate the effect of designation of market makers on various measures of market quality. Of the 654 securities included in our sample, 179 securities are within the estimation bands around 0.3 of the cutoff with 84 securities in the control group and 95 securities in the treatment group. We construct the dependent variables of equation (7) by subtracting the mean value during July to December of 2019 from the mean value during July to December of 2018. In other words, our dependent variables are differences

[11] We try different bandwidths as well as higher-order polynomials to check for robustness in Section 5.

between the values before and after the 2019 market makers are designated.[12] For our controls, we use the averages values of the transaction volume, closing price, return, liquidity ratio, execution rate, bid-ask spread, absolute return, DPA, and market cap from July to December of 2018. We also include sector dummies in order to control industry-specific shocks that may possibly be associated with liquidity and volatility.

[**Table 2 around here**]

Table 2 shows our main results. The coefficient β in equation (7) is labeled as DMM. It shows the effect of designated market makers on each variable of interest. The standard errors are clustered by sector. The estimated coefficients for the dependent variables of transaction volume and price (column (1) and (2)) suggest that securities with DMMs have experienced increases in volume and price, although the coefficient on transaction volume is not statistically insignificant. In columns (3) to (5), the effects of market makers on liquidity are generally positive. However, only the result for the execution rate is statistically significant at the 10% level. The introduction of market makers increases the execution rate (ER) by 5.8 percentage points. This effect is economically meaningful, amounting to more than a 11% increase in the execution rate compared to the average execution rate of 2018 of 52%. The increase in the execution rate suggests that DMMs enhance the quantity and time dimension of liquidity.

Most notably, we find that DMMs increase the volatility of securities. The estimates for DPA show that the daily price amplitude increases by approximate 0.5 standard deviations due to market making. The relative size of estimated coefficients of absolute return is quite similar, as the standard

[12]In Section 5, we report results with the dependent variables constructed based on 2019 *levels* instead of *differences* for robustness.

deviation of absolute value from the summary statistics is between 0.006 and 0.008 while our estimate is approximately 0.003. The results for DPA and AR are significant at the 1% level.

Our findings are broadly consistent with previous findings that show market makers can be effective in improving market quality. However, we also find that volatility increases after market maker designation which has not been widely documented before. In the following sections, therefore, we provide additional analysis of market maker effects by studying their differential effect on various dimensions of ex-ante security quality to gain a better understanding of market maker behavior and their effect on market quality.

4.2 Heterogeneity in the Responses to DMMs

So far, we presented the main results indicating that DMMs generally improve liquidity for a security, but that volatility also increases with market making activities. To examine whether the liquidity and volatility effects of market making are observed across the sample or whether these effects are concentrated in sub-groups based on ex-ante market characteristics, we interact our treatment with various dimensions of security characteristics. We adopt the approach of adding interaction terms to the fuzzy RD setting pioneered by Becker et al.(2013) and used, for example, in Chakravarty et al. (2019).

We first classify the 654 securities in our sample into two groups of above and below the mean value for select variables during the evaluation period lasting from July to December of 2018.[13] We then interact the treatment in equation (7) with a dummy variable taking the value of 1 if either market cap, execution rate or liquidity ratio is above the mean or if one of the remaining

[13]We use market cap, effective spread, execution rate, liquidity ratio, absolute return, and DPA for this purpose. The mean value is separately calculated by sectors where each security belongs.

variables is below the mean. The dummy variable equals 0 otherwise. It means we allow the dummy variable to take the value of 0 when the securities exhibit what we believe to be "undesirable" qualities for each measure, i.e. low liquidity and high volatility. That is, we estimate the following equation with the same IV estimation procedure above,

$$y_i = \alpha + \beta treat_i + \beta_1 H_i + \beta_2 (treat_i \times H_i) + f_1(x_i) + D_i \cdot f_2(x_i) + \epsilon_i \quad (8)$$

where H_i is a dummy variable taking the value of 0 or 1 depending on the value of the market cap, liquidity or volatility measure of the security. Functions f_1 and f_2 are continuous functions of x_i as before. As before, we include the sector dummy and all our controls.

[**Table 3 around here**]

In Table 3 we show the results with heterogeneity in each of our dependent variables as well as market cap. Each panel shows the heterogeneous response based on different ex-ante characteristics. For example, the first panel compares the effect of DMMs on securities with low and high market cap, the second panel compares securities with low and high ex-ante values of the effective spread.

We focus our attention on the heterogeneity results for the effective spread, absolute return, and daily price amplitude, as these dimensions seem to provide more distinct empirical results. Column (1) of Panel A shows that while market making does not seem to improve trading volume for securities with high effective spreads (i.e. low liquidity), it is quite effective in improving the trading volume for high liquidity securities. Our estimates suggest that market makers increase the trading volume of highly liquid securities by 59.1% compared to relatively illiquid securities. This amounts to a 42.8% increase in trading volume for high liquidity securities due to market making. Furthermore, column (3) through (5) indicate that liquidity improvements seem to be concentrated in high liquidity securities. The bid-ask spread decreases, that is, liquidity improves, by an additional 4.8 basis points for high liquidity securities compared to low liquidity securities, for an overall effect of 1.4 basis point drop in the bid-ask spread for high liquidity securities due to market making. The execution rate improvement due to market making is 0.048 percentage points greater for liquidity securities compared to low liquidity securities, for an overall improvement of 0.02 percentage points for high liquidity securities. The liquidity ratio also improves by 40.0% more for highly liquid securities due to market making over low liquidity securities for an implied total improvement of 33.6%. The interaction effects for execution rate and liquidity ratio are statistically significant at the 1% level, while the results for bid-ask spread at the 5% level. Finally, in column (6) and (7), the positive volatility effects of market making see to be homogeneous across sub-samples. Low liquidity securities see increases in both volatility measures, a pattern that changes little with high liquidity securities.

The heterogeneity in the effect of market makers along the volatility dimension, presented in Panel E and F, also shows interesting results. Specifically, market making increases prices of high volatility stocks but does not seem to effect those of low volatility stocks. For securities with an average absolute return of above median in 2018, market making activities increased prices by 21.2%. This effect disappears for securities who had low absolute returns in 2018. Similarly, the price of securities with an average DPA of above median in 2018 increased by 20.6%, but the estimates of the low-DPA interaction term indicate that the effect decreases by 14.8% for securities with low volatility.

Moreover, liquidity improvements due to DMMs were mostly borne by high volatility stocks and those improvements were generally negated for low volatility securities. The execution rate increased by 0.087 percentage points for securities with high absolute return but that increase falls by 0.067 percentage points to an aggregate 0.010 percentage point increase for securities with low absolute returns. Likewise, the liquidity ratio increases by 38.8% for high absolute return stocks but that increase falls by 45.9% for low absolute return stocks, actually implying that securities with low absolute return experienced a 7.1% decrease in the liquidity ratio due to market makers. The results of Table 3 suggest that the execution rate increased by 0.085 percentage points for securities with high DPA but that increase falls by 0.048 percentage points to a quite smaller aggregate increase (0.037 percentage points) for securities with low DPA. This result is consistent with previous findings in the literature that show DMMs are more active in securities with high volatility as dealers see higher margins for profits in volatile securities.

Finally, the volatility increases from market making activities seem to be concentrated in high volatility stocks. The daily price amplitude increased by 0.690 percentage points for securities with high absolute returns but that increase falls by 0.422 percentage points for low absolute return stocks. The absolute return increases by 0.4 percentage points for high absolute return securities but that increase decreases by 0.2 percentage points for low absolute return stocks. The DPA increases by 0.735 percentage points for securities with high DPA in 2018, but that increase drops by 0.405 percentage points for low DPA securities. Absolute returns increase by 0.4 percentage points for securities with high DPA but drops by 0.2% for low DPA securities.

[**Table 4 around here**]

In Tables 4 we include interaction terms for the effective spread and one of either absolute return or DPA simultaneously. The results remain unchanged from those with only a single interaction term – indeed, the results are rather strengthened with both terms. The sizes of our effects remain constant or are strengthened and the statistical significance of some results improve.[14] This suggests that the heterogeneity in the response of securities based on ex-ante characteristics are inherent properties rather than due to spurious correlation across measures.

Our results suggest that DMMs are more effective in providing liquidity for securities with already higher levels of liquidity. This result seems broadly consistent with previous research that suggest market makers are sensitive to liquidity and trading volume as it determines, to a large degree, their ability to offload inventory and mitigate risk exposure. However, the fact that price increases from DMM activity are greater for low liquidity stocks suggest that while DMM activity maybe greater in high liquidity stocks, the internalized benefits from improved liquidity embodied in the price may be larger for low liquidity securities. This mitigates concerns that DMMs are only effective for ex-ante liquid securities that possibly have the lowest needs for DMMs.

We also find evidence that suggest market makers are more active and effective in securities with high volatility. These results are broadly consistent with Handa and Schwartz'(1996) predictions that market making can potentially be more profitable when prices are volatile. Anand and Venkataraman also find that higher volatility is associated with endogenous liquidity provider (market makers) participation using data from the Toronto Stock Exchange. We find similar results for DMMs. This may alleviate potential concerns about the effectiveness of DMMs during times of stress, and reinforce DMMs as a mechanism to secure market stability.

Lastly, we find that increases in volatility is concentrated in high volatility stocks. The volatility increases in ex-ante low volatility stocks are largely mitigated. As our findings regarding the effect of DMM activities on the volatility of securities has not been previously documented in the literature,

[14] The results remain strong when we also add an interaction dummy for high market cap (unreported).

we further pursue possible explanations for the volatility increases resulting from DMM activity, in the following section.

4.3 Potential Channels for the Increases in Volatility

In this section, we test three possible channels for the positive impacts of DMMs on volatility – irrational noise trading, churning via delegated managers, and price discovery acceleration.

Irrational Noise Trading

First, the most straightforward explanation would be that, when DMMs provide liquidity for a security, they may attract noise traders into the security who likely increase volatility through their trades.[15] However, we rule out this channel for the following two reasons.

As we previously report in Tables 2 to 4, price increases from DMM activity is highly correlated with the volatility increases. Although the price increase is documented with the full sample in our main specification reported in Table 2 , a close study of Tables 3 and 4 show that the price increases coincide with the volatility increases. Notably, in Table 4, we observe that price increases are statistically significant especially when volatility increases. Moreover, the coefficients on the interaction terms for ex-ante low volatility stocks indicate that the volatility increases are significantly smaller for these stocks, and we find a similar pattern with the increases in price. We interpret these results as indirect evidence against the irrational noise trader hypothesis, because irrational noise trading would likely to increase investor risk which should then be reflected by lower prices. For example, De Long et al. (1990) show that assets subject to noise trader risks are under-priced.

[15] Noise traders may be thought of as either irrational, a la De Long et al.(1990), or subject to exogenous liquidity events, as in Glosten and Milgrom (1985).

In addition, we also provide more direct evidence against the irrational noise trading channel. Specifically, we use activities of individual traders as a proxy for irrational noise trading and test whether individual investors trade more heavily in the securities with DMMs.

Before presenting our results, we first provide a general overview of trading by investor types. Table 5 shows the trading activity of securities in our sample during the sample period of July to December of 2018 and 2019 respectively.[16] We use data provided publicly on the KRX website. Two points are worth noting. First, trading activities by brokerage firms increase compared to other types of investors both in terms of shares traded (1.62% $\rightarrow$ 1.83%) and trading volume (4.26% $\rightarrow$ 5.79%), a pattern consistent with the fact that designated market makers are classified as brokerage firms in the dataset. Second, while individual investors and brokerage firms trade more in 2019 than in the previous year, all the other investor types decrease trading.

[**Table 5 around here**]

Now turning to the effect of DMMs on individuals' trading behavior, we estimate the changes in the composition of investors due to DMM activity using the equation (7) where the fraction of total trading activity by individuals is the dependent variable y_i.[17] The results reported in columns (1) and (2) of Table 6 indicate that individuals in fact scale down their trading activities in securities with DMMs. This is inconsistent with the irrational noise trader explanation, especially given the fact that individual investors generally traded more in 2019 than they did in 2018. Therefore, in lieu of both the indirect and direct evidence against the irrational noise trading channel,

[16] Trading activity is calculated as the sum of both buying and selling of securities.

[17] We do not include the trading by brokerage firms when computing the total trading volume when constructing the trading fraction of each investor type.

we conclude that this is unlikely to be the explanation for the increase in volatility.

[Table 6 around here]

Delegated Portfolio Management and Churning

The second hypothesis we consider is that volatility increases are due to churning via delegated portfolio management. When a principal hires a portfolio manager but cannot distinguish whether the manager's inactivity is optimally chosen or resulting from lack of effort, an optimal contract incentivizes the manager to engage in noise trading when managers have no information. While this type of trading activity by managers would increase volatility, Dow and Gorton (1997) show that this can lead to more hedging volume, which in turn helps informed trading in the market thereby mitigating risks associated with noise trading and even improving overall welfare. In such circumstances we believe that price increases may well coincide with volatility increases. In addition, Dow and Gorton's careful analysis illustrates why delegated managers would increase trading in securities with DMMs' participation in the first place – hedging volume is necessary for informed managers to trade for profit and in turn generate enough return for the principal to cover the costs of a delegated manager.

Meanwhile, Guerrieri and Kondor (2012) show that managers career concerns distort investment decisions and increase asset price volatility. Managers incentives generate a premium on risky assets that is positive when default risk is high and negative when default risk is low. Thus as the default risk changes over time asset price volatility is amplified. Furthermore, many previous studies show that institutional demand increases the price of securities (Shleifer, 1986, Harris and Gurel, 1986, Carhart et al., 2002, Coval and Stafford, 2007, and Lou, 2012). Bhattacharyya and Nanda (2013) argue that fund managers that are compensated based on net asset values have the incentive to pump their portfolio by additionally buying securities currently in the portfolio, which would also increase their prices and trading activity.

Given the arguments of Dow and Gorton (1997), Guerrieri and Kondor (2012), Bhattacharyya and Nanda (2013) and others, we believe that the fact that the volatility increases from DMMs activity coincide with price increases is consistent with churning behaviors by fund managers. Furthermore, we provide more direct evidence supporting this hypothesis by testing whether the fractions of the trading activities of private equity funds, publicly offered funds, and all funds indeed increases for securities with designated market makers.

Table 6 shows our results. Columns (3) through (8) of Table 6 provide results showing the effect of DMMs on the share of private equity funds, publicly offered funds, and all funds trading in the security. We find positive, but statistically insignificant evidence that private equity funds increase their trading activities with DMM-securities (columns (3) and (4)). We find statistically significant results that publicly offered funds trade more heavily in the securities with DMMs than in the securities without DMMs (columns (5) and (6)), and that the effects are prevalent when we take private and public funds together (columns (7) and (8)). DMM activity increased the trading activity of public offered funds by 1.0% both in terms of shares traded and trading volumes, while total fund activities increase by 1.2%.

Given that our findings in the previous sections indicate that the effects of DMMs, especially the volatility effects, are concentrated in securities which were highly volatile ex-ante, we also test whether increases in funds trading activities are also more pronounced in such ex-ante volatile securities. Table 7 reports the results of regressions similar to those in Section 4.2, with a similar empirical specification with the fraction of funds' trading activities.

Columns (1) and (2) show that private equity funds trade significantly more securities with high ex-ante volatility when DMMs are assigned, but that such effects vanish when we include low-volatility securities in the sample. This result for private equity funds is tightly linked to our result where volatility increases are concentrated in ex-ante high volatility stocks. It also explains why private equity funds trading activity was insignificant for the whole sample. Previous studies such as Anand and Venkataraman (2016) that show that liquidity providers generally prefer high-volatility stocks as they provide better opportunities for profit, which explains why the presence of private equity funds increased mostly in ex-ante high volatility stocks as private equity funds are presumably more sensitive to short-term profits. The fact that volatility increases from DMM activities are concentrated in these securities provides additional support for our hypothesis that churning by delegated managers is an important channel for the volatility increase.

The results of columns (3) and (4) indicate that publicly offered funds increase their trading activities in securities with DMMs regardless of ex-ante volatility levels. Taken together, increases in funds activities caused by DMMs are more prominent in ex-ante high volatility securities than in less volatile securities (columns (5) and (6)), consistent with our findings regarding volatility. Thus, we believe that churning by delegated portfolio managers is an important cause of volatility increases from DMM participation.

[**Table 7 around here**]

Price Discovery Acceleration

Lastly, the third hypothesis that we test conjectures that volatility increases are inherent to DMM activity. If fundamental asset prices are volatile but low liquidity levels slows the realization process, DMM activity could increase volatility by accelerating price discovery. In our setting, the presence of FTTs would exacerbate this process. This hypothesis is consistent with the fact that price increases and volatility increases are correlated. However, we find little evidence that DMMs improved price discovery when we directly test for this effect by employing the "price delay" measure of Hou and Moskowits (2005).

We construct the price delay measures by first regressing the return of a security at time t on the market return at time t, $t-1$, $t-2$, $t-3$ and $t-4$ for each security. If there is no delay of reflecting market information for a security, then the coefficients of the market return from $t-1$ to $t-4$ would be zero. This implies that the restricted version of the above regression excluding the market return from $t-1$ to $t-4$ should have similar explanatory power as the full regression. Therefore, we construct two measures of price delay, one from daily data and the other one from weekly average data, defined as $1-\frac{R_R^2}{R_U^2}$, where R_R^2 is the R-squared from the restricted model and R_U^2 is the R-squared from the full model.

Using the same fuzzy regression discontinuity design we analyze the effect of designated market makers on the price delay measures. The results are reported in Table 8. We test three specifications varying the inclusion of controls and sector dummies. Across all specifications for both measures, the results are small and statistically insignificant. In sum, we do not observe significant changes in the speed of price discovery due to DMM adoption.

[**Table 8 around here**]

4.4 Competition Effects

In this section, we study the effect of competition among market makers on the effectiveness of DMMs. Our objectives are twofold. First, we wish to verify that the presence of competition does not alter our previous findings. Next, the effect of competition in and of itself is of interest as well. This is especially meaningful in our setting, where financial transaction taxes may limit competition for DMMs from other endogenous entities.

Compared to previous studies, our setting provides a distinct advantage in that our distinctions of "monopolistic" versus "competitive" are relatively complete representations of the degree of competition a DMM faces. Few, if any, endogenous liquidity providers should be present in our setting due to relatively high transaction taxes levied on a per transaction basis. Thus, monopolistic market makers would face little to no competition from liquidity providers of any form.

We compare the effectiveness of market makers for monopolistic securities who are assigned only one DMM against competitive securities that are assigned multiple market makers. We adopt a similar approach as in the previous section and interact a dummy variable that takes a value of 1 if the security is a competitive security and zero otherwise with the treatment variable. We also estimate the effect after adding dummy variables indicating securities with high liquidity levels or high volatility levels ex-ante. However, because of limited cross-variation between DMM eligibility and competition, we adopt a sharp RD specification instead of the fuzzy RD specification previously used. To do so, we drop the few observations for which eligible securities were not designated a market maker.

Table 9 shows our results. The first panel shows the results with only the competition dummy, and next two panels show the results when we include interaction terms for high liquidity and high volatility securities along with competition. First, we find that competition does not effect our main results regarding volatility. Volatility increases are consistent across all subgroups with the exception of high volatility stocks even when we include competition effects. The magnitudes of the effects are similar to our previous results as well. Price increases also show the same pattern to our previous findings.

[**Table 9 around here**]

In addition, we find that competition increases the effectiveness of market makers. In Table 9, we find that liquidity improvements from market making are greater for competitive securities compared to monopolistic securities. Although only the interaction effect with the competitive dummy is statistically significant at the 1% level for the execution rate, the point estimates for all three liquidity measures suggest that market making is more effective with multiple market makers. The bid-ask spread drops by 5.1%, the execution rate improves by 7.3% and the liquidity ratio improves by 24.3% more for competitive securities.

These results are consistent even as we add the interaction terms for the effective spread and one of absolute return or DPA, as shown in the second and third panels of Table 9. Furthermore, it becomes evident that prices react positively to market makers and that the price increase is more prominent for securities in which market makers engage in competition. Our findings alleviate concerns that competition between market makers can deteriorate profitability and hence their effectiveness by exacerbating the adverse selection problem, as suggested by Dennert (1993), and instead lend credence to the view that competition between market makers improve overall market quality.

5 Validity and Robustness Checks

5.1 Testing Local Continuity

The main identification assumption for our research design is local continuity, which implies that securities around the cut-offs are comparable. In other words, we need that the characteristics of securities around the cutoff are sufficiently similar before the 2019 market maker designation. Because our eligibility measure and cutoffs are arbitrarily set by KRX, we believe that there is little reason to suspect that securities above and below the cutoffs are systematically different ex-ante, especially within a narrow around the cutoff. Furthermore, because the cutoffs are relative rather than absolute values, it is unlikely that main investors of securities could correctly anticipate and try to manipulate their own market performances in order to gain eligibility, even if they had somehow anticipated the changes in the eligibility criteria beforehand. Therefore, we believe our identification assumptions are reasonable.

Nevertheless, in Table 10, we test our assumptions of local continuity by testing whether the value of any of these variables exhibit significant differences around the cutoffs. We implement our fuzzy RD design on 2018 values of each variable and find that for all the variables the differences around the cutoffs are small and insignificant. That is, there is no statistically significant discontinuity near the cutoff point for any of these variables.

[**Table 10 around here**]

5.2 Robustness Checks

Our analysis so far is based on a local linear regression with a first degree polynomial of the running variable on a bandwidth of 0.3. In this section, we test the robustness of the empirical results to the choice of the bandwidth and the orders of polynomial functions.

Panel A and B of Tables 11 report the regression results on a bandwidth of 0.2 and 0.4, respectively. The effects of DMM on price are estimated to be higher with a smaller bandwidth, but the results are generally consistent qualitatively with the main results reported in Table 2. In particular, the effects of DMM on volatility measures (columns (6) and (7)) remain statistically significant at 1% level.

[Table 11 around here]

In addition, the empirical results using higher degree polynomials of the running variable are reported in Panel C and D of Tables 11, which confirm that our main results are robust to the choice of degrees of polynomial. Indeed, the use of higher order polynomials even strengthen our findings: the estimated coefficients on price, bid-ask spread, execution rate and volatility are more significant, both economically and statistically, with higher order polynomials.

Finally, we also test the empirical models replacing dependent variables with mean values of 2019, whereas the empirical specifications in Section 4 use dependent variables constructed as the differences between the mean values of 2018 and 2019. Again, we find that the effects on liquidity and volatility, as reported in Panel E of Table 11, continue to hold generally.

6 Conclusion

In this paper, we study the effect of designated market makers on market quality and especially market volatility. We make use of the discrete eligibility rule that the KRX imposes when it designates market makers, which allows us to utilize a regression discontinuity design to estimate the causal effect of market making activities on various measures of market quality.

We find that market making activities for a security improves its liquidity but also increases volatility. We show that liquidity improvements are concentrated in securities that have high liquidity and low volatility ex-ante.

Volatility increases for securities in general, but are especially concentrated in securities with already higher levels of volatility. We provide evidence suggesting that the volatility increases are a result of churning behavior of delegated fund managers. Our results suggest that volatility increases from market making activity are not necessarily signs of falling market quality. In addition, we provide evidence showing that competition does not alter our results regarding volatility, and that allowing for competition among market makers increases their effectiveness. All in all, our results suggest DMMs can be effective in improving market quality especially in markets with financial transaction taxation.

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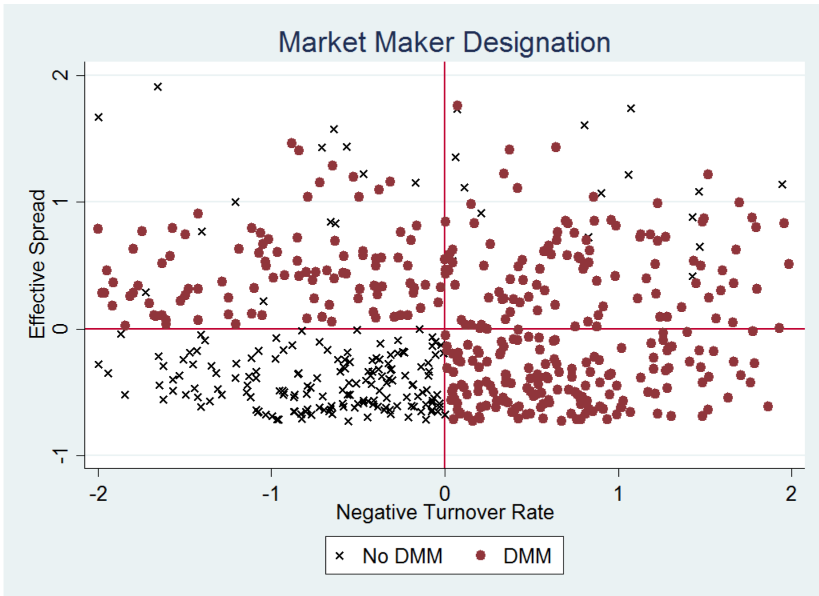


Figure 1: Market Maker designation by security

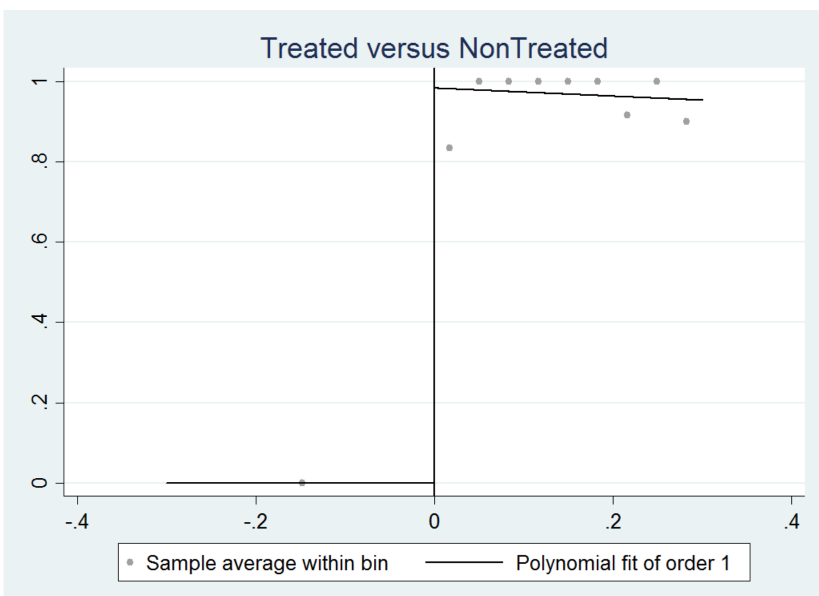
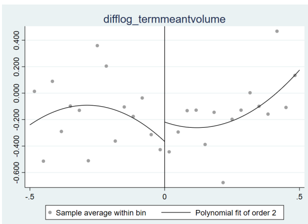
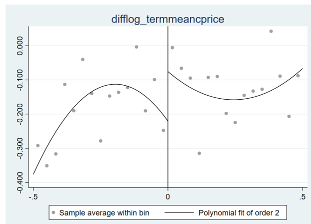


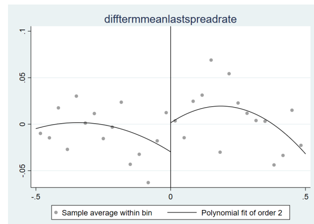
Figure 2: Jump in the probability of treatment around cutoff



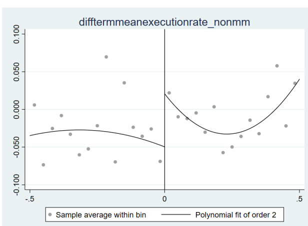
(a) Transaction volume



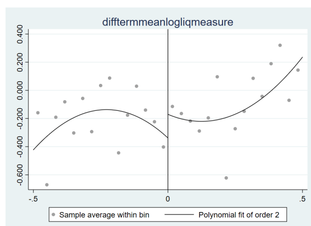
(b) Price



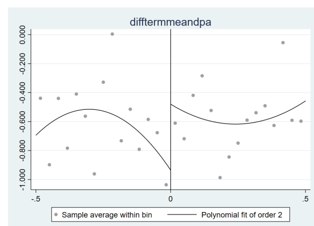
(c) Bid-ask spread



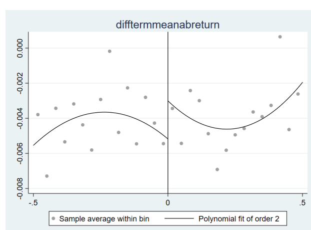
(d) Execution rate



(e) Liquidity ratio



(f) DPA



(g) Absolute return

Figure 3: Regression Discontinuity Plot

Note: polynomial order of 2. bandwidth of 0.3.

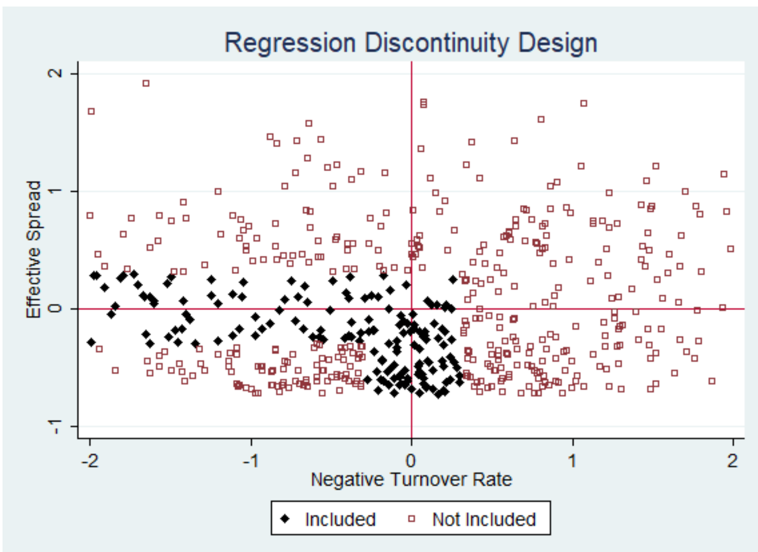


Figure 4: Plot of securities by turnover rate and spread

Table 1: Summary Statistics

	2018		2019	
	Mean	Std.	Mean	Std.
Trading volume (10,000 shares)	32.0	68.1	32.4	101.3
Closing Price (Won)	33,603	84,167	29,040	68,404
Return (%)	-0.121	0.201	-0.100	0.151
Bid-Ask Spread (%)	0.398	0.190	0.371	0.165
Execution Rate (%/100)	0.518	0.179	0.507	0.179
Liquidity Ratio (log)	24.58	1.86	24.53	1.74
DPA (%)	3.70	1.17	3.14	1.00
Absolute Return (100%)	0.021	0.008	0.018	0.006
Observations			654	

Table 2: Main RD Estimation

	General Measure		Liquidity Measure			Volatility Measure	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Variable	Volume	Price	BA	ER	LR	DPA	AR
DMM	0.211	0.123*	0.004	0.058*	0.189	0.506***	0.003***
	(0.201)	(0.074)	(0.027)	(0.032)	(0.187)	(0.102)	(0.001)
Running variable (x_i)	-1.786**	-0.359	-0.081	-0.149	-0.839	-2.072***	-0.012***
	(0.857)	(0.428)	(0.133)	(0.129)	(0.938)	(0.715)	(0.005)
$D_i \times x_i$	1.599	-0.412	0.320*	-0.067	-0.143	0.599	0.001
	(1.026)	(0.484)	(0.187)	(0.177)	(1.143)	(1.025)	(0.007)
MktCap(2018)	-0.336	0.093	0.018	0.028	-0.044	-0.104	-0.001
	(0.216)	(0.072)	(0.023)	(0.029)	(0.192)	(0.160)	(0.001)
Turnover(2018)	-40.028**	8.222	1.520	0.282	-18.451	-11.468	-0.078
	(19.908)	(6.823)	(2.228)	(2.558)	(22.014)	(12.176)	(0.092)
Price(2018)	-0.000	0.000*	0.000	-0.000	0.000	-0.000*	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Volume(2018)	0.001	0.001**	0.000	-0.000	0.002	0.001	-0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
LR(2018)	0.339*	-0.160*	-0.063***	0.019	0.001	0.002	0.001
	(0.192)	(0.083)	(0.020)	(0.024)	(0.169)	(0.133)	(0.001)
ER(2018)	-1.619	0.453	0.245**	-0.623***	-0.949	-1.469*	-0.009
	(1.109)	(0.488)	(0.105)	(0.160)	(1.010)	(0.779)	(0.006)
AR(2018)	-34.631	2.947	-4.651	-3.113	14.775	-81.781***	-1.178***
	(31.527)	(10.458)	(3.309)	(3.889)	(27.582)	(29.785)	(0.175)
DPA(2018)	0.217	-0.119**	0.023	0.039	-0.128	0.206	0.005***
	(0.164)	(0.058)	(0.019)	(0.027)	(0.153)	(0.193)	(0.001)
BA(2018)	-0.031	0.066	-0.533***	-0.151**	0.423	-1.733**	-0.006
	(0.783)	(0.165)	(0.077)	(0.075)	(0.446)	(0.677)	(0.005)
Return(2018)	-0.265	0.328**	0.009	0.034	0.265	-0.435**	-0.000
	(0.197)	(0.147)	(0.018)	(0.024)	(0.212)	(0.171)	(0.001)
Constant	-5.353	3.444**	1.434***	-0.298	1.126	2.194	-0.018
	(3.476)	(1.521)	(0.374)	(0.381)	(2.981)	(2.243)	(0.014)
Observations	654	654	654	654	654	654	654
Eff.Left N	84	84	84	84	84	84	84
Eff.Right N	95	95	95	95	95	95	95
Sector Dummies	Y	Y	Y	Y	Y	Y	Y

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 3: RD Estimation with Heterogeneous Effects

	General Measure		Liquidity Measure			Volatility Measure	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Variable	Volume	Price	BA	ER	LR	DPA	AR
Panel A: Subgroups based on Market Cap							
DMM	0.025	0.055	0.014	0.031	0.019	0.402***	0.003***
	(0.248)	(0.088)	(0.025)	(0.036)	(0.213)	(0.130)	(0.001)
DMM×HighMC	0.359*	0.120	-0.018	0.050**	0.302***	0.205	0.001
	(0.192)	(0.094)	(0.027)	(0.020)	(0.151)	(0.200)	(0.001)
Panel B: Subgroups based on Effective Spread							
DMM	-0.163	0.156*	0.034	0.028	-0.064	0.504***	0.003***
	(0.175)	(0.092)	(0.026)	(0.027)	(0.168)	(0.147)	(0.001)
DMM×LowES	0.591**	-0.054	-0.048**	0.048***	0.400***	0.002	-0.000
	(0.240)	(0.067)	(0.024)	(0.021)	(0.144)	(0.246)	(0.002)
Panel C: Subgroups based on Execution Rate							
DMM	0.098	0.041	-0.000	0.046	0.070	0.424***	0.003***
	(0.280)	(0.096)	(0.025)	(0.051)	(0.250)	(0.154)	(0.001)
DMM×HighER	0.119	0.083	0.007	0.021	0.200	0.144	0.000
	(0.204)	(0.100)	(0.034)	(0.039)	(0.218)	(0.138)	(0.001)
Panel D: Subgroups based on Liquidity Ratio							
DMM	0.289	0.068	0.020	0.063	0.114	0.611***	0.004***
	(0.259)	(0.067)	(0.021)	(0.046)	(0.225)	(0.140)	(0.001)
DMM×HighLR	-0.128	0.089	-0.026	-0.008	0.123	-0.169	-0.002
	(0.154)	(0.063)	(0.032)	(0.032)	(0.157)	(0.167)	(0.001)
Panel E: Subgroups based on Absolute Return							
DMM	0.320	0.212**	-0.003	0.087***	0.388**	0.690***	0.004***
	(0.195)	(0.085)	(0.031)	(0.029)	(0.197)	(0.135)	(0.001)
DMM×LowAR	-0.251	-0.204*	0.015	-0.067*	-0.459	-0.422**	-0.002
	(0.251)	(0.118)	(0.037)	(0.045)	(0.281)	(0.206)	(0.001)
Panel F: Subgroups based on DPA							
DMM	0.244	0.206**	0.016	0.085***	0.317	0.735***	0.004***
	(0.222)	(0.091)	(0.027)	(0.031)	(0.219)	(0.148)	(0.001)
DMM×LowDPA	-0.059	-0.148	-0.021	-0.048	-0.228	-0.405*	-0.002
	(0.262)	(0.102)	(0.032)	(0.044)	(0.276)	(0.211)	(0.001)
Observations	179	179	179	179	179	179	179

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 4: RD Estimation with Heterogeneous Effects: Two Dimensions

	General Measure		Liquidity Measure			Volatility Measure	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Variable	Volume	Price	BA	ER	LR	DPA	AR
Panel A: Subgroups based on Effective Spread and Absolute Return							
DMM	-0.054	0.222**	0.026	0.052*	0.108	0.644***	0.004***
	(0.166)	(0.099)	(0.030)	(0.028)	(0.185)	(0.154)	(0.001)
DMM×LowES	0.648***	-0.012	-0.050**	0.063***	0.488***	0.089	0.000
	(0.250)	(0.065)	(0.023)	(0.016)	(0.138)	(0.251)	(0.002)
DMM×LowAR	-0.335	-0.212*	0.020	-0.077*	-0.525*	-0.450**	-0.002
	(0.264)	(0.117)	(0.038)	(0.043)	(0.288)	(0.213)	(0.001)
Panel B: Subgroups based on Effective Spread and DPA							
DMM	-0.093	0.209**	0.038	0.050*	0.056	0.643***	0.004***
	(0.197)	(0.089)	(0.026)	(0.027)	(0.190)	(0.181)	(0.001)
DMM×LowES	0.771***	-0.008	-0.052**	0.079***	0.598***	0.206	0.001
	(0.288)	(0.085)	(0.026)	(0.021)	(0.223)	(0.245)	(0.002)
DMM×LowDPA	-0.325	-0.145	-0.003	-0.075	-0.434	-0.476**	-0.002
	(0.317)	(0.117)	(0.037)	(0.047)	(0.331)	(0.205)	(0.001)
Observations	179	179	179	179	179	179	179

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 5: Trading statistics by investor types

Panel A: Shares traded				
	Year 2018		Year 2019	
	Numbers (Millions)	fraction	Numbers (Millions)	fraction
Individuals	80.01	80.51%	102.60	83.74%
Brokerage Firms	1.61	1.62%	2.25	1.83%
Private Equity Funds	1.05	1.05%	0.63	0.52%
Publicly Offered Funds	1.11	1.12%	0.84	0.69%
Insurance Firms	0.55	0.55%	0.38	0.31%
Pensions	2.00	2.02%	1.79	1.46%
Foreign Investors	12.12	12.19%	12.98	10.60%
Commercial Banks	0.07	0.07%	0.04	0.03%
Others	0.85	0.86%	1.01	0.83%
Total	99.38	100.00%	122.52	100.00%

Panel B: Trading volume				
	Year 2018		Year 2019	
	Values (W Millions)	fraction	Values (W Millions)	fraction
Individuals	627,021.30	58.20%	469,474.8	59.62%
Brokerage Firms	45,883.96	4.26%	45,592.53	5.79%
Private Equity Funds	29,880.99	2.77%	13,571.07	1.72%
Publicly Offered Funds	31,645.75	2.93%	19,063.21	2.42%
Insurance Firms	17,038.98	1.58%	9,696.39	1.23%
Pensions	65,742.24	6.10%	47,380.41	6.02%
Foreign Investors	244,595.6	22.70%	174,160.70	22.12%
Commercial Banks	2,110.10	0.20%	761.78	0.10%
Others	13,472.03	1.25%	7,765.80	0.99%
Total	1,077,390.95	100.00%	787,466.70	100.00%

Table 6: DMM effect on trading by investor types

	Individuals		Private Equity Funds		Publicly Offered Funds		All Funds	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Shares traded	Trading Volume	Shares traded	Trading Volume	Shares traded	Trading Volume	Shares traded	Trading Volume
DMM	-0.020	-0.021	0.004	0.005	0.010^{**}	0.010^{**}	0.012	0.012
	(0.019)	(0.019)	(0.005)	(0.005)	(0.005)	(0.005)	(0.008)	(0.008)
Observations	644	644	644	644	644	644	644	644
Eff.Left N	84	84	84	84	84	84	84	84
Eff.Right N	92	92	92	92	92	92	92	92

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 7: DMM effect on trading by investor types : Heterogeneity

	Private Equity Funds		Publicly Offered Funds		All Funds	
	(1)	(2)	(3)	(4)	(5)	(6)
	Shares traded	Trading Volume	Shares traded	Trading Volume	Shares traded	Trading Volume
Panel A: Subgroups based on DPA						
DMM	0.009**	0.010***	0.011**	0.011**	0.018***	0.018***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.007)	(0.007)
DMM∗LowDPA	-0.009***	-0.010***	-0.002	-0.002	-0.011*	-0.011*
	(0.003)	(0.003)	(0.005)	(0.243)	(0.006)	(0.006)
Panel B: Subgroups based on Absolute Return						
DMM	0.008**	0.008***	0.011**	0.012**	0.016**	0.017**
	(0.003)	(0.003)	(0.006)	(0.006)	(0.007)	(0.007)
DMM∗LowAR	-0.007*	-0.008*	-0.004	-0.004	-0.011*	-0.011*
	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)
Observations	644	644	644	644	644	644
Eff.Left N	84	84	84	84	84	84
Eff.Right N	92	92	92	92	92	92

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 8: The Effects of DMM on Price Discovery

	Daily data			Weekly data		
	(1)	(2)	(3)	(4)	(5)	(6)
DMM	-0.080	-0.048	-0.086	-0.022	0.037	0.003
	(0.059)	(0.047)	(0.055)	(0.076)	(0.072)	(0.074)
Observations	654	654	654	654	654	654
Eff.Left N	84	84	84	84	84	84
Eff.Right N	95	95	95	95	95	95
Sector Dummies	N	Y	Y	N	Y	Y
Controls	N	N	Y	N	N	Y

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 9: RD Estimation (sharp): Competition

	General Measure		Liquidity Measure			Volatility Measure	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Variable	Volume	Price	BA	ER	LR	DPA	AR
Competition							
DMM	-0.093	0.209**	0.030	0.043	0.069	0.591***	0.004***
	(0.169)	(0.097)	(0.031)	(0.030)	(0.180)	(0.154)	(0.001)
DMM∗competitive	0.704***	-0.024	-0.056**	0.059***	0.503***	0.084	0.000
	(0.254)	(0.070)	(0.024)	(0.017)	(0.164)	(0.223)	(0.002)
Competition, E.Spread and Abs.Return							
DMM	-0.102	0.262**	0.023	0.062*	0.131	0.633***	0.004***
	(0.180)	(0.108)	(0.034)	(0.033)	(0.191)	(0.176)	(0.001)
DMM∗competitive	-0.054	0.235*	-0.041	0.078**	0.205	0.099	0.001
	(0.270)	(0.121)	(0.045)	(0.034)	(0.268)	(0.226)	(0.002)
DMM∗LowES	0.714**	-0.095	-0.042	0.035	0.425**	0.081	0.000
	(0.315)	(0.082)	(0.025)	(0.027)	(0.191)	(0.303)	(0.002)
DMM∗LowDPA	-0.346	-0.220	0.025	-0.079	-0.522	-0.470*	-0.002
	(0.280)	(0.126)	(0.040)	(0.048)	(0.309)	(0.228)	(0.001)
Competition, E.Spread and DPA							
DMM	-0.119	0.240**	0.031	0.058*	0.075	0.637**	0.004***
	(0.228)	(0.098)	(0.030)	(0.030)	(0.203)	(0.223)	(0.001)
DMM∗competitive	0.056	0.223*	-0.051	0.087**	0.289	0.164	0.001
	(0.246)	(0.123)	(0.047)	(0.033)	(0.244)	(0.214)	(0.001)
DMM∗LowES	0.827**	-0.079	-0.047	0.051	0.520*	0.197	0.001
	(0.349)	(0.103)	(0.029)	(0.030)	(0.262)	(0.291)	(0.002)
DMM∗LowDPA	-0.391	-0.157	0.013	-0.075	-0.442	-0.522**	-0.003*
	(0.352)	(0.144)	(0.039)	(0.057)	(0.373)	(0.238)	(0.002)
Observations	179	179	179	179	179	179	179

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 10: RD estimation of Pre-Period Varibles

	General Measure		Liquidity Measure			Volatility Measure	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Variable	Volume	Price	BA	ER	LR	DPA	AR
DMM	-0.385	0.204	-0.030	-0.041	-0.144	-0.203	-0.001
	(0.384)	(0.338)	(0.033)	(0.046)	(0.292)	(0.336)	(0.003)
Observations	654	654	654	654	654	654	654
Eff.Left N	58	58	58	58	58	58	58
Eff.Right N	63	63	63	63	63	63	63
Sector Dummies	Y	Y	Y	Y	Y	Y	Y

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 11: Robustness Checks

Panel A: Main RD Estimation with the 0.2 bandwidth and 1 order polynomial							
	General Measure		Liquidity Measure			Volatility Measure	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Volume	Price	BA	ER	LR	DPA	AR
DMM	0.094	0.288*	-0.034	0.082	0.265	0.534***	0.004***
	(0.259)	(0.149)	(0.027)	(0.050)	(0.293)	(0.200)	(0.001)
Panel B: Main RD Estimation with the 0.4 bandwidth and 1 order polynomial							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Volume	Price	BA	ER	LR	DPA	AR
DMM	0.109	0.078	0.020	0.043	0.073	0.386***	0.003***
	(0.205)	(0.055)	(0.022)	(0.031)	(0.175)	(0.099)	(0.001)
Panel C: Main RD Estimation with the 0.3 bandwidth and 2 order polynomial							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Volume	Price	BA	ER	LR	DPA	AR
DMM	0.249	0.458*	-0.108*	0.184**	0.748	0.935***	0.008***
	(0.570)	(0.257)	(0.062)	(0.080)	(0.545)	(0.333)	(0.002)
Panel D: Main RD Estimation with the 0.3 bandwidth and 3 order polynomial							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Volume	Price	BA	ER	LR	DPA	AR
DMM	0.209	0.458*	-0.105*	0.182**	0.727	0.913***	0.008***
	(0.554)	(0.260)	(0.059)	(0.080)	(0.536)	(0.323)	(0.002)
Panel E: Main RD Estimation with the 2019 level information							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Volume	Price	BA	ER	LR	DPA	AR
DMM	0.176	0.164	0.004	0.058*	0.189	0.506***	0.003***
	(0.220)	(0.236)	(0.027)	(0.032)	(0.187)	(0.102)	(0.001)

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$