ABSTRACT

Title of Dissertation:	ESSAYS ON FINANCIAL MARKETS
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This dissertation contains three essays on financial markets concerning the relationship between short interest and returns in over-the-counter (OTC) equities, the effect of obtaining a rating on municipal bond offering yields, and the use of alternative trading systems (ATS) in the corporate bond market.

Chapter 1 studies short positions among over-the-counter domestic common stocks. Short selling plays an important role in maintaining price efficiency, but short-selling in over-the-counter equities is often perceived as extremely rare. Short selling constraints are indeed high in this market, with the median fee to borrow a security being 2% for stocks with no short interest and 10% for stocks with short interest exceeding 1% of shares outstanding. Despite these constraints, 27% of domestic OTC equities have outstanding short interest positions on a given reporting date. Consistent with theories of short selling constraints such as Miller (1977), these high short selling constraints imply a substantial negative relationship between short interest and future returns. A portfolio of securities with short interest exceeding 1% of shares

underperforms a portfolio of securities with no short interest by 31% annually and panel regressions show the relationship is robust to accounting for other security characteristics. The negative relationship between short interest and future returns suggests short sellers are trading in the direction of correcting mispricing in the OTC market, but the large magnitude and long time horizon over which short positions outperform suggests that there are large potential price efficiency gains from reducing constraints on short selling.

Chapter 2, joint work with Haluk Unal, studies how whether a municipal bond is rated affects its offering yield. Approximately 34% of local municipal bond issues were issued without ratings during 1998 to 2017. We study the circumstances that affect the decision to obtain a rating and whether unrated bonds, controlling for observable risk factors, are more expensive to issue than rated bonds. Results show that issuers are less likely to obtain ratings for smaller issues, negotiated offerings, and bonds with high proxies for risk such as coming from areas with low personal income. We estimate the effect of forgoing a rating on offering yields using a doubly-robust Inverse Probability Weighted Regression Adjustment that controls for confounding that arises from risk and other characteristics affecting both the choice to obtain a rating and the yield. We separately analyze revenue bonds, general obligation bonds, bank qualified, and non-bank qualified bonds and find ratings decrease offering yields by 47, 49, 60, and 42 basis points respectively. The higher offering yields cost municipalities $22.5B in higher interest expense during our sample period. We find the choice of issuers to forgo ratings despite the substantial potential savings appears to be influenced by the underwriters they work with. Underwriters may face a conflict of interest where not obtaining a rating lowers the price investors are willing to pay from the bond, but also lowers the price the underwriter must pay the issuer and thus increases the underwriter's profit.

Chapter 3 is joint work with Matthew Kozora, Bruce Mizrach, Or Shachar, and Jonathan Sokobin. This chapter studies the circumstances when corporate bonds trade via an electronic ATS rather than in the traditional phone market and the relationship between venue choice and transaction costs. Trades on ATS platforms are smaller and more likely to involve investment-grade bonds, suggesting market participants trade via ATS when concerns about information leakage and adverse selection are lower. Trades on ATS platforms are more probable for older, less actively traded bonds from smaller issues, indicating participants are more likely to trade via ATS when search costs are high. Moreover, dealer participation on ATS platforms is associated with lower customer transaction costs of between 24 and 32 basis points.

Essays on Financial Markets

by

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Chapter 1: Short Positions in the OTC Equity Market

Introduction

Theoretical models predict that in the presence of short sale constraints, stocks where the constraints bind will be overpriced and thus have lower future returns. In the model of Miller (1977), this is driven by a divergence of opinions. Even if investors on average accurately price the stock, optimistic investors will buy and push the price up while pessimistic investors cannot profit from trading without establishing a short position unless they already hold the security. Stocks where shot sale constraints bind will be overpriced and thus have lower negative returns. Consequently, short selling plays an important role in maintaining price efficiency, a fact confirmed by international studies of legal restrictions on short-selling such as Bris, Goetzmann, and Zhu (2007).

This paper investigates the role played by short selling in domestic over-the-counter (OTC) common stocks by examining the extent of short positions in this market and the implications of short positions for future returns. High short interest indicates high demand for shorting and thus is commonly used as a proxy for short sale constraints. The negative relationship between short interest and future returns has been extensively studied and generally confirmed among listed equities. For example, Desai et al. (2002) confirm this for Nasdaq stocks while Asquith, Pathak, and Ritter (2005) find the same for NYSE. Studies such as Nagel (2005) show the relationship is strongest among stocks where borrowing shares to sell short is difficult, such as stocks with low institutional ownership.

The relationship between short interest and returns in OTC stocks is interesting for several reasons. One is that short selling is likely to be extremely constrained for OTC stocks.

The prior literature has generally regarded short selling in OTC equities as nearly nonexistent. In the most prominent study of OTC equity returns, Ang, Shtauber, and Tetlock (2013) state "short selling of OTC stocks is difficult, expensive, and rare." In support of this point, they examine whether one discount broker allows short selling for a sample of 50 OTC stocks and find it is possible only for one. Eraker and Ready (2015) mention only that it is "extremely difficult" and note many brokers do not allow it at all or impose extra margin requirements. Both papers hypothesize that extreme constraints short-selling constraints may be responsible for anomalous pricing they find in OTC stocks, but neither actually tests a relationship between establishing short positions and pricing as I do in this paper.

The most relevant constraint on short selling is the difficulty and expense of borrowing shares to deliver. For OTC equities, this constraint is extremely strong but not insurmountable. Securities lending data from Markit indicates that at least approximately 27.8% could be borrowed at any given time, with lending information available for 80.1% of securities at some time in the sample period. However, borrowing these stocks is costly. The median fee is 2.81% and the average is 7.17%.

Despite the high cost of borrowing shares, I show a surprisingly large proportion of domestic OTC common stocks have short interest positions. In a sample covering all domestic OTC equities from 2011 to 2020, I find that 27.1% have a positive short interest position on the average short interest reporting date, with 81.2% reporting short interest on at least one date. Aggregate short interest for this market averages approximately $536 million. Short interest positions tend to be fairly small relative to the shares outstanding but are frequently substantial relative to typical trading volume.

Given the extreme constraints, it is not clear ex ante whether the negative relationship between short interest and returns will be stronger, weaker, or not hold at all in the OTC market. On the one hand, severe constraints on short selling could mean that stocks with relatively high short interest are likely to be severely overpriced. On the other hand, if short sale constraints are strong enough that obtaining large short interest positions is impossible for some securities, high short interest may indicate relatively relaxed constraints rather than high demand. It could also mostly reflect short selling for reasons other than a pessimistic assessment of the current stock price, such as market making or hedging.

The OTC equity market differs in several respects from the listed equity market that could affect the role of short selling. Aside from the OTC market structure, OTC equities are also generally subject to less strict disclosure requirements, less liquid, and held primarily by retail rather than institutional investors (Ang, Shtauber, and Tetlock 2013).

The relatively opaque information environment could also reduce informed short selling. Engelberg, Reed, and Ringgenberg (2012) find a substantial portion of short sellers trading advantage comes from their ability to analyze publicly available information. Desai, Krisnamurthy, and Venkataraman (2006) show short sellers are skilled at detecting poor earnings quality in financial statements. These forms of public information are less available for stocks trading OTC. The opaque environment could also engender a high degree of adverse selection that discourages lending or restricts the counterparties to which owners are willing to lend. However, Cohen, Diether, and Malloy (2007) find that shorting is a stronger predictor of returns in environments with limited public information flow.

High transaction costs and low liquidity are another barrier to sophisticated investors who may otherwise be attracted to correct mispricing via short selling OTC stocks. One might expect short selling to matter less if only retail investors are trading, but Kelly and Tetlock (2017) show retail short selling predicts negative returns in listed stocks, particularly for small firms and firms held mostly by retail traders.

Consistent with asset pricing theories featuring short sale constraints and results in other markets, I find high short interest predicts lower future returns for OTC domestic common stocks. Consistent with short sale constraints being large in this market, the difference in returns is extreme. A portfolio of securities with short interest exceeding 1% of shares underperforms a portfolio of securities with no short interest by 31% annually. Panel regressions controlling for other characteristics including prior returns, size, and trading activity as well as security and date fixed effects predict the average stock in this portfolio would underperform by 14.4% annually. These results indicate that short sellers are trading in the direction of correcting overpricing for OTC stocks. The large magnitude of expected returns indicates that policies relaxing short sale constraints in this market could result in a large price efficiency improvement.

This paper also tests the joint effect of prior returns and short interest constraints on future returns. Daniel, Klos, and Rottke (2021) find a U-shaped pattern, where high short interest listed stocks have lower future returns but the difference is much greater in stocks with extreme prior returns that are either very high or low. They interpret these extreme prior returns as evidence of disagreement among investors and show they are consistent with other proxies such as dispersion in analyst forecasts. A similar pattern is found in corporate bonds by Hendershott, Kozhan, and Raman (2020). I find the same pattern for OTC stocks, which serves as out of sample evidence on this relationship and for their disagreement-based model.

Literature Review

This paper lies at the intersection of two strains of literature, one covering short selling in general and the other covering OTC equities. To the author's knowledge, there is only one other paper that attempts to systematically examine short selling in OTC equities. Jain and Jain (2017) study short selling in a sample of OTC stocks from 2009 to 2016. While that study also addresses the question of whether short selling is informative about future returns for OTC equities, the methodology is substantially different. Most notably, Jain and Jain do not use any measures of short interest in the securities they study. Instead, their measure of short selling is daily short volume as a proportion of total trading volume, which has been referred to elsewhere as "short flow." They find that high short flow predicts negative returns for securities with positive short flow compared to zero short flow at horizons from 1 to 20 days, but that it predicts positive returns for high short flow securities relative to low short flow securities over 20 days.

Theories such as Miller (1977) that predict short selling is necessary to prevent the overpricing of a security assume investors who establish short positions and hold them in anticipation of profiting from price declines. While establishing such a position requires making a trade which contributes to short volume, short trades may have other causes. Short trades made in the process of market making may result in only extremely transient short positions. As Jain and Jain (2017) note, short trades contributing to short volume may arise when a dealer with a customer sell order sells the security and then subsequently fills the sell order. In that case, the dealer never had a true net short position. A market-maker may also switch from long positions to short positions many times within the same day, as documented by Menkveld (2013).

Consequently, short volume may not be indicative of short interest. Empirical studies have confirmed that the relationship is weak. Comerton-Forde, Jones, and Putnins (2016) show for a sample of 350 NYSE-listed stocks that short volume is high even for the lowest short interest quintile. The lowest short interest quintile has short sales comprising 34.2% of dollar volume while the highest short interest quintile has only a bit more at 43.4%. The 25th and 75th percentiles of short volume as a percentage of trades are lower and higher than the averages within the low and high short interest quintiles. The divergence is also documented more systematically in a sample of Australian stocks by Comerton-Forde, Do, Gray, and Manton (2016). In Australia, short interest and short volume are both reported on a daily basis. In the lowest short interest quintile, where short interest only averages 0.23% of shares outstanding, short flow is 14.25%. The highest short interest quintile has 30 times the short interest ratio but only 1.5 times the short flow.

The relationship is likely to be even weaker for securities that cannot be easily borrowed such as OTC equities. Very transient short positions that can be covered without borrowing a share are less affected by difficulty borrowing shares. Consequently, the finding of Jain and Jain (2017) that short volume accounts for 24% of volume in OTC securities does not provide information on the extent of short interest among these securities.

Comerton-Forde, Do, Gray, and Manton (2016) also show that both short flow and short interest predict future returns but encode distinct information. Short flow predicts returns only at short horizons, peaking at 10 days and not extending beyond 20 days. Short interest predicts returns at least through 60 days. Short flow is related to recent buy-sell order imbalance, short interest is not. Short interest embeds information about firm fundamentals and associated mispricing. There is no evidence that short flow is related to mispricing.

Short interest has been extensively studied in listed stocks and generally found to predict lower returns, particularly when short selling is constrained. For a more complete overview, see the review by Reed (2013).

The relationship has also been studied in the corporate bond market. Asquith, Au, Covert, and Pathak (2013) find no evidence that short interest predicts future returns in a sample of corporate bonds from 2004-2007. However, Hendershott, Kozhan, and Raman (2020) examine a longer sample and find that since the financial crisis, short interest does predict bond returns in high-yield bonds. The corporate bond and OTC equities are both traded in OTC markets, but the markets are otherwise quite different. OTC equities are generally traded by retail investors while many large institutions trade corporate bonds. Bonds are less informationally sensitive than equities. The information environment for corporations that issue bonds is generally extremely transparent with regular disclosure and monitoring by ratings agencies, while OTC equities may not even be subject to SEC reporting requirements.

A few papers study the returns of OTC equities. Ang, Shtauber, and Tetlock (2013) study their cross-sectional return premiums. They find that the size, value, and volatility premia are similar in size to those in listed markets. The momentum premium is substantially smaller, while the illiquidity premium is several times higher. The authors explain these findings as consequences of lower disclosure, lower institutional ownership, and barriers to short selling in the OTC market.

Eraker and Ready (2015) find OTC stocks have extremely positively skewed returns with negative average returns and median returns of almost negative fifty percent. They interpret these results as evidence for the model of Barberis and Huang (2008) where investors prefer lottery-like payoffs with a small change of an extremely high return. White (2016) finds similar results using proprietary database of OTC transactions, and also that returns are lower for OTC stocks following a promotional campaign and with weaker disclosure requirements.

Data Overview

Data Sources

Reference data is used to identify active OTC equities during the sample period and to exclude OTC equities other than domestic common stocks. This excludes other equity securities that trade in the OTC equity market, such as preferred shares, foreign shares, American Depository Receipts (ADRs), and Global Depository Receipts (GDRs). Although these securities trade in the United States with a similar market structure, they differ substantially in other ways. Many of these securities either trade themselves or have related securities trading on exchanges. OTC preferred shares are often issued by firms with exchange-listed common stocks. ADRs and GDRs provide indirect ownership of shares that may be exchange-listed in foreign countries. Foreign shares may themselves be exchange-listed in foreign countries. Consequently, the firms underlying these securities are likely subject to different regulatory and disclosure requirements. Short positions in these securities taken in American OTC markets will not be comprehensive, as their exchange-listed counterparts may also be shorted. Another complication for securities listed on foreign exchanges is that their short interest levels may reflect short selling restrictions in their home country. Jain, Jain, McInish, and McKenzie (2013) find that home country restrictions reduce short selling of ADRs by 68%.

Records of individual trades are used to calculate the daily trading volume and end of day prices. Dividends and stock splits are used to adjust prices in order to calculate returns. The trade data spans January 2011 through December 2020.

Short interest data for equities is reported to FINRA by broker-dealers on a bimonthly basis. For OTC equities, short interest is reported my members to FINRA two days after the short interest date. The data is aggregated at the security level and published on the FINRA website five days after the reporting deadline. Short interest data for OTC securities is available from February 2010 to April 2021.

Data on historical shares outstanding is taken from the OTC Markets Group data on WRDS. For a small number of observations relating to 22 securities, short interest appeared to substantially exceed the shares outstanding as reported in the OTC markets data. Shares outstanding was double-checked manually against other sources for these securities and corrected if errors were found. One security was removed from the sample as news sources indicate potentially unauthorized shares were trading. Two securities were removed because shares outstanding could not be confirmed in any data source.

Information on the availability and cost to borrow shares for OTC equities is obtained from IHS Markit via WRDS. The Markit data includes daily information on the lending market for a broad range of equity and fixed income securities. The data includes information regarding shares on loan, shares available for lending, and indicative fees for borrowing. When constructing the data panel, if information was available for any dates since the last short interest reporting date, the most recent was used.

Markit's coverage of other markets is comprehensive enough that its shares on loan data has been used as a high-frequency proxy in several papers. For example, Hendershott, Kozhan, and Raman (2020) do so in a study of corporate bond short selling and Engelberg, Reed, and Ringgenberg (2018) do so for listed equities. However, Markit's coverage of OTC equities is relatively sparse. As shown in Table 1-1, approximately 80% of the panel consists of securities that have information at some point in Markit, but only 28% have information within the most recent short interest reporting period. This rises to 62% for securities with moderate short interest and 92% for securities with high short interest, so lending data may only be reported to Markit in cases where someone has made a relevant inquiry. However, even for those securities that do have recent information in Markit, for those with positive short interest positions, Table 1-1 shows the median position exceeds Markit's reported shares on loan by 48% and the 75th percentile by 320%.

The incongruence between Markit's data and actual short positions does not mean the positions were not covered with stock loans, and the lack of information on shares available does not mean the shares are actually impossible to borrow. This information is sourced by Markit from over 100 securities finance participants within the wholesale securities lending market according to the 2013 Markit Securities Finance Data Feed FAQs. Participants must provide their data in order to receive access to the data. Markit estimates they cover approximately 85% of the OTC securities lending market, but this includes securities such as bonds for which they have extensive coverage. The market participants involved in the lending and shorting of OTC equities may not be members of this group.

Summary Statistics

The aforementioned data sources are combined to create a panel dataset of active OTC domestic equities across reporting dates from 2011 through 2020. Summary statistics for this panel are shown in Panel A of Table 1-1. On the average reporting date, 27.1% of securities have positive short interest. 81.2% are securities that have ever had positive short interest at some point in the sample period.

Figure 1-1 shows the aggregate value of short interest for all domestic OTC equities on each reporting date during the sample period. The figure also includes the dollar volume of trading since the previous short interest reporting date. Short interest positions are valued using the last traded price as of the short interest date. On the average reporting date, short interest aggregated across all OTC domestic common stocks totals approximately $536 million, about 34% of trading volume over the preceding half month. Short interest tends to follow recent trading volume but is more consistent over time.

Figure 1-2 Panel A shows the median indicative fee for securities in the panel across time. Borrowing OTC securities is expensive. As shown in Table 1-1, the median fee is 2.8%, and the average is 7.1%. For comparison, Reed (2013) reports that the typical fee range for liquid listed stocks is 0.05% to 0.25%, with fees rising to 0.35% for midcap stocks. Even the 10th percentile for OTC stocks is 0.94%. Figure 1-2 Panel B and Table 1-1D show that fees are higher for stocks with higher short interest. For stocks with short interest exceeding 1% of shares outstanding, the median fee is 10.0% and the average is 21.0%. Fees may understate the ultimate costs of shorting. Engelberg, Reed, and Ringgenberg (2018) show that short sellers are sensitive to the risk that loans will become more expensive or are recalled early before an investor wishes to close their positions.

This comprehensive sample includes many small and or thinly traded firms, with the 25th percentile of monthly dollar volume being $0 and of market cap being $90,000. Many of the firms that do trade have extremely low prices and returns may be calculated with error or dominated by noise such as bid-ask bounce rather than changes in value. Consequently, before analyzing returns, it is necessary to apply a number of filters.

I employ two sets of filters based on the prior work studying OTC equity returns. The first set of filters derives from Ang, Sthauber, and Tetlock (2013). They require the stock price be at least $1. This restriction is based on Ince and Porter (2006), who find that errors in computed returns are more likely to occur for firms with prices of less than $1. They also require that information on shares outstanding be available, and market capitalization exceed $1 million in order to exclude tiny firms that would otherwise dominate equal-weighted portfolios, Finally, they require positive trading volume in the previous month in order to avoid stale prices. These filters reduce the 12,380 securities in the original sample to 2,748. Summary statistics for this sample are shown in Panel B of Table 1-1.

The above filters are quite restrictive. This ensures the returns and other information used for analysis are reliable but reduces the comprehensiveness of the results. Consequently, I also employ a second set of less restrictive filters based on the least restrictive set of filters used by Eraker and Ready (2015). These filters are substantially less restrictive when it comes to price. Any security that trades for at least $0.01 is eligible for inclusion. The same minimum market capitalization requirement is imposed. Only securities with at least $2,000 in trading volume in the previous month may be included. Eraker and Ready (2015) also apply a few other filters not included here, such as cross-checking returns from different databases and requiring positive trading volume on the day of portfolio formation. This sample covers a broader segment of the OTC domestic equity universe, including 5,235 securities. Summary statistics for this sample are shown in Panel C of Table 1-1.

Panel D of Table 1-1 presents summary statistics separately for stocks with no short interest, short interest that is greater than 0% but less than 1% of shares outstanding, and short interest that is greater than 1% of shares outstanding with the sample based on Eraker and Ready

(2015). Shorted stocks tend to have much higher volume and turnover and be somewhat larger, and highly shorted stocks even more so.

Cross Section of Short Interest and Future Returns

Portfolio Sorting Analysis

To test whether stocks with high short interest underperform, I assign stocks to portfolios based on their scaled level of short interest. Because roughly three quarters of the stocks have no short interest, I do not sort them into quintile portfolios. On each short interest reporting date, I assign stocks to one of three portfolios: 1) no short interest, 2) moderate short interest stocks with short interest greater than 0% but not more than 1% of total shares outstanding, or 3) high short interest stocks with short interest exceeding 1% of total shares outstanding. I then calculate the average buy-and-hold equal-weighted returns of the portfolios over several horizons, as well as for long-short portfolios that go long the moderate and high short interest portfolios and short the no short interest portfolios. Using buy-and-hold portfolios rather than dynamically rebalancing will reduce the effect of bid-ask bounce, which is likely to be relatively high for OTC stocks (Blume and Stambaugh 1983). Because the portfolio holding periods overlap, I use Newey and West (1987) standard errors to test whether returns are statistically significant.

Panel A of Table 1-2 shows the returns for each of the short interest portfolios for the AST sample. The results show strong underperformance for shorted stocks at longer horizons. The high short interest portfolio underperforms the no short interest portfolio by 38.3% annually and the moderate short interest portfolio underperforms the no short interest portfolio by 12.9%. Returns are negative and significant at the 20, 60, and yearly horizons for both long-short portfolios. At shorter horizons, the results are only significant for the high short interest portfolio at 10 days, although the average returns are always negative. Panel A of Table 1-3, showing the same results for the E&R sample, confirms the results.

Panel C of Table 1-2 and 1-3 shows the risk-adjusted returns of these portfolios, calculated using the Fama-French Four-Factor model. The risk-adjusted returns are also generally negative and significant at longer horizons.

Panel B of Table 1-2 and Table 1-3 shows the same results for portfolios weighted by the prior month's gross returns, as suggested by Asparouhova, Bessembinder, and Kalcheva (2013). These ABK weights are often used in studies of returns for OTC stocks or other low liquidity securities because they account for a positive bias induced by the bid-ask bounce or other noise in arithmetic returns first noted by Blume and Stambaugh (1983). The long-short portfolio returns for these weighted portfolios generally become insignificant for the AST sample except for the high – none portfolio at a yearly horizon. For the E&R sample, the results at horizons 20 days and beyond remain significantly negative, although their magnitude is reduced.

However, the ABK weights may be problematic for studying the relationship between short-selling and returns, because there is an established relationship between the predictiveness of short selling and prior returns. Daniel, Klos, and Rottke (2021) show for listed stocks that high or low prior period returns are associated with high levels of disagreement among investors, and that short interest in constrained stocks most negatively predicts higher returns when stocks have high investor disagreement. Panels A and C of Table 1-3 find this U-shaped pattern is also present in OTC stocks, with the relationship being strongest for stocks with recent price declines, which are underweighted by this methodology. The ABK-weighted long-short portfolios become negative and significant for both samples within each prior return tercile. Both sets of portfolios have generally negative and significant alphas.

Cross-Sectional Regressions

The portfolio analysis shows that portfolios of heavily shorted stocks underperform, but cannot rule out that the relationship between short interest and return is driven by other factors correlated with short interest. Consequently, I also employ regression analysis while controlling for other characteristics. These specifications are conservative, to the extent that short sellers identify overvalued stocks based on the controlled variables the coefficient on short interest will understate their abilities.

First, I use the Fama-Macbeth approach with Newey and West (1987) standard errors. On each short interest reporting date *t*, I estimate the following cross-sectional regression:

$$r252_{i,t} = \alpha + \beta_1 SIR_{i,t} + \beta_2 r1M_{i,t} + \beta_{32} \ln{(Market\ Cap)_{i,t}} + \beta_3 Turnover_{i,t} + \beta_4 \ln{(Average\ Volume)_{i,t}} + \varepsilon_{i,t}$$

The choice of variables is based on Boehmer et al. (2008). We then average each coefficient over the time-series with Newey and West (1987) standard errors. Panel A of Table 1-5 presents the estimation results. For the AST sample, the effect of short interest ratio on future returns is negative and significant at the 0.1% level. However, there is no significant relationship found in the E&R sample.

I also estimate a similar panel regression model that also includes security and date fixed effects.

$$r252_{i,t} = \alpha_i + \gamma_t + \beta_1 SIR_{i,t} + \beta_2 r1M_{i,t} + \beta_{32} \ln{(Market\ Cap)_{i,t}} + \beta_3 Turnover_{i,t} + \beta_4 \ln{(Average\ Volume)_{i,t}} + \varepsilon_{i,t}$$

The security fixed effects provide a strong control for unobservable security-level characteristics that may be associated with both returns and short interest. The results, shown in Panel B of Table 1-5, are fairly similar to the Fama-Macbeth results, with a similar coefficient on short interest ratio in the AST sample that is significant at the 1% level. Again there is no significant relationship in the E&R sample.

The lack of a significant relationship in the E&R sample may be due to mismeasurement of the total shares outstanding for the penny stocks included in this sample, which is the denominator for short interest ratio. This could be due to either errors in the data or the shares outstanding being a poor indicator of the security's float. I therefore estimate a similar panel regression replacing short interest ratio with the value of the short position. This would not be ideal for portfolio sorts because when the short position is not scaled by firm size it may covary with other characteristics affecting returns, but in a regression framework those other characteristics can be directly controlled for. The estimated model is:

$$r252_{i,t} = \alpha_i + \gamma_t + \beta_1 ShortValue_{i,t} + \beta_2 r1M_{i,t} + \beta_{32} \ln{(Market\ Cap)_{i,t}} + \beta_3 Turnover_{i,t} + \beta_4 \ln{(Average\ Volume)_{i,t}} + \varepsilon_{i,t}$$

The results, shown in Table 1-5.2A, are now consistent in the AST and E&R samples, with a negative and highly significant result of similar size in each. As shown in Table 1-5.2B, the lower of the two estimates implies an annual underperformance of -14.33% for the highly shorted portfolio.

Cross-Sorted Portfolio Analysis

The previous regressions indicated that size and trading activity may also be associated with future returns, so I also examine whether the relationship between short interest and returns persists across size and turnover quintiles. The number of stocks in some buckets of the high short interest portfolio is small, so erratic returns may be expected.

Tables 1-6 and 1-7 present results for portfolios double sorted by short interest ratio and market capitalization for the AST and E&R samples respectively. The results generally show negative and significant returns on the long-short portfolios, although there are exceptions. Tables 1-8 and 1-9 present results from a similar analysis using turnover quintiles. The long-short portfolios always experience substantially negative returns which are significant for all but the high-low short interest low volume portfolio and the moderate – low short interest, high volume portfolio.

Delisting and the Short Interest – Return Relationship

One potential concern with the results thus far is that they may be drive by recently delisted securities. Investors may have acquired large short positions in these securities when they were listed and borrowing was less constrained, followed by poor performance that resulted in stock failing to meet an exchange's listing requirements. The security may then continue it's downward trajectory after delisting. To address this concern, I perform portfolio sorts on short interest among only OTC stocks that have always been OTC stocks, excluding any that previously traded on exchanges. The results, shown in Table 1-10, confirm the negative relationship holds in this subsample.

Conclusion

I provide novel evidence on the extent of short positions in OTC stocks and their implications for future returns. Short selling constraints are high for OTC stocks. When they are available to borrow, the median fee is 2%, much higher than for listed stocks. For stocks where short interest exceeds 1% of total shares outstanding, the median fee jumps dramatically to 10%. Securities lending databases only have information available for 27.8% of securities at any given time.

Despite these constraints, aggregate short interest in OTC domestic equities averages over $500 million. 26.6% of OTC stocks have short interest positions at a given time, with 81.5% having short interest at some point in my sample.

Asset pricing theories predict and prior work in other markets has found that short interest negatively predicts future returns, especially for stocks where short selling is more constrained. Consistent with these findings and the high cost of shorting for OTC stocks, short interest predicts lower future returns and the magnitude of the effect is large. A portfolio of stocks with short interest greater than 1% of shares outstanding underperforms stocks with no short interest by 31.0% annually. A portfolio of stocks with moderate short interest underperforms stocks with no short interest by 21.5% annually. The negative relationship between short interest and future returns is robust to exhaustive controls using multivariate panel regressions or bivariate portfolio sorts. The relationship is strongest for stocks with returns that are extremely high or low, consistent with theories that emphasize the role of investor disagreement.

The negative relationship between short interest and future returns indicates that short sellers are trading in the direction of correcting mispricing. However, the long horizon over which their short positions overperform and the large magnitude of overperformance indicates they are restricted by high short sale constraints. Policies that relax short sale constraints in this market are likely to result in substantially more efficient prices.

Figures

Figure 1-1: Aggregate Short Interest for OTC Domestic Common Stocks

Figure 1-1 shows the dollar value aggregate short interest for all OTC domestic common stocks as of each short interest reporting date. Short interest is valued using the last traded price as of the short interest date. Figure 1 also shows the dollar volume of OTC domestic common stock trading during the time from the day after the previous short interest reporting date through the current short interest reporting date.

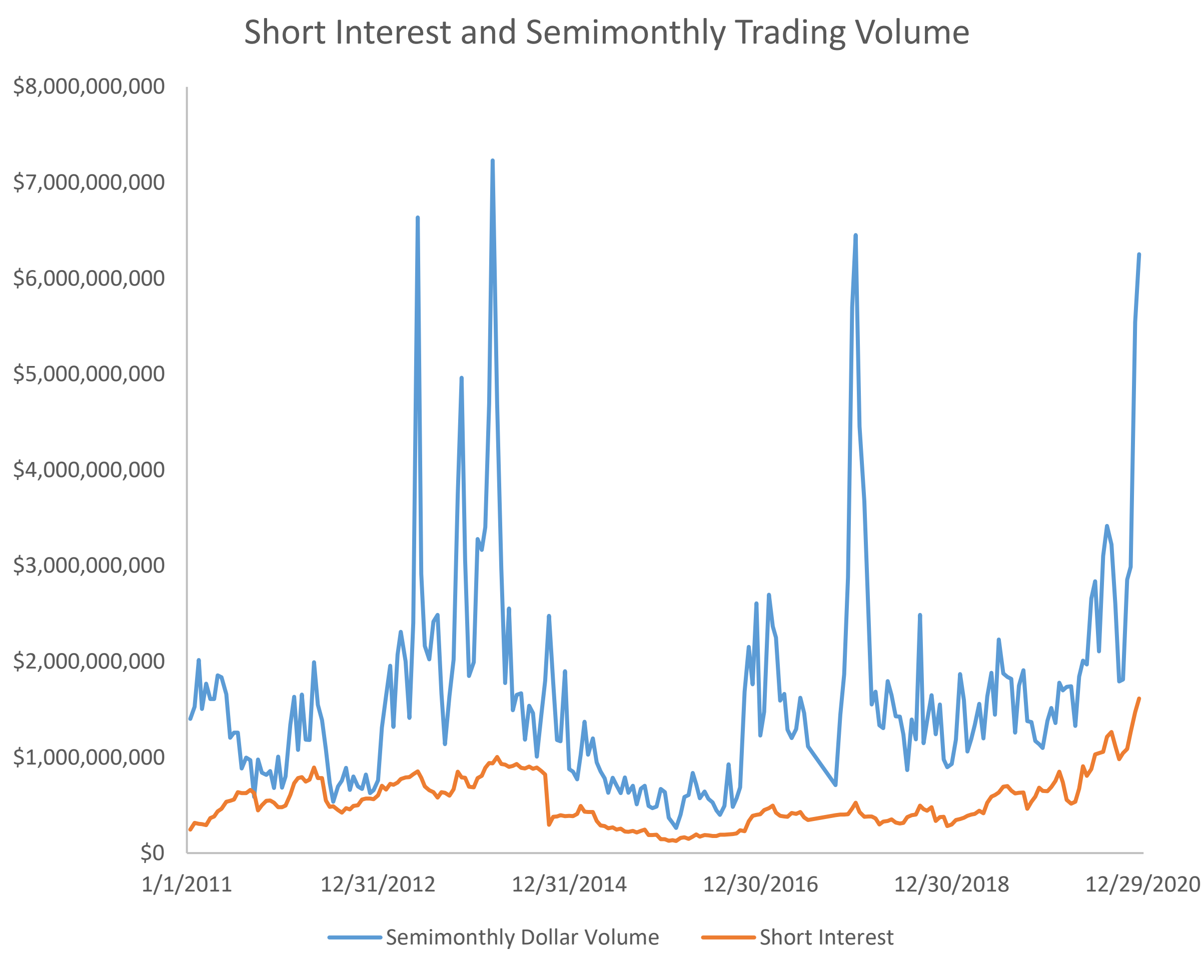
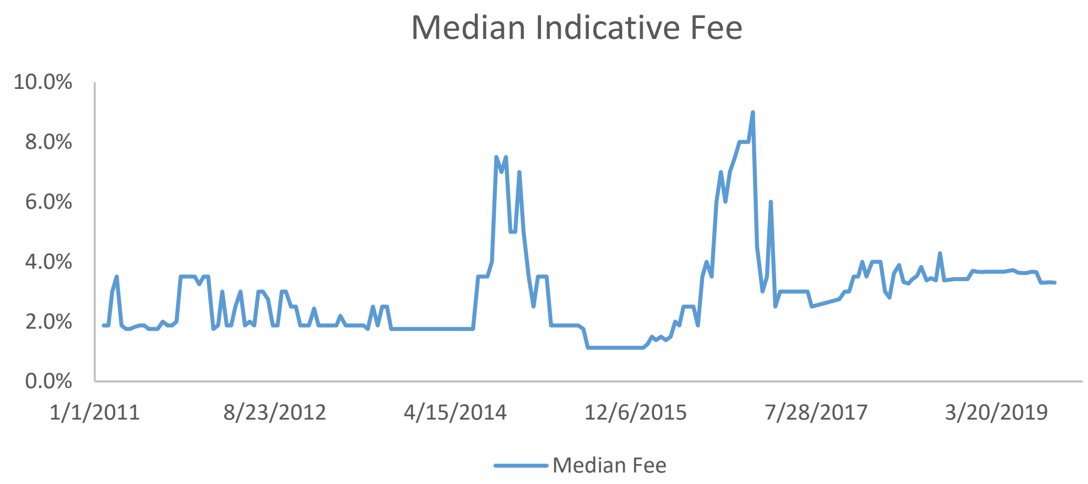


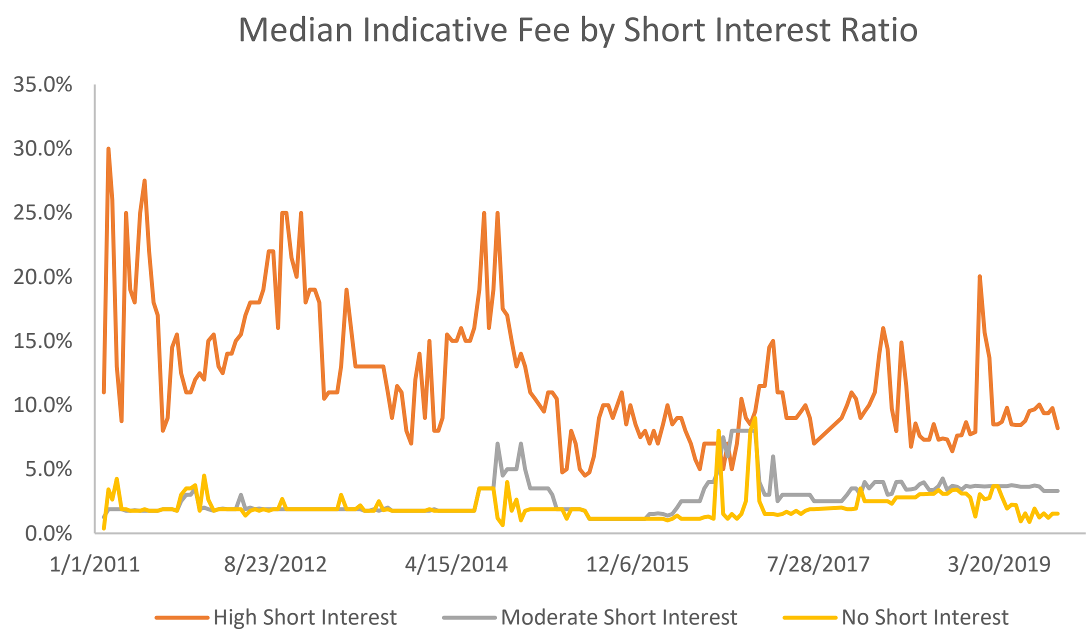
Figure 1-2: Median Lending Fees

Figure 1-2 shows the median indicative lending fee from Markit from securities in the panel as of each short interest reporting date. Panel A is the overall median, while Panel B shows the median lending fee for securities with no short interest, with short interest less than 1% of shares outstanding, and with short interest greater than or equal to 1% of shares outstanding.

Panel A: All Domestic OTC Equities



Panel B: Domestic OTC Equities Categorized by Short Interest Level



Variable Definitions

Short Interest > 0: A dummy variable equal to 1 if the short interest for a security is greater than 0 as of the short interest reporting date.

Short Interest Ever > 0: A dummy variable equal to 1 for a security with short interest greater than 0 as of any reporting date in the sample.

Security in Markit: A dummy variable equal to 1 if the security has shares available or an indicative fee in Markit within the past two weeks.

Security Ever in Markit: A dummy variable equal to 1 if the security ever has shares available in Markit within the sample period.

Short Interest / Lendable Quantity in Markit: For securities with positive short interest, the ratio to the quantity of shares available for lending in Markit.

Short Interest / Quantity on Loan in Markit: For securities with positive short interest, the ratio to the quantity of shares on loan according to Markit.

Indicative Fee: The indicative fee to borrow the security in Markit.

Short Interest ($): The short interest shares multiplied by the last closing price.

Short Interest / TSO: The ratio of short interest to total shares outstanding.

Short Interest / Average Monthly Volume: The ratio of short interest ($) to the average monthly dollar volume over the preceding 6 months.

Monthly Dollar Volume: The average monthly dollar volume over the preceding 6 months.

Share Price: The last trade price of the security

Market Capitalization: The total shares outstanding multiplied by the last traded price of the security.

Turnover: The average monthly share volume over the preceding six months divide by the total shares outstanding.

1Y Return: The price of the security in 1 year divided by the current price minus 1.

Tables

Table 1-1: Summary Statistics

Table 1-1 provides mean, standard deviation, and percentiles for variables in the panel dataset of OTC equities with bimonthly observations. Panel A includes all domestic OTC common equities. Panel B is filtered according to the criteria used in Ang, Shtauber, and Tetlock (2013). Pancel C is filtered according to the criteria used in Eraker and Ready (2015). Refer to Appendix A for variable definitions.

Panel A: All OTC Securities

Variable	Mean	Standard Deviation	10th	25th	Median	75th	90th
Short Interest > 0	26.6%						
Security where SI is Ever > 0	81.5%						
Security in Markit	27.8%						
Security Ever in Markit	80.1%						
Short Interest / Lendable Quantity in Markit (SI>0 Only)	20602%	2187615%	1%	5%	56%	277%	1482%
Short Interest / Quantity On Loan in MarkIt (SI>0 Only)	36501%	2830162%	42%	100%	148%	420%	1823%
Indicative Fee	7.17%	14.28%	0.94%	1.75%	2.81%	8.00%	14.00%
Short Interest ($)	$87,074	$2,815,731	$0	$0	$0	$4	$1,078
Short Interest / TSO	0.0%	0.7%	0.0%	0.0%	0.0%	0.0%	0.0%
Short Interest / Average Monthly Volume	407378970.5%	128601536973.6%	0.0%	0.0%	0.0%	0.2%	22.4%
Short Interest ($) (Only When SI > 0)	$294,812	$5,175,160	$1	$20	$267	$2,503	$26,738
Short Interest / TSO (Only When SI > 0)	0.2%	1.3%	0.0%	0.0%	0.0%	0.0%	0.2%
Short Interest / Average Monthly Volume (Only When SI > 0)	Inf		0.1%	0.8%	6.3%	79.2%	3670.5%
Monthly Dollar Volume	$2,434,021	$81,282,458	$0	$90	$9,924	$234,950	$1,522,630
Share Price	$57.31	$1,469.90	$0.00	$0.00	$0.03	$0.52	$9.37
Market Cap	$64,950,772	$2,581,994,614	$5,816	$80,815	$744,057	$7,987,032	$40,792,510
Turnover (Monthly Share Volume/Shares Outstanding)	62.7%	4983.5%	0.0%	0.0%	0.2%	1.0%	4.3%
1Y Return	14314.6%	1841604.6%	-90.0%	-64.0%	-8.8%	33.3%	240.0%
Unique Securities	12,380						

Panel B: Ang, Shtauber, Tetlock (2013) Filters

Variable	Mean	Standard Deviation	10th	25th	Median	75th	90th
Short Interest > 0	38.6%						
Security where SI is Ever > 0	97.9%						
Security in Markit	38.1%						
Security Ever in Markit	88.7%						
Short Interest / Lendable Quantity in Markit (SI>0 Only)	2559%	38853%	1%	7%	80%	358%	1330%
Short Interest / Quantity On Loan in MarkIt (SI>0 Only)	1229%	18127%	36%	93%	127%	289%	897%
Indicative Fee	7.42%	15.26%	0.38%	1.13%	2.82%	8.00%	15.00%
Short Interest ($)	$289,626	$4,521,160	$0	$0	$0	$1,050	$12,592
Short Interest / TSO	0.1%	0.5%	0.0%	0.0%	0.0%	0.0%	0.0%
Short Interest / Average Monthly Volume	71.6%	4978.8%	0.0%	0.0%	0.0%	0.1%	2.3%
Short Interest ($) (Only When SI > 0)	$750,411	$7,253,727	$110	$530	$2,389	$13,900	$147,869
Short Interest / TSO (Only When SI > 0)	0.1%	0.8%	0.0%	0.0%	0.0%	0.0%	0.2%
Short Interest / Average Monthly Volume (Only When SI > 0)	185.8%	8021.1%	0.0%	0.0%	0.4%	2.4%	10.6%
Monthly Dollar Volume	$9,171,046	$197,790,647	$19,284	$107,030	$460,119	$1,601,499	$4,585,632
Share Price	$167.58	$2,113.44	$1.40	$2.70	$8.87	$23.28	$54.60
Market Cap	$216,454,687	$2,098,222,790	$6,094,643	$14,022,592	$33,821,090	$84,639,963	$216,523,009
Turnover (Monthly Share Volume/Shares Outstanding)	51.0%	5463.8%	0.0%	0.1%	0.3%	0.7%	1.8%
1Y Return	9.2%	394.8%	-68.3%	-25.0%	1.6%	23.3%	52.1%
Unique Securities	2,748						

Panel C: Eraker and Ready (2015) Filters

Variable	Mean	Standard Deviation	10th	25th	Median	75th	90th
Short Interest > 0	50.7%						
Security where SI is Ever > 0	99.0%						
Security in Markit	44.0%						
Security Ever in Markit	94.5%						
Short Interest / Lendable Quantity in Markit (SI>0 Only)	7648%	161357%	2%	15%	109%	472%	1900%
Short Interest / Quantity On Loan in MarkIt (SI>0 Only)	2888%	75839%	47%	100%	155%	414%	1419%
Indicative Fee	7.57%	15.12%	1.00%	1.50%	3.05%	8.00%	15.00%
Short Interest ($)	$201,586	$4,198,228	$0	$0	$3	$1,060	$9,483
Short Interest / TSO	0.1%	0.5%	0.0%	0.0%	0.0%	0.0%	0.0%
Short Interest / Average Monthly Volume	679.8%	35095.7%	0.0%	0.0%	0.0%	2.1%	13.4%
Short Interest ($) (Only When SI > 0)	$397,461	$5,888,396	$40	$197	$1,014	$5,602	$45,541
Short Interest / TSO (Only When SI > 0)	0.1%	0.7%	0.0%	0.0%	0.0%	0.0%	0.2%
Short Interest / Average Monthly Volume (Only When SI > 0)	1344.3%	49343.1%	0.0%	0.3%	2.0%	9.0%	36.4%
Monthly Dollar Volume	$6,336,952	$142,158,789	$36,293	$112,307	$418,641	$1,510,963	$4,792,537
Share Price	$84.05	$1,511.45	$0.03	$0.10	$0.65	$8.25	$28.50
Market Cap	$113,952,733	$1,350,840,182	$2,074,925	$4,694,840	$14,139,927	$41,353,941	$111,342,922
Turnover (Monthly Share Volume/Shares Outstanding)	33.1%	3966.4%	0.0%	0.2%	0.5%	1.4%	3.9%
1Y Return	2.1%	514.1%	-87.4%	-61.5%	-15.0%	17.9%	62.2%
Unique Securities	5,235						

Table 1D: Summary Statistics by Ratio of Short Interest to Shares Outstanding

Table 1-1D shows the distribution of selected attributes for securities within securities assigned to the No Short Interest, Moderate Short Interest (up to 1% of TSO), and High Short Interest (more than 1% of TSO) portfolios in the panel constructed using Eraker and Ready (2015) filters.

SIR Portfolio	Variable	Mean	SD	P10	P25	P50	P75	P90
0	Monthly Dollar Volume	$990,048	$9,558,683	$22,326	$63,657	$214,933	$729,789	$2,014,800
1	Monthly Dollar Volume	$5,559,695	$42,636,001	$75,973	$227,954	$775,659	$2,547,909	$7,924,068
2	Monthly Dollar Volume	$230,685,308	$1,173,826,580	$169,374	$779,815	$5,905,848	$43,673,065	$342,549,987
0	Turnover	3.5%	259.4%	0.0%	0.1%	0.3%	0.7%	1.6%
1	Turnover	42.1%	4175.3%	0.1%	0.3%	0.8%	2.3%	6.3%
2	Turnover	789.4%	22965.2%	0.3%	1.4%	4.8%	13.0%	32.4%
0	Indicative Fee	3.45%	6.06%	0.75%	1.13%	1.88%	3.50%	8.00%
1	Indicative Fee	7.15%	14.21%	1.00%	1.50%	3.06%	8.00%	14.00%
2	Indicative Fee	21.05%	27.26%	1.46%	3.90%	10.00%	25.00%	60.43%
0	Market Capitalization	$72,580,523	$1,274,978,676	$1,896,922	$4,116,714	$12,897,544	$38,791,147	$99,829,059
1	Market Capitalization	$147,863,853	$1,427,644,272	$2,330,655	$5,374,911	$15,272,828	$43,370,837	$119,052,243
2	Market Capitalization	$345,429,202	$1,129,062,748	$2,045,975	$5,054,789	$18,551,449	$114,077,140	$808,759,890
0	Market Closing Price	$143.21	$1,576.65	$0.04	$0.12	$1.69	$15.90	$43.00
1	Market Closing Price	$27.15	$1,466.43	$0.03	$0.09	$0.40	$2.50	$13.95
2	Market Closing Price	$8.98	$74.84	$0.07	$0.20	$0.70	$2.64	$12.74
0	1-Year Future Return	12.12%	694.11%	-80.61%	-46.67%	-3.14%	22.72%	62.50%
1	1-Year Future Return	-7.43%	231.33%	-91.30%	-70.29%	-29.67%	11.32%	62.34%
2	1-Year Future Return	-15.37%	170.83%	-91.67%	-73.59%	-39.38%	0.00%	45.25%
0	Short Interest ($)	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00
1	Short Interest ($)	$98,498.65	$1,600,797.04	$37.50	$184.54	$923.52	$4,561.59	$26,648.73
2	Short Interest ($)	$9,490,196.88	$30,432,380.52	$37,811.40	$103,159.05	$414,607.39	$2,224,416.00	$19,255,721.99
0	Short Interest / TSO	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%	0.0000%
1	Short Interest / TSO	0.0470%	0.1233%	0.0003%	0.0014%	0.0062%	0.0256%	0.1150%
2	Short Interest / TSO	2.7695%	2.8976%	1.1440%	1.3699%	1.8346%	3.0635%	4.8665%
0	SI / Lendable							
1	SI / Lendable	78.09	1655.96	0.01	0.13	1.01	4.33	17.80
2	SI / Lendable	49.11	500.41	0.39	1.04	3.71	12.23	46.88
0	SI / On Loan							
1	SI / On Loan	21.78	451.16	0.44	1.00	1.49	4.06	14.32
2	SI / On Loan	142.90	2554.11	1.04	1.52	2.47	4.95	12.25
0	SI($) / Volume ($)	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1	SI($) / Volume ($)	5.13	309.80	0.00	0.00	0.02	0.08	0.31
2	SI($) / Volume ($)	316.87	2352.45	0.03	0.10	0.38	3.55	20.29

SIR Portfolio	Ever in Markit	Ever Short	In Markit
0	91.1%	98.0%	24.3%
1	97.9%	100.0%	62.2%
2	97.9%	100.0%	91.8%

Table 1-2: Returns on Portfolios Sorted by Short Interest Ratio – Sample with Ang, Shtauber, and Tetlock (2013) Filters

Table 1-2 presents returns for portfolios sorted based on short interest. The sample includes all OTC domestic equities from 2011-2019 meeting the Ang, Shtauber, and Tetlock (2013) criteria. These criteria include non-missing data on shares outstanding, returns, a stock price that exceeds $1, market capitalization that exceeds $1 million, and positive trading volume in the preceding month. Securities are assigned to a portfolio as of each bimonthly short interest date and portfolios are held for the specified return horizon. Returns are not annualized. t-Statistics based on the time series of portfolio returns using Newey-West (1987) standard errors with an automated number of lags selected according to Newey-West (1994) are reported in parentheses. ABK-Weighted portfolios use the prior month's gross returns as weights. Risk-adjusted returns are calculated using the Fama-French Four-Factor model.

Panel A: Future Returns of Equal-Weighted Portfolios

	k-Trading Day Return Horizon											
	1		5		10		20		60		252	
No Short Interest	0.1%	(0.88)	0.6%	(1.97)	1.1%	(2.07)	2.3%	(2.44)	4.9%	(2.78)	18.5%	(3.43)
Moderate Short Interest (Up to 1% of TSO)	0.1%	(0.24)	0.0%	(-0.01)	0.1%	(0.16)	0.0%	(-0.04)	1.1%	(0.48)	5.6%	(1.20)
High Short Interest (More than 1% of TSO)	0.0%	(-0.08)	-0.8%	(-0.70)	-1.7%	(-1.03)	-3.8%	(-1.46)	-8.4%	(-2.04)	-20.0%	(-3.52)
Moderate SI - No SI	-0.1%	(-0.30)	-0.6%	(-1.12)	-0.9%	(-1.12)	-2.3%	(-1.93)	-3.8%	(-1.65)	-12.9%	(-2.24)
High SI - No SI	-0.2%	(-0.27)	-1.5%	(-1.17)	-2.8%	(-1.64)	-6.1%	(-2.23)	-13.3%	(-3.27)	-38.3%	(-5.74)

Panel B: Future Returns of ABK-Weighted Portfolios

	k-Trading Day Return Horizon											
	1		5		10		20		60		252	
No Short Interest	-1.1%	(-1.31)	-3.5%	(-1.41)	-4.6%	(-1.38)	-5.1%	(-1.23)	-10.3%	(-1.47)	-2.2%	(-0.24)
Moderate Short Interest (Up to 1% of TSO)	-0.3%	(-0.37)	-2.0%	(-1.15)	-1.1%	(-0.34)	-3.8%	(-1.35)	-4.7%	(-1.32)	-4.3%	(-0.74)
High Short Interest (More than 1% of TSO)	-0.1%	(-0.08)	-0.8%	(-0.63)	-1.7%	(-0.97)	-4.3%	(-1.52)	-9.4%	(-2.19)	-21.0%	(-3.51)
Moderate SI - No SI	0.8%	(0.63)	1.5%	(0.42)	3.5%	(0.63)	1.4%	(0.26)	5.7%	(0.73)	-2.1%	(-0.20)
High SI - No SI	1.1%	(0.88)	2.7%	(0.99)	3.0%	(0.81)	1.0%	(0.19)	1.1%	(0.14)	-17.9%	(-1.73)

Panel C: Risk-Adjusted Future Returns of Equal-Weighted Portfolios

	k-Trading Day Return Horizon											
	1		5		10		20		60		252	
No Short Interest	0.1%	(1.06)	0.6%	(2.19)	1.0%	(2.22)	2.0%	(2.65)	3.3%	(2.09)	8.7%	(2.21)
Moderate Short Interest (Up to 1% of TSO)	0.0%	(0.17)	0.0%	(-0.13)	0.0%	(0.10)	-0.2%	(-0.16)	-0.5%	(-0.47)	-2.9%	(-1.03)
High Short Interest (More than 1% of TSO)	-0.1%	(-0.23)	-0.9%	(-1.01)	-1.9%	(-2.31)	-4.4%	(-2.40)	-11.3%	(-3.90)	-35.4%	(-7.45)
Moderate SI - No SI	-0.1%	(-0.55)	-0.6%	(-1.37)	-0.9%	(-1.12)	-2.2%	(-1.32)	-3.9%	(-1.68)	-11.6%	(-2.65)
High SI - No SI	-0.3%	(-0.52)	-1.5%	(-1.16)	-2.9%	(-3.28)	-6.4%	(-3.45)	-14.7%	(-4.90)	-43.8%	(-7.42)

Panel D: Risk-Adjusted Future Returns of ABK-Weighted Portfolios

	k-Trading Day Return Horizon											
	1		5		10		20		60		252	
No Short Interest	-1.0%	(-2.05)	-3.1%	(-1.61)	-4.8%	(-1.74)	-5.0%	(-1.91)	-13.1%	(-4.26)	-12.5%	(-1.50)
Moderate Short Interest (Up to 1% of TSO)	-0.5%	(-1.09)	-2.4%	(-1.38)	-1.0%	(-0.34)	-4.3%	(-1.93)	-5.6%	(-2.21)	-10.7%	(-2.62)
High Short Interest (More than 1% of TSO)	-0.2%	(-0.19)	-1.0%	(-0.72)	-1.9%	(-1.97)	-4.8%	(-2.56)	-12.1%	(-3.89)	-36.2%	(-6.72)
Moderate SI - No SI	0.6%	(0.56)	0.7%	(0.26)	3.8%	(0.78)	0.8%	(0.20)	7.5%	(1.34)	1.8%	(0.17)
High SI - No SI	0.9%	(0.47)	2.2%	(1.22)	3.0%	(1.10)	0.3%	(0.08)	1.1%	(0.24)	-23.7%	(-2.32)

Table 1-3: Returns on Portfolios Sorted by Short Interest Ratio – Sample with Eraker and Ready (2015) Filters

Table 1-3 presents returns for portfolios sorted based on short interest. The sample includes all OTC domestic equities from 2011-2019 meeting criteria based on those used in Eraker and Ready (2015). These criteria include non-missing data on shares outstanding and returns, a stock price that is greater than or equal to $0.01 at the time the security is first included, a market capitalization that exceeds $1 million, at least $2,000 in trade volume during the previous month. Securities are assigned to a portfolio as of each bimonthly short interest date and portfolios are held for the specified return horizon. Returns are not annualized. t-Statistics based on the time series of portfolio returns using Newey-West (1987) standard errors with an automated number of lags selected according to Newey-West (1994) are reported in parentheses. ABK-Weighted portfolios use the prior month's gross returns as weights. Risk-adjusted returns are calculated using the Fama-French Four-Factor model.

Panel A: Future Returns of Equal-Weighted Portfolios

	k-Trading Day Return Horizon											
	1		5		10		20		60		252	
No Short Interest	0.4%	(1.78)	1.0%	(2.23)	1.4%	(2.24)	2.3%	(2.11)	4.4%	(1.67)	10.6%	(1.95)
Moderate Short Interest (Up to 1% of TSO)	0.3%	(1.19)	0.0%	(0.00)	-0.4%	(-0.43)	-1.5%	(-1.13)	-4.4%	(-1.84)	-10.9%	(-3.03)
High Short Interest (More than 1% of TSO)	-0.2%	(-0.36)	-0.8%	(-0.59)	-1.7%	(-0.96)	-3.1%	(-1.13)	-10.0%	(-2.52)	-20.3%	(-2.37)
Moderate SI - No SI	-0.1%	(-0.35)	-1.0%	(-1.74)	-1.8%	(-2.20)	-3.7%	(-3.38)	-8.8%	(-3.58)	-21.5%	(-4.59)
High SI - No SI	-0.7%	(-0.97)	-1.8%	(-1.37)	-3.2%	(-1.82)	-5.4%	(-2.09)	-14.3%	(-3.61)	-31.0%	(-4.39)

Panel B: Future Returns of ABK-Weighted Portfolios

	k-Trading Day Return Horizon											
	1		5		10		20		60		252	
No Short Interest	0.0%	(-0.03)	-0.7%	(-0.56)	-0.4%	(-0.29)	-0.3%	(-0.20)	0.0%	(-0.01)	3.6%	(0.63)
Moderate Short Interest (Up to 1% of TSO)	-1.0%	(-0.77)	-2.3%	(-1.95)	-3.4%	(-2.22)	-4.6%	(-2.17)	-8.0%	(-2.40)	-16.1%	(-3.79)
High Short Interest (More than 1% of TSO)	-0.5%	(-0.49)	-1.1%	(-0.75)	-2.5%	(-1.22)	-4.0%	(-1.41)	-11.2%	(-2.68)	-21.7%	(-2.45)
Moderate SI - No SI	-0.9%	(-0.48)	-1.7%	(-0.86)	-3.0%	(-1.36)	-4.2%	(-1.60)	-8.0%	(-1.64)	-19.7%	(-3.44)
High SI - No SI	-0.4%	(-0.24)	-0.4%	(-0.22)	-2.0%	(-0.86)	-3.6%	(-1.17)	-11.2%	(-2.18)	-25.2%	(-2.89)

Panel C: Risk-Adjusted Future Returns of Equal-Weighted Portfolios

	k-Trading Day Return Horizon											
	1		5		10		20		60		252	
No Short Interest	0.4%	(2.20)	1.0%	(2.71)	1.4%	(2.59)	1.9%	(2.54)	2.9%	(1.60)	7.5%	(1.12)
Moderate Short Interest (Up to 1% of TSO)	0.3%	(1.58)	-0.1%	(-0.34)	-0.5%	(-0.79)	-1.9%	(-1.50)	-6.9%	(-5.82)	-16.1%	(-5.61)
High Short Interest (More than 1% of TSO)	-0.2%	(-0.54)	-1.0%	(-1.19)	-2.2%	(-2.01)	-3.8%	(-2.06)	-11.1%	(-4.47)	-9.6%	(-0.88)
Moderate SI - No SI	-0.2%	(-0.66)	-1.1%	(-3.25)	-1.9%	(-1.97)	-3.8%	(-5.61)	-9.8%	(-10.69)	-23.7%	(-3.86)
High SI - No SI	-0.7%	(-1.31)	-2.0%	(-2.34)	-3.5%	(-2.67)	-5.7%	(-3.43)	-14.0%	(-5.82)	-17.2%	(-1.33)

Panel D: Risk-Adjusted Future Returns of ABK-Weighted Portfolios

	k-Trading Day Return Horizon											
	1		5		10		20		60		252	
No Short Interest	0.1%	(0.06)	-0.7%	(-0.77)	-0.3%	(-0.28)	-0.8%	(-0.64)	-1.7%	(-0.80)	0.4%	(0.05)
Moderate Short Interest (Up to 1% of TSO)	-1.0%	(-0.93)	-2.3%	(-2.60)	-3.4%	(-3.61)	-4.8%	(-2.27)	-8.7%	(-4.88)	-19.7%	(-5.95)
High Short Interest (More than 1% of TSO)	-0.5%	(-0.71)	-1.4%	(-1.31)	-2.8%	(-1.30)	-4.5%	(-2.50)	-12.0%	(-6.04)	-10.3%	(-0.98)
Moderate SI - No SI	-1.1%	(-0.75)	-1.6%	(-0.73)	-3.1%	(-2.53)	-4.0%	(-1.55)	-7.1%	(-2.38)	-20.1%	(-2.58)
High SI - No SI	-0.6%	(-0.39)	-0.7%	(-0.44)	-2.6%	(-1.40)	-3.7%	(-1.86)	-10.3%	(-2.80)	-10.7%	(-0.69)

Table 1-4: Returns on Portfolios Double-Sorted by Short Interest Ratio and Past Returns

Table 1-4 presents returns for portfolios double-sorted based on short interest and returns over the previous month. The left 6 columns include all OTC domestic equities from 2011-2019 meeting criteria based on those used in Ang, Shtauber, and Tetlock (2013) and the right 6 columns meeting criteria based on those used in Eraker and Ready (2015). The primary difference is the first sample includes only shares with share prices of $1 or greater while the second includes shares with prices of $0.01 or greater. Securities are assigned to a portfolio as of each bimonthly short interest date and portfolios are held for the specified return horizon. Returns are not annualized. t-Statistics based on the time series of portfolio returns using Newey-West (1987) standard errors with an automated number of lags selected according to Newey-West (1994) are reported in parentheses. ABK-Weighted portfolios use the prior month's gross returns as weights. Risk-adjusted returns are calculated using the Fama-French Four-Factor model.

Panel A: Future Returns of Equal-Weighted Portfolios

	Ang, Shtauber, and Tetlock (2013) Filters						**Eraker and Ready (2015) Filters**					
	Low		Medium		High		Low		Medium		High	
No Short Interest	13.3%	(2.95)	12.0%	(3.75)	11.3%	(3.03)	7.8%	(1.75)	12.1%	(3.89)	7.1%	(2.11)
Moderate Short Interest	-6.9%	(-1.68)	5.4%	(1.63)	-0.5%	(-0.17)	-18.2%	(-5.32)	1.3%	(0.41)	-8.9%	(-3.38)
High Short Interest	-21.9%	(-2.30)	-9.6%	(-1.19)	-23.5%	(-3.18)	-26.8%	(-2.67)	-3.9%	(-0.36)	-16.7%	(-1.54)
Moderate SI - No SI	-20.2%	(-4.22)	-6.6%	(-2.29)	-11.8%	(-3.39)	-25.9%	(-7.14)	-10.8%	(-4.31)	-16.0%	(-5.39)
High SI - No SI	-34.7%	(-3.43)	-22.2%	(-2.70)	-33.8%	(-4.43)	-33.6%	(-3.35)	-16.1%	(-1.51)	-22.6%	(-2.05)

Panel B: Future Returns of ABK-Weighted Portfolios

	Ang, Shtauber, and Tetlock (2013) Filters						**Eraker and Ready (2015) Filters**					
	Low		Medium		High		Low		Medium		High	
No Short Interest	11.5%	(2.78)	11.1%	(3.20)	7.4%	(1.53)	5.5%	(1.30)	11.9%	(3.81)	4.5%	(1.21)
Moderate Short Interest	-7.4%	(-1.86)	5.0%	(1.49)	-4.4%	(-1.19)	-18.4%	(-5.36)	1.0%	(0.32)	-12.8%	(-4.29)
High Short Interest	-21.8%	(-2.30)	-9.5%	(-1.17)	-24.5%	(-3.27)	-25.8%	(-2.53)	-3.6%	(-0.33)	-18.2%	(-1.67)
Moderate SI - No SI	-18.9%	(-4.33)	-6.1%	(-1.87)	-11.8%	(-2.34)	-23.9%	(-6.49)	-10.8%	(-4.31)	-17.3%	(-4.61)
High SI - No SI	-32.6%	(-3.29)	-20.8%	(-2.43)	-30.7%	(-3.58)	-30.2%	(-2.98)	-15.6%	(-1.46)	-21.3%	(-1.90)

Panel C: Risk-Adjusted Future Returns of Equal-Weighted Portfolios

	Ang, Shtauber, and Tetlock (2013) Filters						**Eraker and Ready (2015) Filters**					
	Low		Medium		High		Low		Medium		High	
No Short Interest	5.6%	(2.28)	5.2%	(3.01)	2.4%	(1.50)	-2.9%	(-0.97)	7.6%	(6.38)	1.6%	(1.28)
Moderate Short Interest	-19.6%	(-6.31)	0.9%	(0.55)	-9.2%	(-4.54)	-29.9%	(-11.41)	-4.8%	(-2.63)	-16.8%	(-9.09)
High Short Interest	-40.1%	(-5.68)	-28.5%	(-4.80)	-33.4%	(-6.13)	-38.5%	(-3.27)	-12.8%	(-0.97)	-9.4%	(-0.51)
Moderate SI - No SI	-25.1%	(-5.71)	-4.3%	(-1.70)	-11.6%	(-5.02)	-27.0%	(-7.81)	-12.4%	(-6.00)	-18.4%	(-8.17)
High SI - No SI	-46.1%	(-5.54)	-34.4%	(-6.69)	-36.5%	(-8.09)	-35.6%	(-2.63)	-20.9%	(-1.55)	-11.2%	(-0.60)

Panel D: Risk-Adjusted Future Returns of ABK-Weighted Portfolios

	Ang, Shtauber, and Tetlock (2013) Filters						**Eraker and Ready (2015) Filters**					
	Low		Medium		High		Low		Medium		High	
No Short Interest	3.2%	(1.19)	3.9%	(1.73)	-4.1%	(-1.17)	-4.5%	(-1.43)	7.5%	(6.44)	-2.3%	(-1.29)
Moderate Short Interest	-20.1%	(-6.70)	0.4%	(0.21)	-12.9%	(-4.58)	-30.8%	(-11.52)	-5.0%	(-2.63)	-19.5%	(-8.38)
High Short Interest	-38.8%	(-5.23)	-28.7%	(-5.31)	-34.8%	(-6.51)	-35.6%	(-2.78)	-12.5%	(-0.97)	-12.5%	(-0.70)
Moderate SI - No SI	-23.4%	(-7.21)	-3.5%	(-1.18)	-8.8%	(-2.37)	-26.3%	(-9.29)	-12.5%	(-6.08)	-17.2%	(-6.57)
High SI - No SI	-42.4%	(-5.73)	-32.7%	(-6.05)	-31.0%	(-5.87)	-31.0%	(-2.23)	-20.5%	(-1.52)	-10.4%	(-0.56)

Table 1-5: Regressions Predicting 1-Year Future Returns With Short Interest / Shares Outstanding

Panel A of Table 1-5 presents the results of Fama-Macbeth (1973) regressions predicting 1-year returns. For each date, a cross-sectional regression predicting 1-year returns is fit. The time-series average of the cross-sectional coeficients is reported along with the t-value calculated using Newey and West (1987) standard errors with the number of lags selected according to Newey and West (1994).
Panel B of Table 1-5 presents the results of panel regressions predicting 1-year returns. t-values are calculated using Driscoll and Kraay standard errors.

Panel A: Fama-MacBeth Regressions

	Ang, Shtauber, and Tetlock (2013) Sample	**Eraker and Ready (2015) Sample**
Short Interest Ratio	-17.13***	2.17
	(-3.40)	(0.39)
Previous Month Returns	-0.03	-0.02**
	(-1.14)	(-3.11)
Log(Market Cap)	-0.06***	-0.01
	(-10.55)	(-0.43)
Turnover	-0.97	-0.26**
	(-1.62)	(-3.00)
Log(Average Volume)	0.02	-0.03***
	(1.58)	(-5.36)
Adjusted R-Squared	1.91%	0.63%

Panel B: Panel Regressions

	Ang, Shtauber, and Tetlock (2013) Sample	**Eraker and Ready (2015) Sample**
Short Interest Ratio	-15.89**	1.71
	(-3.12)	(0.16)
Previous Month Returns	0.00	0.00
	(0.58)	(-0.71)
Log(Market Cap)	0.00***	0.00*
	(-3.45)	(-2.37)
Turnover	0.00	0.00
	(1.37)	(1.32)
Log(Average Volume)	0.00**	0.00*
	(-2.75)	(-2.69)
Date Fixed Effects	Y	Y
Security Fixed Effects	Y	Y
Adjusted R-Squared	1.97%	0.53%

Table 1-5.2: Regressions Predicting 1-Year Future Returns with Short Interest ($)

Panel A of Table 5.2 presents the results panel regressions predicting 1-year returns. t-values are calculated using Driscoll and Kraay standard errors.
Panel B of Table 5.2 shows the implied effect of the average short interest in each E&R portfolio on returns.

Panel A: Regressions of 1-Year Future Returns on Short Interest ($)

	Ang, Shtauber, and Tetlock (2013) Sample	Eraker and Ready (2015) Sample
Short Value	-1.78E-8***	-1.51E-8***
	(-4.04)	(-4.01)
Previous Month Returns	2.32E-8	-4.03E-8
	(0.59)	(-0.71)
Log(Market Cap)	-1.98E-11***	-3.20E-11*
	(-3.41)	(-2.37)
Turnover	2.82E-6	3.31E-5*
	(0.18)	(2.20)
Log(Average Volume)	-6.02E-10**	-9.71E-10*
	(-2.85)	(-2.32)
Date Fixed Effects	Y	Y
Security Fixed Effects	Y	Y
Adjusted R-Squared	1.91%	4.50%

Panel B: E&R Short Value Coefficient Applied to Average Portfolio Short Value

SIR Portfolio	Average Short Interest ($)	Effect on Returns
None	$0.00	0.00%
Moderate	$98,498.65	-0.15%
High	$9,490,196.88	-14.33%

Table 1-6: Portfolio Double Sorts on Short Interest and Market Capitalization – AST Filters

Table 1-6 presents returns for portfolios double-sorted based on short interest and market capitalization formed from all OTC domestic equities from 2011-2019 meeting criteria based on those used in Ang, Shtauber, and Tetlock (2013) Securities are assigned to a portfolio as of each bimonthly short interest date and portfolios are held for the specified return horizon. Returns are not annualized. t-Statistics based on the time series of portfolio returns using Newey-West (1987) standard errors with an automated number of lags selected according to Newey-West (1994) are reported in parentheses. ABK-Weighted portfolios use the prior month's gross returns as weights. Risk-adjusted returns are calculated using the Fama-French Four-Factor model.

Panel A: Future Returns of Equal-Weighted Portfolios

	Small		2		3		4		Large	
0	27.8%	(2.81)	17.7%	(3.10)	16.0%	(3.75)	24.0%	(2.10)	1.7%	(0.53)
1	11.8%	(1.54)	2.8%	(0.54)	12.3%	(1.47)	20.9%	(1.37)	-10.7%	(-2.58)
2	-24.3%	(-3.44)	-17.4%	(-1.67)	-51.5%	(-4.82)	-35.7%	(-2.98)	-7.7%	(-0.81)
1 - 0	-16.0%	(-1.34)	-14.9%	(-3.04)	-3.7%	(-0.41)	-3.1%	(-0.17)	-12.4%	(-3.34)
2 - 0	-55.1%	(-4.11)	-44.3%	(-2.74)	-67.6%	(-6.76)	-40.8%	(-3.29)	-8.2%	(-0.94)

Panel B: Future Returns of ABK-Weighted Portfolios

	Small		2		3		4		Large	
0	14.6%	(1.95)	14.4%	(2.19)	13.6%	(2.28)	16.2%	(1.45)	-13.3%	(-1.76)
1	8.7%	(0.94)	-0.1%	(-0.01)	6.3%	(0.89)	13.1%	(1.05)	-15.3%	(-3.31)
2	-23.9%	(-3.23)	-18.5%	(-1.83)	-51.5%	(-4.76)	-35.6%	(-2.96)	-8.5%	(-0.90)
1 - 0	-5.9%	(-0.50)	-14.4%	(-2.14)	-7.3%	(-0.80)	-3.1%	(-0.19)	-1.9%	(-0.23)
2 - 0	-38.8%	(-3.23)	-39.5%	(-2.52)	-65.7%	(-5.43)	-36.4%	(-2.72)	7.0%	(0.60)

Panel C: Risk-Adjusted Future Returns of Equal-Weighted Portfolios

	Small		2		3		4		Large	
0	18.3%	(1.16)	12.4%	(3.71)	6.2%	(2.59)	6.1%	(1.60)	-4.5%	(-2.20)
1	13.9%	(1.37)	-1.6%	(-0.38)	2.3%	(0.29)	5.4%	(0.41)	-26.2%	(-8.69)
2	-30.2%	(-5.00)	-30.4%	(-2.29)	-56.2%	(-8.09)	-14.0%	(-1.38)	-32.3%	(-4.32)
1 - 0	-4.4%	(-0.34)	-14.0%	(-3.88)	-3.9%	(-0.43)	-0.6%	(-0.04)	-21.7%	(-8.48)
2 - 0	-52.4%	(-2.86)	-46.6%	(-3.39)	-66.1%	(-9.30)	-16.1%	(-1.40)	-28.0%	(-4.37)

Panel D: Risk-Adjusted Future Returns of ABK-Weighted Portfolios

	Small		2		3		4		Large	
0	-4.1%	(-0.46)	8.4%	(2.26)	11.9%	(0.88)	-0.4%	(-0.07)	-23.5%	(-2.91)
1	2.1%	(0.22)	-4.5%	(-0.79)	5.0%	(0.63)	-2.3%	(-0.25)	-28.6%	(-7.28)
2	-29.1%	(-3.97)	-34.9%	(-2.74)	-55.0%	(-7.80)	-14.7%	(-1.30)	-32.2%	(-4.39)
1 - 0	6.2%	(0.44)	-12.9%	(-2.00)	-6.9%	(-0.41)	-2.0%	(-0.19)	-5.1%	(-0.64)
2 - 0	-27.1%	(-1.85)	-53.8%	(-4.45)	-77.5%	(-4.33)	-10.3%	(-0.83)	-8.1%	(-0.81)

Table 1-7: Portfolio Double Sorts on Short Interest and Market Capitalization – ER Filters

Table 1-7 presents returns for portfolios double-sorted based on short interest and market capitalization formed from all OTC domestic equities from 2011-2019 meeting criteria based on those used in Eraker and Ready (2015). Securities are assigned to a portfolio as of each bimonthly short interest date and portfolios are held for the specified return horizon. Returns are not annualized. t-Statistics based on the time series of portfolio returns using Newey-West (1987) standard errors with an automated number of lags selected according to Newey-West (1994) are reported in parentheses. ABK-Weighted portfolios use the prior month's gross returns as weights. Risk-adjusted returns are calculated using the Fama-French Four-Factor model.

Panel A: Future Returns of Equal-Weighted Portfolios

	Small		2		3		4		Large	
0	19.9%	(1.50)	8.6%	(1.02)	2.7%	(0.63)	7.3%	(2.11)	12.9%	(1.66)
1	-6.2%	(-0.92)	-13.7%	(-2.53)	-15.1%	(-2.97)	-8.6%	(-1.71)	-10.4%	(-2.37)
2	15.7%	(0.30)	-43.2%	(-8.63)	8.6%	(0.31)	-31.1%	(-2.78)	-10.8%	(-1.39)
1 - 0	-26.1%	(-1.97)	-22.3%	(-2.93)	-17.8%	(-3.71)	-16.0%	(-3.34)	-23.3%	(-3.09)
2 - 0	-5.3%	(-0.11)	-53.0%	(-5.24)	5.9%	(0.21)	-38.6%	(-3.69)	-23.6%	(-2.47)

Panel B: Future Returns of ABK-Weighted Portfolios

	Small		2		3		4		Large	
0	10.3%	(0.81)	2.3%	(0.31)	0.0%	(0.00)	6.7%	(1.25)	8.1%	(0.94)
1	-12.3%	(-1.98)	-15.9%	(-2.80)	-17.3%	(-3.12)	-12.6%	(-2.64)	-12.9%	(-2.84)
2	21.1%	(0.37)	-42.9%	(-7.89)	7.8%	(0.28)	-31.4%	(-2.76)	-11.4%	(-1.46)
1 - 0	-22.7%	(-1.85)	-18.2%	(-2.45)	-17.3%	(-3.11)	-19.2%	(-2.85)	-21.0%	(-2.42)
2 - 0	9.7%	(0.18)	-46.1%	(-4.75)	7.6%	(0.27)	-38.3%	(-3.41)	-19.5%	(-1.91)

Panel C: Risk-Adjusted Future Returns of Equal-Weighted Portfolios

	Small		2		3		4		Large	
0	18.2%	(0.99)	13.6%	(1.02)	-0.3%	(-0.08)	1.3%	(0.69)	0.3%	(0.13)
1	-11.4%	(-1.87)	-12.7%	(-2.60)	-15.1%	(-2.76)	-17.7%	(-6.78)	-23.3%	(-6.58)
2	92.6%	(1.03)	-40.4%	(-11.46)	97.5%	(1.25)	-25.9%	(-1.88)	-27.8%	(-5.38)
1 - 0	-29.6%	(-1.59)	-26.3%	(-1.91)	-14.8%	(-3.94)	-19.0%	(-7.45)	-23.7%	(-5.30)
2 - 0	75.5%	(0.85)	-56.8%	(-4.37)	97.5%	(1.20)	-27.2%	(-1.69)	-28.3%	(-5.02)

Panel D: Risk-Adjusted Future Returns of ABK-Weighted Portfolios

	Small		2		3		4		Large	
0	19.4%	(0.83)	7.4%	(0.68)	-3.5%	(-0.77)	1.8%	(0.23)	-7.0%	(-1.56)
1	-13.1%	(-1.90)	-10.8%	(-1.59)	-18.3%	(-3.07)	-20.2%	(-6.08)	-26.5%	(-7.40)
2	105.6%	(1.10)	-39.9%	(-9.25)	99.3%	(1.22)	-26.2%	(-1.88)	-27.9%	(-6.00)
1 - 0	-32.5%	(-1.42)	-18.2%	(-1.59)	-14.8%	(-3.08)	-22.0%	(-2.34)	-19.5%	(-3.45)
2 - 0	87.1%	(0.91)	-49.7%	(-4.32)	102.3%	(1.20)	-28.0%	(-1.60)	-21.1%	(-3.03)

Table 1-8: Portfolio Double Sorts on Short Interest and Average Turnover – AST Filters

Table 1-8 presents returns for portfolios double-sorted based on short interest and turnover formed from all OTC domestic equities from 2011-2019 meeting criteria based on those used in Ang, Shtauber, and Tetlock (2013) Securities are assigned to a portfolio as of each bimonthly short interest date and portfolios are held for the specified return horizon. Returns are not annualized. t-Statistics based on the time series of portfolio returns using Newey-West (1987) standard errors with an automated number of lags selected according to Newey-West (1994) are reported in parentheses. ABK-Weighted portfolios use the prior month's gross returns as weights. Risk-adjusted returns are calculated using the Fama-French Four-Factor model.

Panel A: Future Returns of Equal-Weighted Portfolios

	Low Volume		2		3		4		High Volume	
0	7.1%	(1.18)	15.1%	(3.49)	20.5%	(3.66)	26.5%	(2.50)	23.1%	(1.96)
1	-10.0%	(-1.73)	-1.7%	(-0.27)	6.1%	(0.82)	15.9%	(1.86)	8.1%	(1.47)
2	0.1%	(0.01)	-11.3%	(-1.71)	-16.5%	(-2.54)	-1.3%	(-0.18)	-26.6%	(-3.44)
1 - 0	-17.1%	(-2.01)	-16.8%	(-2.27)	-14.4%	(-1.94)	-10.6%	(-0.85)	-15.0%	(-1.27)
2 - 0	-11.1%	(-0.86)	-30.6%	(-3.16)	-28.3%	(-3.31)	-32.8%	(-1.71)	-40.4%	(-4.18)

Panel B: Future Returns of ABK-Weighted Portfolios

	Low Volume		2		3		4		High Volume	
0	-15.7%	(-1.76)	14.7%	(2.69)	19.1%	(3.30)	21.0%	(2.97)	17.1%	(1.42)
1	-20.0%	(-3.06)	-3.4%	(-0.48)	4.2%	(0.60)	12.2%	(1.80)	5.1%	(0.86)
2	0.0%	(0.00)	-11.2%	(-1.70)	-16.5%	(-2.54)	-1.6%	(-0.21)	-27.5%	(-3.46)
1 - 0	-4.3%	(-0.37)	-18.1%	(-2.08)	-14.9%	(-2.09)	-8.7%	(-1.05)	-12.0%	(-0.95)
2 - 0	18.7%	(1.44)	-31.0%	(-2.67)	-27.4%	(-3.14)	-16.0%	(-1.83)	-35.6%	(-3.45)

Panel C: Risk-Adjusted Future Returns of Equal-Weighted Portfolios

	Low Volume		2		3		4		High Volume	
0	-6.6%	(-1.43)	16.2%	(2.15)	8.1%	(3.70)	22.8%	(1.90)	2.6%	(0.68)
1	-32.1%	(-5.03)	-11.6%	(-1.88)	-3.1%	(-0.61)	7.9%	(0.99)	6.0%	(0.92)
2	-21.8%	(-2.51)	-36.2%	(-4.49)	-36.7%	(-6.01)	-25.8%	(-2.56)	-36.2%	(-7.40)
1 - 0	-25.5%	(-3.18)	-27.8%	(-2.81)	-11.2%	(-2.11)	-14.9%	(-1.05)	3.4%	(0.36)
2 - 0	-32.6%	(-2.32)	-61.8%	(-3.69)	-45.5%	(-8.67)	-87.3%	(-1.79)	-37.7%	(-6.69)

Panel D: Risk-Adjusted Future Returns of ABK-Weighted Portfolios

	Low Volume		2		3		4		High Volume	
0	-33.1%	(-4.47)	19.0%	(1.29)	7.4%	(2.78)	11.2%	(3.36)	-1.5%	(-0.35)
1	-35.2%	(-6.74)	-22.5%	(-4.51)	-2.8%	(-0.51)	2.3%	(0.52)	4.3%	(0.71)
2	-21.8%	(-2.50)	-36.3%	(-4.47)	-36.7%	(-6.00)	-26.0%	(-2.57)	-36.7%	(-8.90)
1 - 0	-2.1%	(-0.21)	-41.5%	(-2.67)	-10.2%	(-1.54)	-8.9%	(-1.72)	5.8%	(0.63)
2 - 0	4.2%	(0.25)	-70.2%	(-2.97)	-42.7%	(-8.11)	-39.1%	(-4.00)	-35.7%	(-5.85)

Table 1-9 – Portfolio Double Sorts on Short Interest and Turnover – E&R Filters

Table 1-9 presents returns for portfolios double-sorted based on short interest and turnover formed from all OTC domestic equities from 2011-2019 meeting criteria based on those used in Eraker and Ready (2015). Securities are assigned to a portfolio as of each bimonthly short interest date and portfolios are held for the specified return horizon. Returns are not annualized. t-Statistics based on the time series of portfolio returns using Newey-West (1987) standard errors with an automated number of lags selected according to Newey-West (1994) are reported in parentheses. ABK-Weighted portfolios use the prior month's gross returns as weights. Risk-adjusted returns are calculated using the Fama-French Four-Factor model.

Panel A: Future Returns of Equal-Weighted Portfolios

	Low Volume		2		3		4		High Volume	
0	16.7%	(1.68)	11.1%	(2.45)	14.1%	(1.97)	5.8%	(0.80)	-9.2%	(-1.44)
1	-10.7%	(-1.89)	-5.9%	(-0.98)	-1.0%	(-0.21)	-7.0%	(-1.58)	-21.8%	(-4.52)
2	-8.7%	(-1.14)	-19.3%	(-2.89)	-24.7%	(-2.67)	-18.5%	(-2.14)	-19.7%	(-1.79)
1 - 0	-27.4%	(-2.49)	-17.0%	(-2.69)	-15.0%	(-1.89)	-12.8%	(-1.94)	-12.6%	(-2.24)
2 - 0	-27.0%	(-2.05)	-29.0%	(-3.47)	-39.6%	(-3.01)	-26.7%	(-2.39)	-11.0%	(-1.13)

Panel B: Future Returns of ABK-Weighted Portfolios

	Low Volume		2		3		4		High Volume	
0	11.4%	(0.92)	6.5%	(1.40)	10.7%	(1.48)	-1.3%	(-0.24)	-12.9%	(-1.92)
1	-18.3%	(-3.22)	-9.2%	(-1.49)	-3.6%	(-0.66)	-9.4%	(-2.13)	-23.8%	(-5.02)
2	-8.8%	(-1.14)	-19.5%	(-2.88)	-25.0%	(-2.69)	-19.1%	(-2.24)	-20.9%	(-1.86)
1 - 0	-29.7%	(-2.20)	-15.7%	(-2.40)	-14.4%	(-1.67)	-8.1%	(-1.68)	-10.9%	(-1.75)
2 - 0	-21.1%	(-1.39)	-24.9%	(-2.82)	-36.9%	(-2.79)	-19.5%	(-2.03)	-8.6%	(-0.87)

Panel C: Risk-Adjusted Future Returns of Equal-Weighted Portfolios

	Low Volume		2		3		4		High Volume	
0	23.5%	(1.31)	5.3%	(1.73)	1.1%	(0.34)	2.7%	(0.31)	-11.8%	(-2.77)
1	-21.2%	(-3.34)	-14.2%	(-3.47)	-9.5%	(-2.25)	-18.0%	(-4.63)	-17.3%	(-3.40)
2	-40.7%	(-3.91)	-27.0%	(-4.97)	-21.1%	(-1.95)	-0.3%	(-0.02)	-3.9%	(-0.30)
1 - 0	-44.7%	(-2.47)	-19.5%	(-3.99)	-10.6%	(-2.18)	-20.8%	(-2.24)	-5.5%	(-1.02)
2 - 0	-87.3%	(-2.49)	-35.2%	(-4.77)	-22.0%	(-2.44)	-3.5%	(-0.18)	7.3%	(0.47)

Panel D: Risk-Adjusted Future Returns of ABK-Weighted Portfolios

	Low Volume		2		3		4		High Volume	
0	29.6%	(1.15)	-2.1%	(-0.58)	-2.5%	(-0.63)	-10.3%	(-2.17)	-16.4%	(-3.29)
1	-32.0%	(-4.92)	-14.8%	(-4.34)	-9.5%	(-1.67)	-16.6%	(-4.32)	-18.6%	(-3.68)
2	-41.3%	(-3.80)	-27.4%	(-4.87)	-21.1%	(-2.02)	-2.0%	(-0.13)	-4.9%	(-0.36)
1 - 0	-61.6%	(-2.38)	-12.8%	(-2.78)	-6.9%	(-0.99)	-6.3%	(-1.53)	-2.3%	(-0.35)
2 - 0	-98.2%	(-2.20)	-28.4%	(-4.06)	-16.6%	(-1.67)	8.3%	(0.47)	10.1%	(0.78)

Table 1-10: Returns on Portfolios Sorted by Short Interest Ratio – Sample Excluding Previously Listed Stocks

Table 1-10 presents returns for portfolios sorted based on short interest. Panels A and B are based on a sample filtered using Ang, Shtauber, and Tetlock (2013) criteria. Panels C and D are based on a sample filtered using Eraker and Ready (2015) criteria. For both samples, an additional filter removing previously listed OTC securities was applied. Securities are assigned to a portfolio as of each bimonthly short interest date and portfolios are held for the specified return horizon. Returns are not annualized. t-Statistics based on the time series of portfolio returns using Newey-West (1987) standard errors with an automated number of lags selected according to Newey-West (1994) are reported in parentheses. ABK-Weighted portfolios use the prior month's gross returns as weights. Risk-adjusted returns are calculated using the Fama-French Four-Factor model.

Panel A: Future Returns of Equal-Weighted Portfolios in Ang, Shtauber, and Tetlock (2013) Sample

	k-Trading Day Return Horizon											
	1		5		10		20		60		252	
No Short Interest	0.1%	(0.79)	0.6%	(1.65)	1.0%	(1.79)	2.2%	(2.18)	4.5%	(2.45)	17.6%	(3.25)
Moderate Short Interest (Up to 1% of TSO)	0.1%	(0.24)	-0.3%	(-0.47)	-0.3%	(-0.31)	-0.6%	(-0.44)	-0.1%	(-0.02)	1.7%	(0.24)
High Short Interest (More than 1% of TSO)	-0.4%	(-0.43)	-1.5%	(-0.72)	-2.1%	(-0.78)	-4.0%	(-1.02)	-9.9%	(-1.76)	-28.5%	(-3.85)
Moderate SI - No SI	-0.1%	(-0.19)	-0.8%	(-1.31)	-1.3%	(-1.36)	-2.8%	(-1.87)	-4.6%	(-1.36)	-15.9%	(-1.99)
High SI - No SI	-0.6%	(-0.61)	-2.1%	(-1.03)	-3.1%	(-1.12)	-6.4%	(-1.50)	-14.4%	(-2.37)	-42.7%	(-4.69)

Panel B: Risk-Adjusted Future Returns of Equal-Weighted Portfolios in Ang, Shtauber, and Tetlock (2013) Sample

	k-Trading Day Return Horizon											
	1		5		10		20		60		252	
No Short Interest	0.1%	(0.87)	0.6%	(3.80)	1.0%	(2.72)	2.0%	(2.74)	3.3%	(2.10)	7.4%	(1.67)
Moderate Short Interest (Up to 1% of TSO)	0.0%	(0.25)	-0.3%	(-0.57)	-0.4%	(-0.53)	-0.8%	(-0.90)	-2.2%	(-0.89)	-9.9%	(-1.77)
High Short Interest (More than 1% of TSO)	-0.5%	(-0.55)	-1.7%	(-0.86)	-2.4%	(-1.05)	-4.8%	(-2.14)	-14.3%	(-3.71)	-43.2%	(-8.74)
Moderate SI - No SI	-0.1%	(-0.23)	-0.8%	(-1.08)	-1.3%	(-2.01)	-2.8%	(-4.31)	-5.5%	(-3.73)	-17.3%	(-2.79)
High SI - No SI	-0.7%	(-1.16)	-2.4%	(-1.20)	-3.3%	(-2.05)	-7.0%	(-2.49)	-18.1%	(-4.58)	-52.1%	(-7.86)

Panel C: Future Returns of Equal-Weighted Portfolios in Eraker and Ready (2015) Sample

	k-Trading Day Return Horizon											
	1		5		10		20		60		252	
No Short Interest	0.5%	(1.72)	1.1%	(2.04)	1.5%	(2.10)	2.3%	(1.92)	4.3%	(1.47)	9.0%	(1.51)
Moderate Short Interest (Up to 1% of TSO)	0.4%	(1.11)	0.0%	(0.00)	-0.7%	(-0.62)	-2.3%	(-1.42)	-6.8%	(-2.33)	-17.8%	(-3.96)
High Short Interest (More than 1% of TSO)	-0.3%	(-0.22)	-0.9%	(-0.33)	-4.8%	(-1.24)	-6.5%	(-1.16)	-13.1%	(-1.89)	-23.7%	(-2.00)
Moderate SI - No SI	-0.1%	(-0.26)	-1.1%	(-1.46)	-2.2%	(-2.06)	-4.6%	(-3.29)	-11.1%	(-3.73)	-26.8%	(-4.76)
High SI - No SI	-0.9%	(-0.65)	-2.3%	(-0.81)	-6.6%	(-1.71)	-9.5%	(-1.67)	-19.6%	(-2.60)	-35.3%	(-2.57)

Panel D: Risk-Adjusted Future Returns of Equal-Weighted Portfolios in Eraker and Ready (2015) Sample

	k-Trading Day Return Horizon											
	1		5		10		20		60		252	
No Short Interest	0.5%	(2.60)	1.0%	(2.45)	1.4%	(4.26)	2.0%	(2.26)	2.8%	(1.26)	8.4%	(0.96)
Moderate Short Interest (Up to 1% of TSO)	0.3%	(1.14)	-0.1%	(-0.14)	-0.8%	(-1.48)	-2.8%	(-1.70)	-9.7%	(-5.86)	-21.1%	(-5.21)
High Short Interest (More than 1% of TSO)	-0.2%	(-0.17)	-1.0%	(-0.44)	-4.7%	(-1.64)	-6.7%	(-2.11)	-15.3%	(-3.22)	-4.7%	(-0.25)
Moderate SI - No SI	-0.1%	(-0.71)	-1.1%	(-2.54)	-2.3%	(-2.87)	-4.7%	(-5.10)	-12.6%	(-7.90)	-29.6%	(-3.76)
High SI - No SI	-0.8%	(-0.70)	-2.4%	(-0.94)	-6.5%	(-3.22)	-9.4%	(-2.63)	-20.6%	(-4.42)	-17.3%	(-0.69)

Chapter 2: Do Municipalities Pay More to Issue Unrated Bonds?

Joint work with Haluk Unal[1]

Introduction

Municipalities do not obtain ratings for a significant portion of the bonds they issue. We use a sample of bonds that municipalities issued from 1998 to 2017. Of the sample, 34% of the approximately 200,000 bond offerings did not have a rating. This percentage accounted for 14% of the $3.7 trillion worth of municipal bonds issued. This feature of bond issues can have cost implications for municipalities. In the absence of a rating to assess the risk of a bond, investors can require higher compensation for the potential risk. A rating is valuable information for investors because it reduces the information risk these bonds might expose them to when purchased.[2] In other markets, investors may want ratings for other reasons, such as regulatory concerns or investment standards. For example, in the corporate bond market Murray and Nikolova (2021) show ratings-based capital requirements affect insurer demand and thus bond pricing. However, ratings are unlikely to play this role for municipal bonds. Retail investors are likely to be more reliant on ratings as a source of information compared to institutional investors, as deHaan, Li, and Watts (2021) find in corporate bond markets.

We conjecture that in the absence of a rating, investors can assume the bond issuer avoided one because managers expected to receive a poor rating. Consequently, investors will assume the bond is very risky and require a correspondingly higher yield rather than an appropriate yield corresponding to the actual risk of the bond. Further, the absence of a rating can also cause investors who are not confident in their ability to assess risk to avoid investing in

[1] University of Maryland, Smith School of Business and FDIC CFR
[2] Bhojraj and Sengupta (2003) define information risk as managers having private information that adversely affects the default risk of the bond.

the issue. These factors can raise the issue yield to the municipality. To the extent that issuing an unrated bond is more expensive to a municipality, it is a missed opportunity to increase investment in public goods or decrease the tax burden. Thus, an understanding of why municipalities forgo obtaining ratings for bond issues and whether unrated bonds are more expensive than rated bonds is of economic and policy interest.

The primary cost to issuers of getting a rating is the fee that they pay to an agency for that rating. Beatty, Gillette, Petacchi, and Weber (2019) report that the median fees of a sample of California and Texas municipal bonds are approximately 0.1% of the issued amount. Issuers can incur other costs associated with preparing information for ratings agencies, such as hiring third-party financial experts.

In this study, our goal is to quantify the possible savings that can result from obtaining a rating for a municipal bond. However, an estimation of how a rating affects the offering yield is complicated by the fact that an issuer's decision to obtain a rating can be affected by the rating the issuer expects the bond to receive, which will be determined by the risk factors that also affect the yield. In fact, we find evidence that issuers of riskier bonds are less likely to obtain a rating. We address this challenge by using an Inverse Probability Weighted Regression Adjustment (IPWRA) model that controls for the decision to obtain a rating and the other factors that affect the yield.

When applying the IPWRA, we first estimate a logistic model for the municipality's decision to obtain a rating as a function of the bond characteristics as well as of the proxies for local economic conditions and the financial strength of the local government. We then use the predicted probabilities of municipalities obtaining a rating for each bond that are implied by the logistic model to generate weights to form a pseudo-sample, in which rated and unrated bonds are equally likely to get a rating. We give low weights to rated bonds that seem likely to get a rating and to unrated bonds that seem unlikely to get a rating. We give high weights to rated bonds that seem unlikely to get ratings and unrated bonds that seem likely to get ratings. We use these weights in a linear regression that predicts the bond's yield spread to Treasuries as a function of whether municipalities get a rating for the bond, its characteristics, and local economic and financial conditions.

Other studies have applied the IPWRA approach to address confounding arising from circumstances that affect both the treatment decision and the outcome of interest. The following are some examples: Cornaggia, Hund, and Nguyen (2022) use IPWRA to control for the decision to obtain insurance on municipal bonds. Schweitzer and Barkley (2017) use the technique to explain the decision to borrow from online lenders. Stuart and Yim (2010) use the approach to control for the selection of board members when studying the effect of directors having previous experience with private equity deals when becoming a target. Lin, Schmid, and Xuan (2018) use it to control for the determination of employee representation when studying its effect on financial leverage. IPWRA is similar to propensity score matching. However, IPWRA has the advantage of using the full population for analysis. Further, Wooldridge (2007), Imbens and Wooldridge (2009), and Wooldridge (2010) show that IPWRA is doubly robust, meaning that if either the first stage or second stage is correctly specified, the estimate of the effect of the treatment on the outcome is consistent. To the best of our knowledge such property has not been shown for propensity score matching.

The results of our logistic regression show systematic differences between rated and unrated bonds. In general, municipalities are less likely to get bonds rated if they have characteristics that indicate higher risk. For example, issuers with lower local incomes and higher liability-to-asset ratios are less likely to get a bond rated. Issuers are also less likely to obtain ratings for revenue bonds. We also find that smaller bond offerings and offerings that are sold in a negotiated rather than competitive placement are less likely to get rated.

Using an IPWRA model that controls for the decision of obtaining a rating, we estimate that forgoing a rating increases offering yields by 47 basis points for revenue bonds and 49 basis points for general obligation bonds during our sample period from 1998 to 2017. These increased offering yields correspond to $22.5 billion (in 2015 dollars) in aggregate costs to municipalities from interest payments net of rating fees. These findings are much higher than the 10-basis point yield spread reported by Reeve and Herring (1986) who use a limited sample from an earlier period. The size of potential savings if issuers had obtained ratings for unrated issues indicates they underestimate the benefits of obtaining a rating.

A rational issuer should obtain a rating for an issue when the expected benefit exceeds the expected cost. However, our findings show that some local governments are irrationally leaving money on the table by not getting a rating. There are two possible reasons for this result. One reason is that unsophisticated local government officials might not realize the extent to which obtaining a rating would lower costs. The second is local officials rely on underwriters and advisors for advice on this decision and they may not receive optimal advice from some underwriters. We find underwriter fixed effects provide a large increase in fit for a logistic model predicting whether a rating will be issued. This result might reflect variation in the financial sophistication of underwriters. Indeed, we show that issuers are less likely to obtain ratings for issues underwritten by smaller underwriters.

Underwriters can also be motivated against recommending ratings by conflicts of interest. An underwriter who serves as a financial advisor for an issuer or is otherwise particularly well informed about the issuer has a competitive advantage over other potential underwriters that is stronger if the issuer is more opaque. Maintaining higher opacity by not obtaining a rating can increase the underwriter's profits by lowering the price paid to the issuer even if it also reduces the price paid by investors. Garrett (2021) shows that preventing financial advisors from also serving as underwriters for competitive issues they advised decreased offering yields. Consistent with Garrett (2021) findings, we find a strong negative association between dual underwriters and obtaining a rating for competitive offerings. In addition, we find some evidence of this relationship for negotiated placements, where there is no auction to underwrite the bond but maintaining opacity can still help the issuer retain the business.

Alternatively, issuers might appear to leave money on the table by forgoing a rating because they are considering information that is publicly unobservable but discoverable by ratings agencies when deciding whether to obtain a rating. For example, Caton et al. (2011) find rating agencies tend to assign lower ratings to firms that inflate their reported earnings. In this case, issuers who are aware of this information risk rationally anticipate the issue would receive a lower rating than the observable information might suggest. Investors, in turn, rationally anticipate that issuers who do not obtain a rating have hidden risks and require higher yields to invest in those issues than in rated issues with similar characteristics. This self-selection of riskier issuers into unrated status falls into the category of adverse selection problems explored by Akerlof (1970), which has been applied to the choice of corporations to solicit a rating by Bannier, Behr, and Guttler (2010). In any case, our results show that taxpayers should closely scrutinize unrated bond issues and that local governments need to step up efforts to reduce the cost of their bond issues.

The rest of the study is organized as follows: We discuss the related literature in Section 2 and present the institutional background and data in Section 3. In Section 4, we describe the empirical approach to estimating the impact of obtaining a rating on yields. Section 5 presents the results. Section 6 concludes.

Related Literature

Despite the extensive literature on the effect of receiving a particular rating, few studies exist on the determinants and consequences of not getting a rating for an issue. In the corporate bond market, Gonis, Salima, and Tucker (2012) study a sample of UK corporations and find that firms with lower leverage and more financial flexibility are more likely to obtain a rating. However, more profitable firms are less likely to obtain a rating. This finding can indicate less need for certification. The authors do not address the impact of forgoing a rating on the yields of the bonds.

Two studies specifically address unrated municipal bonds. Reeve and Herring (1986) examined 7,802 offerings between 1977 and 1980. Comparing average characteristics of rated and unrated municipal bonds, they find the unrated bonds have smaller issue sizes and are from smaller population cities. Using a linear regression, they show that unrated municipal bonds have higher yields than rated municipal bonds, especially for larger issues. The market prices smaller (less than $1,000,000 par value) nonrated bonds on average 10 basis points below the lowest investment grade tier, while it prices larger nonrated issues on average 30 basis points higher than the lowest investment grade tier. This regression does not include any proxies for risk or otherwise attempt to differentiate between the effect of an issue's riskiness and the effect of the rating on the yield. Ziebell and Rivers (1992) examine a sample of 440 cities in 1984 with a logistic regression. They find that unrated municipal bonds come from smaller cities on the Pacific coast and that higher local incomes are associated with rated issues.

Both of these studies involve relatively short and small samples compared to our study, which covers over 200,000 offerings over a 20-year period. Their samples also cover a time when investors would have found it more difficult to obtain information and the financial market was also less sophisticated. Neither study attempts to estimate the effect of obtaining a rating on the offering yield while controlling for other offering characteristics.

Our study is also related to those on the effect of the information environment on municipal bonds. For example, Cuny and Dube (2021) show that better disclosure by municipal bond issuers protects against downgrades and yield increases after housing price shocks. Gao, Lee, and Murphy (2020) find that the closing of local newspapers leads to more opaque information on local government activities that increases the yields of municipal bonds. Our finding that investors require higher yields in the absence of information from a rating agency is consistent with these findings.

There are other studies that examine whether the rating assigned to a security affects its price. For municipal bonds in particular, several studies use a 2010 ratings recalibration as a natural experiment. Moody's and Fitch, but not Standard & Poor's (S&P), recalibrated their rating scales for municipal bonds. The recalibration resulted in some issuers receiving improved ratings despite no change in their risk. Cornaggia, Cornaggia, and Israelsen (2018) show that bond yields decreased for issuers with improved ratings both in the secondary market and for new offerings. This result means that at least some investors were reliant on ratings to judge a bond's risk. The effect was strongest for less transparent issuers. Adelino, Cunha, and Ferreira (2017) show that the resulting lower yields on new issues led to increased expenditures and borrowing. Beatty, Gillette, Petracchi, and Weber (2019) show that Moody's and Fitch charged higher fees after the recalibration and increased their market share relative to S&P.

Beck, Parsons, and Sorensen (2021) predict ratings for a sample of municipal bonds from California and Texas and show that unexpectedly high ratings are associated with slightly lower yields, while unexpectedly low ratings are associated with both substantially higher yields and higher rating fees.

These studies show that investors rely on bank ratings as well as public information and rating differential has cost consequences.

Institutional Features and Data

Institutional Background

Municipal bonds have two main characteristics: who purchases the bonds and who backs the bonds. There are two types of backing: general obligation bonds (GOs) and revenue bonds (RBs). GOs are backed by the full faith and credit of the government issuing the bond. Revenue bonds are backed only by a specified revenue source, often from a project funded by the bonds. RBs and GOs differ in several ways that could affect the costs and benefits of obtaining a rating. Because RBs depend on a specific revenue source, they are riskier. The risks of a certain revenue source can be more opaque to investors, and that can increase the value of a rating. This is consistent with Livingston and Zhou (2016) who find additional ratings are more valuable for more opaque corporate bonds. However, a rating for a RB is more costly to obtain. Conversations with officers of rating agencies indicate that rating fees are higher for RBs than GOs in general and vary based on the type of project. Rating fees for RBs backed by airport or healthcare revenue are around 20% higher than for GOs, while the rating fees for affordable or military housing and charter schools are approximately 75% higher because of the due diligence and site visits required.

The municipal bond market is largely dominated by retail investors. However, certain municipal bonds from small issuers are bank qualified, meaning that banks can purchase these bonds and deduct interest expense to finance the purchase. In general, banks cannot deduct the interest expense incurred to acquire or carry tax-exempt municipal bonds. This restriction effectively eliminates the tax benefit of municipal bonds. But the IRS Code of 1986 created an exemption that allows banks to deduct 80% of the carrying cost of a "qualified tax-exempt obligation." There is a limit to the amount of debt an issuer can issue per year for its municipal bonds to be bank qualified. The IRS Code of 1986 set the limit at $10 million per year and this limit was in effect for most of our sample period, although the American Recovery and Reinvestment Act of 2009 (ARRA) temporarily raised the limit to $30 million effective February 2009 through December 2010. Dagostino (2019) shows that banks hold approximately 80% of the bank-qualified bonds. The study also shows that the issuer values the ability to place their debt with banks. Many issuers of bank-qualified bonds raised close to the maximum amount possible without exceeding the limit required to retain their qualified status, and they expanded their borrowing when ARRA temporarily raised the limit.[3]

We predict that ratings will provide less value to banks than to retail investors. Banks are sophisticated investors capable of conducting their own due diligence. In addition, to the extent that local banks purchase the bank-qualified bonds, they can access the private information that

[3] Indirect evidence that different types of investors place different values on a rating comes from Boyer and Postenau (2020) who study the effect of reforms that reduced money market fund holdings of municipal bonds. Of issuers who had previously placed bonds with money market funds, those that issued unrated bonds were most affected.

local officials might have. During our sample period, banks lacked a regulatory reason to care about municipal bond ratings. Since the passage of the Dodd-Frank Act required all federal agencies to remove references to credit ratings in their regulations, the Office of the Comptroller of the Currency and Federal Deposit Insurance Corporation actually discouraged reliance on ratings by banks.[4] Ratings do not affect the risk-weighting for capital requirements under Basel III. Any GO receives a 20% risk weight, while every RB receives a 50% risk weight regardless of whether it has a rating or what that rating is (Dagostino 2020). Therefore, we predict that bank-qualified bonds will be issued without a rating more frequently compared to nonbank-qualified bonds.

There are two major issuance methods for municipal bonds. The most common method is a negotiated sale, which is like book-building in the corporate bond market. In a negotiated sale, the issuer selects one or more underwriters who make an offer to purchase bonds from the issuer. The underwriter is sometimes involved in setting the terms of the issue in addition to negotiating the price. The underwriter can seek orders from investors before the issuer determines the offering yield and then adjust the price based on investor interest. After finalizing the terms and price, the underwriter purchases bonds from the issuer and sells them to investors. The other major issuance method is a competitive sale, which is essentially an auction. The bonds are advertised with set terms to underwriters, and the bonds are sold to the underwriter or group of underwriters who bid the lowest yield. The underwriters then resell the bonds to investors.

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[4] See "Alternatives to the Use of External Credit Ratings in the Regulations of the OCC"
Final Rule issued by the Office of the Comptroller of the Currency, Treasury (OCC) on 6/13/2012.
https://www.govinfo.gov/content/pkg/FR-2012-06-13/pdf/2012-14169.pdf and
"Alternatives to References to Credit Ratings With Respect to Permissible Activities for Foreign Branches of Insured State Nonmember Banks and Pledge of Assets by Insured Domestic Branches of Foreign Banks"
Final Rule issued by the Federal Deposit Insurance Corporation on 3/5/2018.
https://www.federalregister.gov/documents/2018/03/05/2018-04255/alternatives-to-references-to-credit-ratings-with-respect-to-permissible-activities-for-foreign

Ratings are likely to be more valuable in a competitive offering, which involves a wider range of potential underwriters and investors who are less familiar with the issue.

Data Sources

We study the decision to obtain a rating and the effect of obtaining a rating on yields by utilizing several data sources. Our primary source of data on municipal bonds is the Mergent Municipal Bond Securities Database. This database provides the issuer name, state of issuance, issuance date, lead underwriter, placement type, maturity date, offering yield, coupon rate, type of coupon, use of funds, and the bond's rating. It also specifies whether a bond has put or call options, is insured, is bank-qualified, and is a general obligation or a revenue bond.
While the Mergent database records some bonds issued as early as the nineteenth century, the database does not have full coverage of that time. In particular, the coverage of the bond rating dataset seems sparse in the early years. For this reason, we restrict our analysis to bonds issued in or after 1998, the first year in which we can identify at least 1,000 bond issues rated by Moody's, Fitch, and S&P.

Prior to 2017, the Mergent database did not track the full ratings history of bonds. If a bond was downgraded or upgraded by a ratings agency, Mergent would replace the old rating with the new rating. For our analysis, this is not a problem because we only need to identify if the issue was rated or unrated. Issuers have no incentive to seek a rating for an originally unrated issue after selling it to investors, so we are still able to determine whether the issue was originally rated even if we are not confident about the original rating it received.

To capture observable risk factors that affect the bonds, we supplement the Mergent data with information on local economic and government financial conditions at the county level. We obtain annual fiscal data on local governments from the Bloomberg Government Portal.

Specifically, we obtain liabilities, assets, and the proportion of revenue derived from property taxes. The Bloomberg data are only available after 2002, so specifications including variables based on these data exclude earlier bond issues. We use annual data on local personal income per capita from the Bureau of Economic Analysis. Following Gao, Lee, and Murphy (2019), we analyze the spread between the offering yield and the same-duration US Treasury yield rather than the offering spread itself to account for the time variation in interest rates. Daily data on parameters to compute the entire US Treasury yield curve, as described in Gürkaynak, Sack, and Wright (2007), are provided by the Federal Reserve Board.

To link the bonds to these datasets, we first must identify where bonds were issued. Using the state of issue and the issuer name, we match each municipal bond at the county level by searching for names of cities, counties, and census-designated places within the issuer names. For the unmatched bond issues, we hand-match them to their county of issue using information from the prospectus in addition to their name. For a small number of issuers, accounting for 0.1% of the dollar amount issued within the sample, we were unable to identify a match.

We find that approximately 51% of the municipal bond issues in the database are issued by entities above the county level. Many of these issuers are state-level entities, such as the "Arizona State Lottery Revenue" or the "California Statewide Financing Authority Tobacco Settlement." They also include multi-county entities such as the "North Texas Municipal Water District" that covers 10 counties, and a small number of cities that cross county borders, such as Ackley, Iowa which is partially in Hardin and Franklin counties. We exclude these issuers from our sample because they could not be matched to county-level conditions. The remaining issuers consist of counties or county-equivalent cities, smaller municipalities such as cities and towns contained entirely with a single county, and special districts contained within a single county.

We also exclude a small number of bonds that are neither GOs nor RBs, which is approximately 3% of the sample by dollar amount. The resulting sample comprises 46% of the bonds in Mergent by amount issued and 67% by number of bonds.

Figure 2-1 shows the dollar amount of municipal bonds issued each year that are covered in the Mergent database and that are in our sample. The figure also shows the annual issuance of municipal bonds according to the Securities Industry and Financial Markets Association (SIFMA) that is the trade association for broker-dealers, investment banks, and asset managers which tracks the issuance of fixed-income securities. The amount issued according to their reports closely tracks the amount we see issued in the Mergent data throughout our sample period and indicates that the sample we use fully covers this market.

Figures 2-A1 through 2-A3 in the appendix show the trends in the issuances of municipal bonds over our sample period broken down into RBs and GOs and bank-qualified and nonbank-qualified samples. GOs have become relatively more prevalent over time, particularly since the financial crisis. The average size of GO issues is consistent, while the average RB issue has grown larger. There is substantial variation in what issuers use bonds for over time. For RBs in particular, what the purpose is may be important to the decision to obtain a rating or the required offering yields because the bonds are often funded by revenue associated with a project. For this reason, we add fixed effects for use of funds in our specifications. There was a temporary spike in bank-qualified issues in 2009 and 2010 due to the temporary change in the threshold, but bank-qualified issues have also grown as a proportion of the market over time. The change in the threshold is evident in Figure 2-A3 that shows the average size of bank-qualified and nonbank-qualified issues each year.The percentage of rated issues was consistent over time, although slightly more GOs were rated in the pre-crisis period and slightly more RBs afterwards.

Distribution of Ratings

Table 2-1 shows the proportion of rated and unrated municipal bonds in our sample. The number of unrated bonds accounts for 34.2% of the total number of bond offerings, while the dollar amount of unrated bonds represents 13.7% of the total dollar amount of all offerings.

In Table 2-2, we further break down the distribution of ratings. A higher proportion of bank-qualified bonds go unrated. A somewhat larger proportion of GOs get a rating compared to RBs as a percentage of the number of issues, but not as a percentage of the amount issued.

Figure 2-2 shows the number and dollar amount of rated issues over time. Rated bonds have increased over time. There was a dip in the issuance of unrated bonds after the financial crisis, and the issuance has stayed relatively consistent since then. Figure 2-3 separately shows the time series of ratings for GOs and RBs. A higher proportion of GOs got a rating prior to the financial crisis and a higher proportion of RBs got a rating afterwards. The drop in RB issues after the crisis could have caused this trend. It is likely that the investors' appetite for the riskier RBs decreased, and as we will show, riskier bonds are generally less likely to get a rating. Figure 2-3 also shows the time-series of ratings separately for bank-qualified and nonbank-qualified bonds. Those that are bank-qualified get ratings less, but the two categories move in parallel and rated bonds increase as a proportion of both after the financial crisis.

Table 2-3 shows the distribution of defaults. Of all the municipal bonds in our sample, 0.54% experience a default at some point. In contrast, 1.24% of unrated bonds default. Yang and Abbas (2020) find a significant relationship between the lack of a rating and default risk. Default risk accounts for most of the municipal bond yield spread relative to Treasuries after adjusting for tax-exempt status with a liquidity component accounting for 16%-26% (Schwert 2017) or 8%-19% (Wang, Wu and Zhang 2008). Several studies address how specific sources of default risk affect bond yields. For example, Gao, Lee, and Murphy (2019) show that the state policies that allow municipalities unconditional access to Chapter 9 bankruptcy lead to higher yields.

Empirical Setup

Our objective is to understand how obtaining a rating affects the cost of issuance. We model the determinants of offering yield spread over comparable maturity Treasury yield as a function of issuer riskiness, issue characteristics, and market conditions. We estimate the following linear model:

$$\begin{aligned} &YieldSpread_i \\ &= f(Rated, BankQualified_i, RevenueBond_i, CompetitiveOffering_i, \\ &\quad ln\,PersonalIncomePerCapita_i, .\frac{Liabilities}{Assets}_i, \frac{Property\,Tax}{Total\,Revenue_i}, \\ &\qquad \ln Maturity\ Size_i, \ln Time\ to\ Maturity_i, Put_i, Call_i, Insured_i, \\ &\qquad\quad BAA - AAASpread_i, F_{quarter}, F_{state}, F_{Use\ of\ Funds}) \end{aligned} \tag{1}$$

In Equation 1, Personal Income per Capita, Liabilities to Assets of the issuing county, and property tax revenue as a percentage of total county revenue are proxies for issuer riskiness. Personal income per capita is an indicator of local economic strength, and one of the primary factors that ratings agencies consider. The ratio of liabilities to assets is an indicator of the local government's financial position, while the ratio of property tax to total revenue is an indicator of the consistency of its future revenue.[5]

We also control for several issue characteristics. A larger issue size may be associated with higher liquidity, which should decrease the yield. During our sample period interest rates

[5] Property taxes are generally less volatile and particularly more stable during recessions than alternative sources of revenue such as sales or income taxes (McCubbins and Moule 2010).

experienced large swings causing issuers and bond buyers seek protection against interest rate risk. In a high interest rate environment, bond issuers seek protection against falling rates by issuing callable bonds and accept paying higher yields in exchange for this protection. In contrast, in a low interest rate environment, bond buyers seek protection against rising rates by purchasing bonds with a put option and are willing to accept lower yields in return. Hence, the call and put options in bonds influence issue yields.

We control for whether the bond is insured. Insurance may indicate lower risk because the insurer has guaranteed payments in the event the issuer defaults. However, Cornaggia, Hund, and Nguyen (2022) find that insured issues are more likely to face be downgraded in the future, suggesting insurance may actually indicate higher risk of a default occurring. of the insurance or higher risk that drove the decision to insure. Investors may worry that the benefits of insurance are not adequate to address this risk. There may be delays in payment even if an insurer covers the default, and investors may not have confidence in the insurer's guarantee, particularly after the downgrading of large monoline insurers following the financial crisis.

Revenue bonds are riskier than general obligation bonds because they are backed only by a specific source of revenue rather than the full faith and credit of a municipality. We include an indicator for whether the bond is bank qualified because the inclusion of banks as potential investors is likely to lower the offering yield. In addition, we add offering type of the issue. Competitive offerings can result in lower yields by increasing underwriter competition (Cestau, Green, Hollifield, and Schurhoff 2019).

The BAA-AAA spread is included to capture time variation in the risk premium. State fixed effects capture institutional differences between states and differences in risk related to state support for municipalities, quarterly fixed effects capture changes yields over time, and use-of-funds fixed effects capture differences in the risk of RBs.

The results are shown in Table 2-6. A rating is associated with a decrease in offering yield of between 50 and 52 basis points. The control variables have the expected signs. Higher income and higher reliance on property tax indicate lower risk and are associated with lower yields. A higher liabilities / assets ratio indicates higher risk and is associated with higher yields for general obligation bonds. Revenue bonds are riskier and have higher yields. Bank qualified bonds have lower yields. Maturity size, indicating liquidity, is generally associated with lower yields except among not bank qualified bonds where it is insignificant. Yields are lower if investors have a put option and higher if the issuer has a call option. Competitive offerings have lower yields than negotiated offerings. However, the decision to obtain a rating for a municipal bond is confounded because the characteristics that affect that decision could also affect the bond's yield. Of particular concern, issuers could have more of an incentive to obtain ratings for bonds that are less risky because they will receive good ratings. As the riskiness of a bond is the primary factor that affects its yield, a comparison of the yields of unrated and rated bonds would capture the effect of risk on the yield rather than the effect of the rating.

To address this confounding concern, we use a matched sample approach that uses inverse probability weights to estimate the yield regression model of Equation 1. The inverse probability weighted regression approach (IPWRA) controls the selection effects by augmenting the regression of the offering yields (the outcome variable) with probability weights derived from a logistic model for the rating selection variable (the treatment). In the first stage, we estimate a logistic regression to predict the probability that a municipality will get a bond rated based on its observable characteristics. In the second stage, we estimate a linear regression model that uses the weights that control for the decision to obtain a rating by creating a pseudo-sample in which rated and unrated bonds have similar characteristics other than their rating.

These weights are calculated using predicted probabilities of obtaining a rating from the first stage as follows:

$$\begin{cases} \dfrac{\hat{P}(rated = 1)}{\hat{P}\,(rated = 1 \mid X \; = \; x_i)} \; if \; rated \; = \; 1 \\ \dfrac{1 - \hat{P}(rated = 1)}{1 \; - \; \hat{P}\,(rated = 1 \mid X \; = \; x_i)} \; if \; rated \; = \; 0 \end{cases} \tag{2}$$

The procedure gives high weights to the bonds that seem unlikely to get rated but are actually rated, such as bonds from low-income areas; and low weights to the bonds that seem likely to get rated and are rated, such as bonds from high-income areas. The procedure also gives high weights to the bonds that seem likely to get rated but are not, such as bonds from high-income areas; and low weights to the bonds that seem likely to go unrated and are not rated, such as bonds from low-income areas. The result is a sample where weighted and unweighted bonds appear to have similar characteristics based on proxies for risk such as local income and other factors that affect the decision to obtain a rating. We then estimate a linear model for yield spreads using the weights. The IPWRA estimator has the property of double robustness in which the estimates of the effect of the rating on the yield are consistent if either the logistic regression for obtaining a rating or the yield regression is correctly specified (Wooldridge 2007).

Results

The Decision to Obtain a Rating

The logistic model of the decision to obtain a rating that we estimate in the first stage is as follows:

$$\Pr(Rated_i) = f(\ln IssueSize_i\,,\ BankQualified_i,\quad RevenueBond_i,\ ln\,PersonalIncomePerCapita_i\,,.\ \frac{Liabilities}{Assets}_i, \frac{Property\ Tax}{Total\ Revenue}_i,\ Insured_i, BAA - AAASpread_i, F_{quarter}, F_{state}, F_{Use\ of\ Funds}) \tag{3}$$

We include several characteristics of the offering that affect the decision to obtain a rating. We include the logarithm of issue size because it is a proxy for liquidity, access to a large number of investors, and scale economies in issue costs**.** In addition, we include an indicator for whether a bond is bank-qualified because these bonds are primarily held by banks that we predict will value ratings less than retail investors. Whether a bond is a GO or a RB may affect the decision for several reasons**.** We include an indicator for whether the issuers place the bond in a competitive (as opposed to negotiated) offering because that setting is likely to involve a wider group of potential underwriters and investors who are less familiar with the issuer.

We include several variables related to the risk of the bond. The risk of the bond may be relevant to the decision to obtain a rating in two conflicting ways. An issuer may be more inclined to seek a rating if that rating is likely to be good in which case issuers are less likely to obtain ratings for riskier issues. However, an issuer with observable characteristics that indicate low risk might decide that those characteristics are sufficient to assure investors of the bond's safety. As in equation 1, we include personal income per capita, the ratio of liabilities to assets, the ratio of property tax to total revenue, an indicator for revenue bonds, and various fixed effects as risk proxies.

Table 2-7 shows the results of the logistic regressions that predict whether bond issues will get a rating using the specification in equation 3. We estimate the model separately for two splits of the sample based on whether the bond is a GO or a RB and whether it is bank-qualified. As expected, we find that placing the bonds in a competitive offering is associated with obtaining a rating in all subgroups. Also as predicted, larger bond issues are more likely to get a rating.

Proxies for higher risk are generally associated with forgoing a rating. Higher personal income per capita is positively associated with obtaining a rating in all subgroups. A higher liability-to-asset ratio, which indicates an issuer with less financial strength, is negatively associated with obtaining a rating in the GO and bank-qualified samples but is insignificant in the RB and not bank-qualified samples. The lack of significance in the RB sample makes sense because revenue bonds are backed by a specific source of revenue, so the overall financial health of the local government is less relevant. Property taxes as a proportion of total revenue is positively associated with obtaining a rating in all but the not bank-qualified subsample, where it is not significant.

Revenue bonds are less likely to be rated than GOs. Bank-qualified bonds are less likely to get a rating if they are also RBs but more likely to get a rating if they are GOs.

The model does a good job of predicting whether a bond will be rated, correctly predicting rating status for 78%-82% of bonds depending on the sample. The McFadden's pseudo-R-squared range from 20% to 34%, indicating excellent fit.

Table 2-8 shows the standardized differences of the covariates between the rated and unrated bonds before and after applying the inverse probability weights (IPW). Before IPW, the rated and unrated bonds in our sample have large, standardized differences in most characteristics. After weighting, the rated and unrated bonds appear similar. Rubin (2001) suggests a cutoff of 0.25 for checking the covariate balance; a standard we always meet after IPW. Some other authors suggest a stricter cutoff of 0.1 that we meet except for a few covariates in the GO sample and one covariate in the not bank-qualified sample. These standardized differences indicate the IPW were successful at creating a pseudo-sample in which rated and unrated bonds are similar.

The Effect of a Rating on Yield

We re-estimate Equation 1 using the weights shown in Equation 2 based on predicted probabilities obtained from fitting the model in Equation 3.

Panel A of Table 2-9 shows the results from a linear regression of yield spread on whether a bond gets a rating and control variables after applying the IPW. The results indicate that a rating is associated with a decrease in the offering yield of 42 to 60 basis points when controlling for the decision to obtain a rating and other characteristics that affect the yield. This is quite substantial considering the average offering yield of an unrated municipal bond in our sample is 4.03% and the median is 4.25%. It is also large relative to the costs of obtaining a rating, generally a 1-time cost of around 10 basis points. Our estimate is also substantially higher than the 10 basis point difference found by Reeve and Herring (1986) in a limited sample. It is also large compared to other effects on municipal yields that have been studied. For example, Gao, Lee, and Murphy (2020) find newspaper closures increase yields by 5 to 11 basis points. Cestau, Green, Hollifield, and Schurhoff (2020) find the use of negotiated sales increases yields by 15-17 basis points.

Robustness Tests

One important advantage of IPWRA is that it is doubly robust. For the estimation to be valid, the IPWRA must correctly specify all the elements that go into the decision to obtain a rating or that affect the yield of the issue. In other words, the credit risk profile of an issuer is a crucial element in this decision. The goal is conditional on fully and correctly capturing the risk profile of an issuer, to estimate the marginal effect of the presence/absence of a rating. In this section, we undertake additional tests to capture fully the credit risk profile of the issuers.

Some of our control variables are measured at the county level, and the financial variables measure the financial strength of the local government rather than the financial strength of the project backing revenue bonds. Consequently, we estimate our model on a subsample consisting only of GO bonds issued by county governments. For this subsample where we are especially confident in our risk proxies, we find that a rating is associated with a decrease of 52 basis points in the offering yield, which is consistent with our prior results.

Another robustness test pertains to the spillover effects between rated and unrated municipal bonds issued by the same or related issuers. Panel B of Table 2-10 shows the results of estimating our model on a sample including only issuers that issue either all unrated bonds or all rated bonds. Panel A of Table 2-10 shows the distribution of percentage rated issues by issuer. There are many such issuers. We find the effect of a rating on offering yields is stronger, ranging from 60 to 74 basis points. This is consistent with unrated bonds receiving some spillover benefits from related rated issues.

Addressing the same issue, we estimate the model on a sample including only counties that issue fewer than 20% or more than 80% of their bonds with ratings. Panel A of Table 2-11 shows the distribution of percent rated issues by county. Unlike the issuer level, there are fewer counties that exclusively issue rated or unrated bonds, but many that mostly issue rated or unrated bonds. We find a somewhat stronger effect than when analyzing the full sample, with ratings reducing offering yields by 43 to 60 basis points. This is also consistent with unrated bonds receiving some spillover benefits from related rated issues.

The accumulating evidence from these robustness tests show that as we define the risk profiles better the significance of forgoing a rating on yields increases. This result provides strong support for our prior results.

Heterogenous Effects of a Rating on the Yield

The previous results give an average treatment effect, and an estimate of how much a rating reduces the yield for a typical bond in the sample. However, the amount a typical rated bond's yield would increase if it did not get a rating and the amount a typical unrated bond's yield would decrease if it got a rating might be different. With different weighting schemes, we can estimate the effect of not obtaining a rating on the yields of rated bonds or the effect of obtaining a rating on unrated bonds.

To estimate how much getting a rating would decrease the offering yield for unrated bonds, we compare unrated bonds to rated bonds that were unlikely to get rated, such as bonds from low-income areas. This is accomplished by using the weights:

$$\begin{cases} \dfrac{1-\hat{P}(rated = 1 \mid X = x_i)}{\hat{P}\,(rated = 1 \mid X = x_i)} \; if\ rated = 1 \\ 1\ if\ rated = 0 \end{cases} \tag{4}$$

To estimate how much not having a rating would increase the yields for rated bonds, we compare rated bonds to unrated bonds that were likely to get rated, such as bonds from high-income areas. This is accomplished by using the weights:

$$\begin{cases} \dfrac{\hat{P}(rated = 1 \mid X = x_i)}{1 - \hat{P}\,(rated = 1 \mid X = x_i)} \; if\; rated = 0 \\ 1\; if\; rated = 1 \end{cases} \tag{5}$$

Panel A of Table 2-12 shows the results using the weighting to estimate the effect on unrated bonds, while Panel B shows the results using the weighting to estimate the effect on rated bonds. We estimate larger decreases in the offering yield from getting a rating for rated bonds that range from 46 to 69 basis points, and smaller decreases in offering yields from getting a rating for unrated bonds that range from 37 to 48 basis points.

Counterfactual Results

We quantify the inflation-adjusted net dollar value of the reduction in offering spreads. Every unrated bond is treated as if it is a fixed semi-annual coupon bond sold at par. The reduction in yield is thus interpreted as a reduction in each coupon payment. We calculate the hypothetical savings for each coupon payment, then discount those savings back to the time of issuance using the risk-free rate to compute the (historic) present value. We subtract an assumed 0.1% rating fee based on the fees reported in Beatty, Gillette, Petacchi, and Weber (2019), then convert to 2015 dollars using the consumer price index. Table 2-13 shows that our main specification results in \$4.2 billion in savings for GOs and \$18.3 billion for RBs.

Value of a Rating Over Time

To investigate the possibility that the value of obtaining a rating varies across time, we re-estimate the model specified in equation 3 by replacing the indicator for whether a bond gets a rating with the interaction of whether a bond gets a rating with variables for the year. The coefficients for each year's interaction term estimate the value of obtaining a rating in that year. For this analysis, we need to omit the ratio of assets to liabilities and the percentage of revenue from property taxes from the specification because these data are only available starting in 2004. These results are shown in Figure 2-4 with corresponding counterfactual savings shown in Table 2-14.

The results show substantial temporal variation in which the yield reduction from obtaining a rating is particularly high for periods following the 2001 recession and the 2008 financial crisis. Using the annual estimates of the reduction in the offering yield, we find forgoing ratings is associated with approximately $17.6 billion in costs to municipalities between 1998 and 2017.

Underwriters and the Choice to Obtain a Rating

In previous sections, we show that there is a large reduction in offering yield and savings net of costs of obtaining a rating in municipal bond offerings. These findings raise the question of why municipalities issue so many unrated bonds. In this section, we focus on one explanation, which stems from the conflict of interest between advisers/underwriters and municipal bond issuers.

We use Garrett's (2021) framework to argue that advisors and underwriters can affect whether the issuer obtains a rating but may influence the choice to benefit themselves rather than the issuer. From the issuer's perspective, obtaining a rating is optimal if it lowers the cost of interest payments by more than the cost of the rating. However, the underwriter wants to maximize its profits by increasing the difference between the price at which it purchases the bonds from the issuer and the price at which it sells the bonds to investors. A rating will generally increase the price investors are willing to pay for the bonds but can increase the price the underwriter must pay the issuer even more and thus reduce the underwriter's profits. This conflict of interest is particularly strong for the competitive offerings because underwriters bid in an auction to underwrite the issue. The financial advisor plays a critical role in the bond issue process, by providing a comprehensive plan for the bond issue. The advisor to an offering has private information about the offering that is more valuable in the auction when opacity is higher. Obtaining a rating reduces the advisor's asymmetric information advantage, so an advisor who plans to bid on the bonds as an underwriter has an incentive to discourage obtaining a rating. When the underwriter acts as a financial advisor (dual advisor) additional conflict of interest can arise because dual advisors can direct the municipalities to structure the bond offering to the best interest of the underwriter. Indeed, Garrett (2021) shows that when advisors were prohibited from underwriting the issues they advise by the Dodd-Frank act, issuers who previously used dual advisors became more likely to obtain ratings and their cost of borrowing decreased.

Within this framework, we analyze the relationship between underwriters and the decision to obtain a rating in three ways with alterations to our selection model specified in equation 3.

First, we examine whether individual underwriters systematically influence the decision to obtain a rating. To address this question, we re-estimate the model in equation 3 adding fixed effects for the lead underwriter. Table 2-15 shows the results of this model. To ensure a sufficient number of observations per underwriter, we remove the 5% of the sample whose lead underwriters underwrote the fewest number of issues in our sample period. The cutoff is 78 issues across the sample period. This exclusion has negligible effect on the model fit. However, adding the lead underwriter fixed effects improves the fit substantially. The pseudo-R-squared increases by between 0.10 to 0.17 while the percentage correctly classified increases by 4%-6%. These results show underwriters play a strong role in deciding whether to obtain a rating.

Next, we investigate whether certain characteristics of underwriters affect the decision to obtain a rating. We estimate the model specified in equation 3 while adding the lead underwriter's market share decile in the offering year as a control variable. Cornaggia, Hund, and Nguyen (2022) show underwriters in higher market share deciles lead issuers to purchase insurance even when it costs more than it saves in offering yield, suggesting influential underwriters are better able to mislead issuers. However, market share could also proxy for the financial sophistication of the underwriter. Table 2-16 shows that higher underwriter market share is positively associated with obtaining a rating. This result shows that conflict of interest is more prevalent for issues that have smaller underwriters, in which case the issuer is less likely to obtain ratings.

In addition, we test the effect of a financial advisor also serving as the lead underwriter on an issue. For this analysis, we include only issues with financial advisor information available in Mergent. As Garrett (2021) showed, advisors have a strong incentive to not recommend ratings for competitive offerings they advise. The type of offering is also correlated with advisor conflicts. For these reasons, we test the effect of dual underwriters separately for competitive and non-competitive offerings.

In our sample issues with dual underwriters are more frequently unrated. Among non-competitive offerings, 57.3% of dual-underwriter issues are unrated compared to 17.9% of issues with non-conflicted advisors. Among competitive offerings, 45.4% of dual-underwriter issues are unrated compared to 28.1% of issues with non-conflicted advisors.

Table 2-17 shows the results of estimating our logistic model described in equation 3 while controlling for dual-underwriter status. Panel A shows the results for competitive offerings. Consistent with Garrett (2021), a dual underwriter consistently has a negative and highly significant relationship with obtaining a rating. Panel B shows the results for non-competitive offerings. The relationship here is not as strong as for competitive offerings but the results indicate the conflict of interest likely plays a role for non-competitive offerings as well. The point estimates are consistently negative across samples, but the coefficient is significant at the 5% level only in the not bank-qualified sample. It is also significant at the 10% level for revenue bonds. These results suggest conflicted underwriters can fail to sufficiently encourage issuers to obtain ratings.

Conclusion

We demonstrate that a substantial percentage of municipal bonds do not obtain ratings: 14% by dollars issued and 34% by number of issues.

Issuers are more likely to forgo ratings for a bond that is riskier. In particular, issuers are less likely to obtain a rating if they have lower local income. For general obligation bonds, which are backed by the faith and credit of the local government rather than a particular revenue source, they are less likely to obtain a rating if they are more indebted or are more reliant on revenue sources other than property taxes. Issuers are also less likely to obtain ratings for revenue bonds which could be due to their higher risk or due to difficulties evaluating their risk. These results are consistent with issuers forgoing ratings for bonds that they expect will receive poor ratings.

Some characteristics of the offering not directly related to risk also affect the decision to obtain a rating. Bonds placed in a negotiated offering are less likely to get a rating than bonds placed in a competitive offering. Contrary to our expectations, bank-qualified issues are not generally less likely to get a rating. Bank-qualified issues are more likely to get a rating for general obligation bonds, but less likely to get a rating for revenue bonds.

If issuers make fully informed and rational decisions to avoid obtaining ratings, we predict that any potential effect from obtaining ratings on the offering yields to be small and less than the cost of obtaining a rating. However, ratings appear to cause an economically significant decrease on the cost of issuance. The results of our primary specification indicate that unrated bonds could lower offering yields by 47 basis points for revenue bonds and 49 basis points for general obligation bonds by obtaining a rating. When we consider only a subsample where we are sure we accurately measure risk, county-level GO bonds, we find a similar reduction of 52 basis points. These yield reductions are substantially higher than the typical fees that rating agencies charge and are a one-time cost at issuance of approximately 0.10% the amount issued. These increased offering yields correspond to $22.5 billion (in 2015 dollars) in aggregate cost to municipalities net of rating fees between 1998 and 2017.

These potential savings indicate issuers do not fully appreciate the value of obtaining a rating. We find suggestive evidence that issuer's failure to obtain ratings may be driven by the advice they receive from underwriters or advisors. Underwriter fixed effects provide a large increase in fit for a logistic model predicting whether a rating will be obtained. Issuers are less likely to obtain ratings for issues underwritten by smaller and potentially less sophisticated underwriters. Issuers are also less likely to obtain ratings when working with financial advisors who also underwrite the issue.

Variation Among Municipal Bond Issues

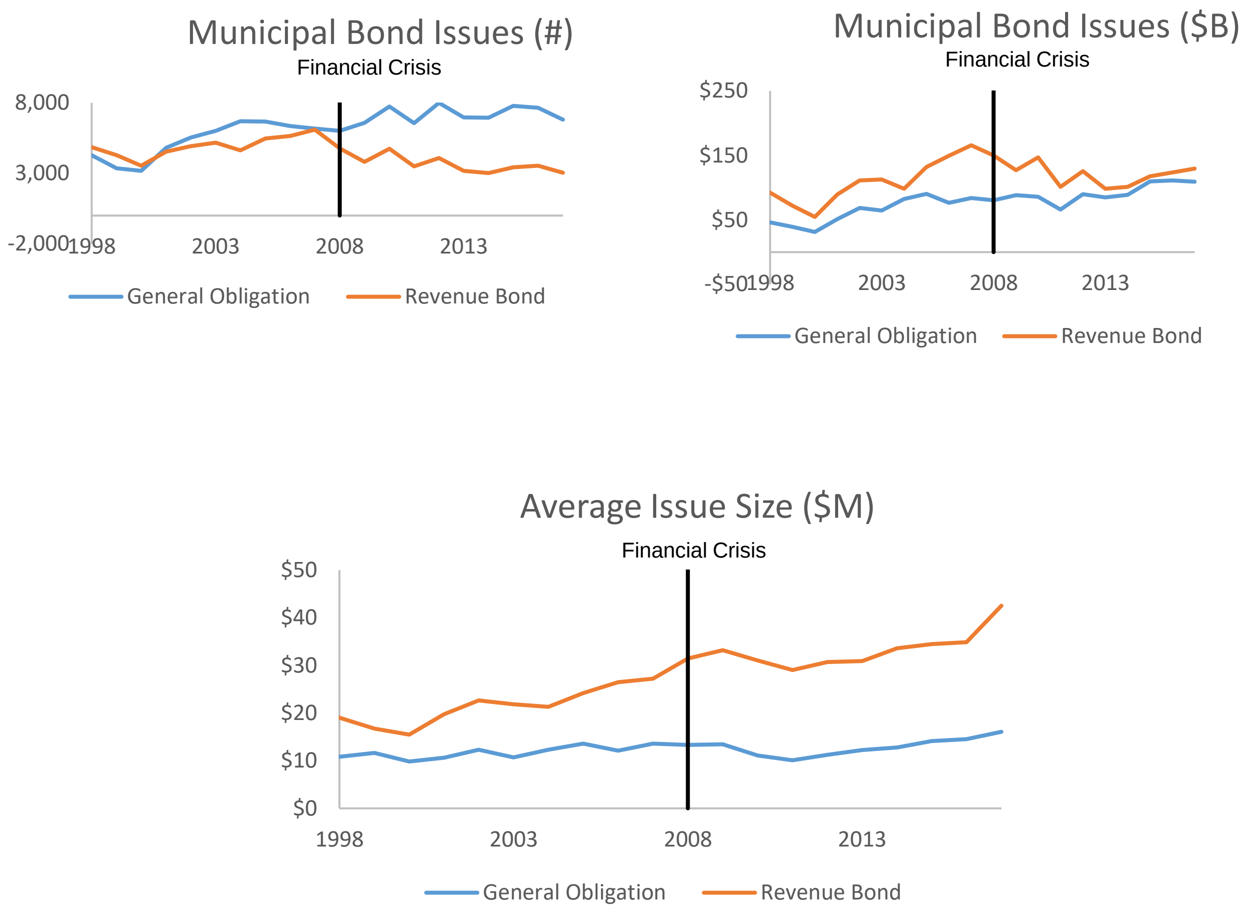
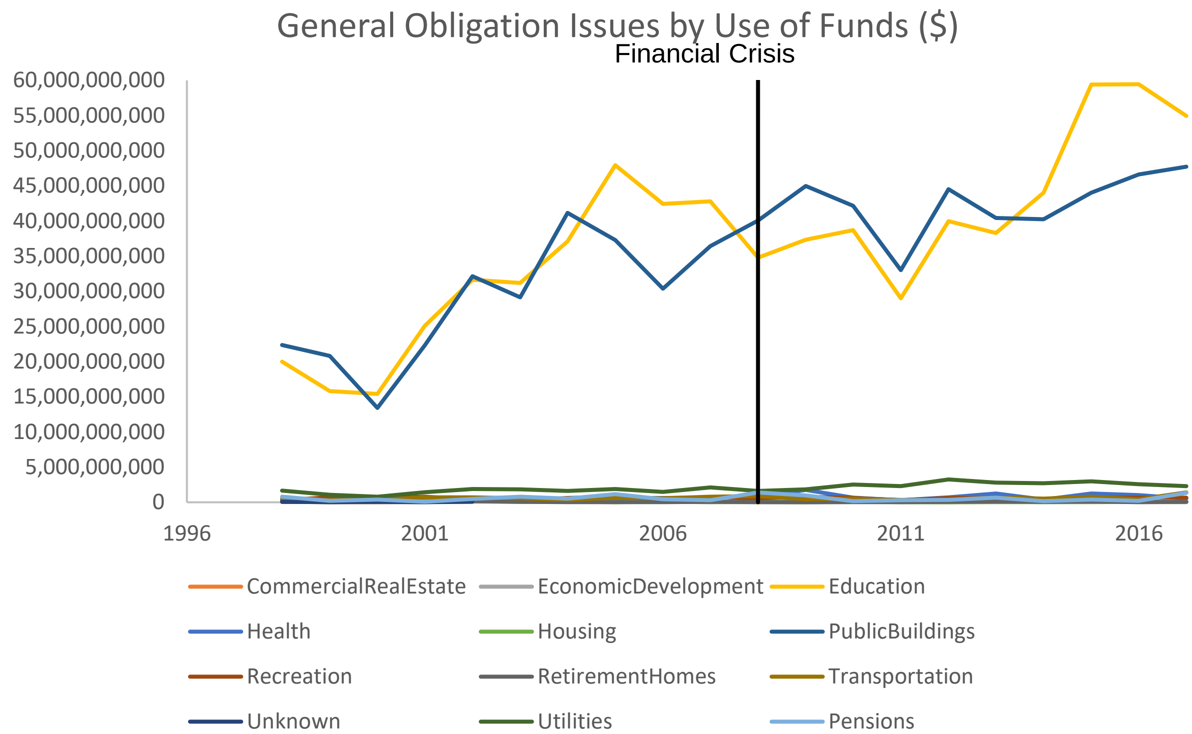


Figure 2-A1 Issuance of general obligation and revenue bonds over time within our sample.



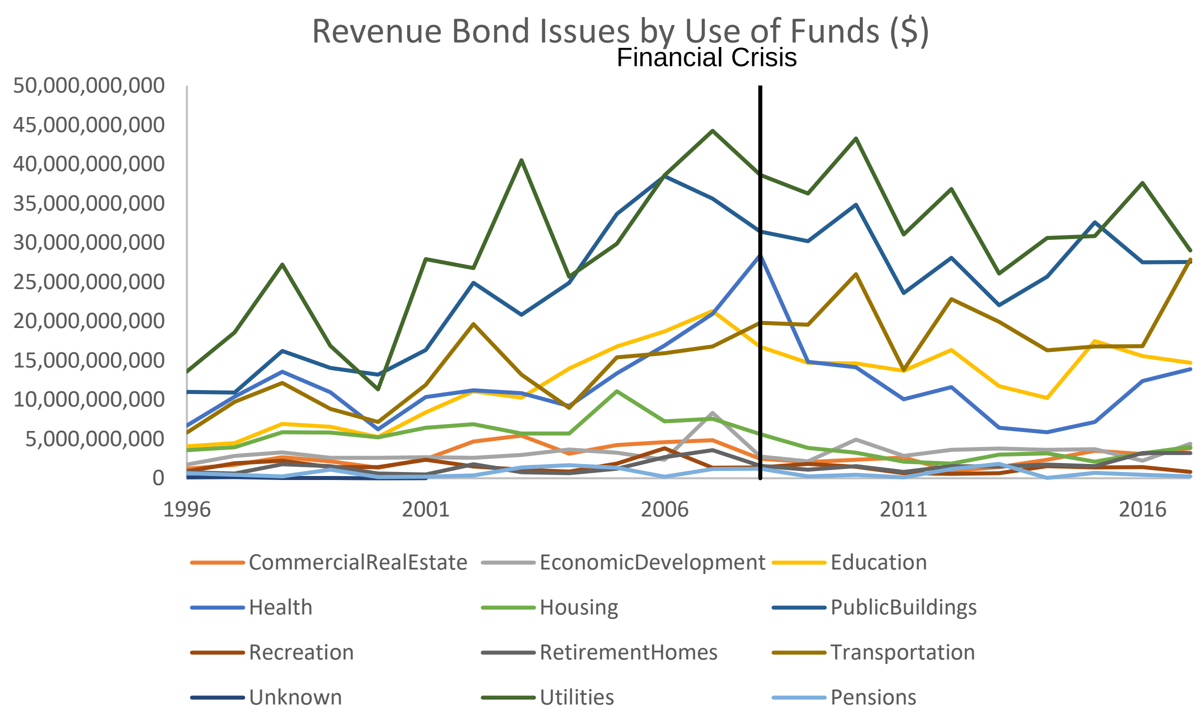
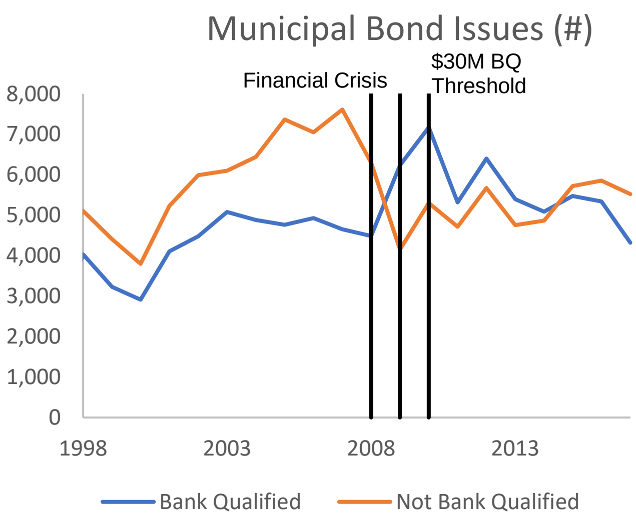
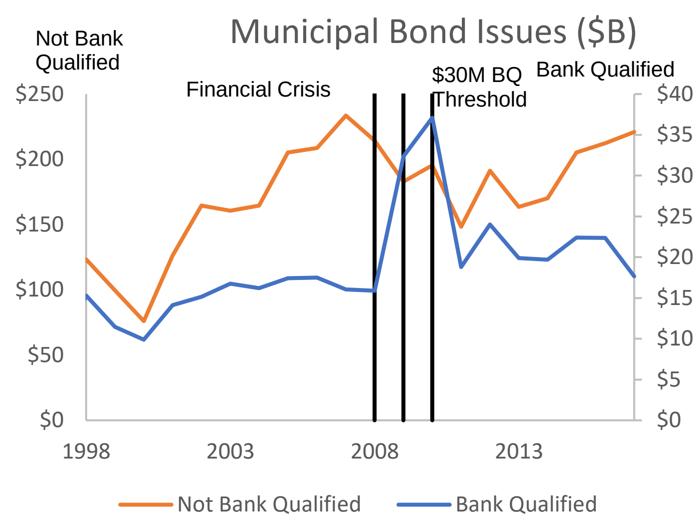
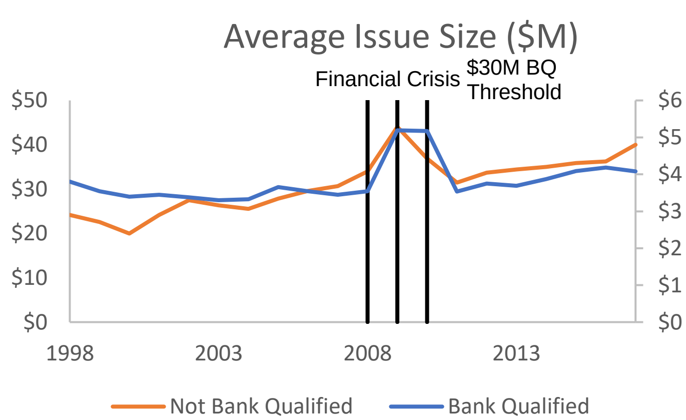


Figure 2-A2 The distribution of revenue bonds and general obligations by use of funds.







Figures 2-A3. The time-series of bank-qualified and nonbank-qualified bond issues.

Tables

Table 2-1: Distribution of Ratings at Time of Issue

Table 2-1 shows the proportion of rated and unrated bonds both by number of bond offerings and amount issued for the entire sample.

Rating Status	Bond Offerings	(%)	Issue Amount	(%)
Rated	132,417	65.8%	$3,192,013,225,149	86.3%
Unrated	68,690	34.2%	$507,019,433,532	13.7%
Total	**201,107**	**100%**	**$3,699,032,658,681**	**100%**

Table 2-2: Proportion of Rated Bonds by Bank-qualified Status and Type of Bond

Table 2-2 shows the proportion of rated bonds in our sample both by number of bond offerings of amount issued within offerings that are bank-qualified or not bank-qualified (Panel A) and whether the bond is a general obligation or revenue bond (Panel B).

Panel A

	Bank-Qualified				Not Bank-Qualified			
Rating Status	**Bond Offerings**	**(%)**	**Issue Amount**	**(%)**	**Bond Offerings**	**(%)**	**Issue Amount**	**(%)**
Rated	55,163	57.8%	$273,368,161,583	74.7%	77,254	73.1%	$2,918,645,063,566	87.6%
Unrated	40,257	42.2%	$92,665,408,058	25.3%	28,433	26.9%	$414,354,025,474	12.4%
Total	**95,420**	**100%**	**$366,033,569,641**	**100%**	**105,687**	**100%**	**$3,332,999,089,040**	**100%**

Panel B

	General Obligation				Revenue Bond			
Rating Status	**Bond Offerings**	**(%)**	**Issue Amount**	**(%)**	**Bond Offerings**	**(%)**	**Issue Amount**	**(%)**
Rated	81,095	67.4%	$1,300,821,919,019	86.2%	51,322	63.6%	$1,891,191,306,130	86.4%
Unrated	39,300	32.6%	$208,768,343,598	13.8%	29,390	36.4%	$298,251,089,934	13.6%
Total	**120,395**	**100%**	**$1,509,590,262,617**	**100%**	**80,712**	**100%**	**$2,189,442,396,064**	**100%**

Table 2-3: Default Rates Among Municipal Bond Offerings

Table 2-3 shows the number and percentage of defaults, both by number of offerings and amount issued, for various categories of municipal bonds.

	Issued (#)	Issued ($)	Defaults (#)	Defaults ($)	Default Rate (#)	Default Rate ($)
All Municipal Bonds	210,310	$3,847,438,089,123	1,130	$26,809,908,885	0.54%	0.70%
Rated	141,620	$3,340,418,655,591	276	$14,854,125,014	0.19%	0.44%
Unrated	78,529	$690,050,359,076	973	$20,509,325,601	1.24%	2.97%
Bank Qualified	98,329	$380,119,117,221	155	$714,193,548	0.16%	0.19%
Not Bank Qualified	111,981	$3,467,318,971,902	975	$26,095,715,337	0.87%	0.75%
General Obligation	124,104	$1,548,451,547,482	83	$2,085,376,548	0.07%	0.13%
Revenue Bond	86,206	$2,298,986,541,641	1,047	$24,724,532,337	1.21%	1.08%

Table 2-4: Variable Definitions

Table 2-4 defines the variables included in the regression analysis.

Variable	Definition
Rated	An indicator variable equal to 1 if the bond has received a credit rating and 0 otherwise.
Log(Personal Income Per Capita)	The natural logarithm of the personal income per capita in the county of the bond's issuer in the year of issuance.
Property Tax / Total Revenue	The proportion of total revenue raised from property taxes in the county of the bond's issuer in the year of issuance.
Liabilities / Assets	The ratio of total liabilities to total assets in the county of the bond's issuer in the year of issuance.
Log(Maturity Size)	The natural logarithm of the total amount of the bond issued.
Put	An indicator variable equal to 1 if the bond includes a put option for the holder to sell the bonds back to the issuer and 0 otherwise.
Call	An indicator variable equal to 1 if the bond includes a call option for the issuer to purchase the bonds from investors and 0 otherwise.
Insured	An indicator equal to 1 if the issuer of the bond purchased insurance and 0 otherwise. If the issuer purchases bond insurance at the time of issuance, the insurer guarantees payments of interest and principal to bond holders in the event the issuer defaults.
Revenue Bond	An indicator variable equal to 1 if the bond is a revenue bond backed only by a specific source of revenue and 0 if it is a general obligation backed by the full faith and credit of the issuer.
Bank Qualified	An indicator variable equal to 1 if the bond is issued by a bank qualified issuer and thus banks can benefit from its tax-deductibility and 0 otherwise.
Competitive Offering	An indicator variable equal to 1 if the bond is placed in competitive offering where underwriters bid for the bond and 0 otherwise.
BAA-AAA Spread	The yield spread between Baa and Aaa rated corporate bonds.

Table 2-5: Summary Statistics on Regression Sample

Table 2-5 presents the means and standard deviations of variables used in the regression analysis in Table 2-6 within the sample used in Table 2-6.

	Revenue Bonds		General Obligation		Bank Qualified		Not Bank Qualified	
	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
Competitive Offering	36.9%		60.8%		60.5%		45.7%	
Log(Time to Maturity)	1.87	0.76	1.84	0.77	1.79	0.77	1.90	0.76
Put	0.2%		0.0%		0.0%		0.1%	
Call	33.0%		32.4%		34.0%		31.4%	
Insured	36.3%		38.2%		37.9%		37.3%	
Log Maturity Size	13.21	1.43	12.85	1.41	12.23	1.09	13.61	1.37
Liabilities / Assets	47.9%	29.7%	53.5%	32.0%	47.6%	29.9%	55.0%	32.1%
Log(Personal Income Per Capita)	3.80	0.31	3.82	0.27	3.77	0.25	3.85	0.31
Property Tax / Total Revenue	30.4%	14.9%	35.5%	16.4%	35.4%	16.4%	32.3%	15.6%

Table 2-6: OLS Estimates of the Effect of Rating on Offering Yield Spread

Table 2-6 shows the results of a regression of municipal bond offering yield spreads on whether the bond gets a rating and other explanatory variables. *Competitive Offering* is equal to one if the offering is competitive and zero otherwise. *Log(Size)* is the natural logarithm of the amount issued in the offering. *Log(Personal Income per Capita)* is the natural logarithm of the personal income per capita in the county where the bond was issued. *Property Tax / Total Revenue* is the proportion of the local government's revenue raised from property taxes. *Liabilities / Assets* is the ratio of assets to liability of the local government. *Bank Qualified* is equal to one if the bond offering is bank-qualified and zero otherwise. *Revenue Bond* is equal to one if the bond offering is a revenue bond and zero if it is a general obligation bond. *Log(Time to Maturity)* is the natural logarithm of the time from the offering date until the maturity date. *Put* is equal to one if the bond has an option for investors to sell the bond back and zero otherwise. *Call* is equal to one if the bond has an option for the issuer to buy back the bond and zero otherwise. *Insured* is equal to one if the bond has insurance and zero otherwise. *BAA-AAA Spread* is the yield spread between BAA and AAA rated corporate bonds. Continuous variables are standardized to have a mean of zero and a standard deviation of one. Standard errors are adjusted for clustering at the bond issue level.

	Bond Yield Spread Regression - IPWRA							
	Revenue Bonds		General Obligation		Bank Qualified		Not Bank Qualified	
	Estimate	p-Value	Estimate	p-Value	Estimate	p-Value	Estimate	p-Value
Rated	-0.51	0.00	-0.50	0.00	-0.51	0.00	-0.52	0.00
Risk Proxies								
Log(Personal Income Per Capita)	-0.04	0.00	-0.01	0.03	-0.01	0.00	-0.01	0.00
Property Tax / Total Revenue	-0.01	0.06	-0.03	0.00	-0.03	0.00	-0.03	0.00
Liabilities / Assets	-0.01	0.03	0.01	0.00	0.01	0.02	-0.01	0.00
Bond Characteristics								
Log(Maturity Size)	-0.01	0.00	-0.02	0.00	-0.06	0.00	0.00	0.33
Log(Time to Maturity)	-0.10	0.00	-0.17	0.00	-0.18	0.00	-0.11	0.00
Put	-0.80	0.00	-0.71	0.03	-0.13	0.92	-0.80	0.00
Call	0.22	0.00	0.27	0.00	0.20	0.00	0.32	0.00
Insured	-0.01	0.15	0.09	0.00	0.05	0.00	0.06	0.00
Revenue Bond					0.05	0.00	0.21	0.00
Bank Qualified	-0.12	0.00	-0.10	0.00				
Offering Characteristics								
Competitive Offering	-0.09	0.00	-0.07	0.00	-0.07	0.00	-0.09	0.00
BAA-AAA Spread	0.30	0.00	0.26	0.00	0.25	0.00	0.34	0.00
Quarter Fixed Effects	Yes		Yes		Yes		Yes	
State Fixed Effects	Yes		Yes		Yes		Yes	
Use of Funds Fixed Effects	Yes		Yes		Yes		Yes	
R-Square	0.65		0.65		0.65		0.66	
Observations	215,722		407,585		287,638		335,669	

Table 2-7: Logistic Regression Predicting Rating (Rated=1, Unrated = 0)

Table 2-7 shows the results of a logistic regression that predicts whether a bond offering gets a rating. *Competitive Offering* is equal to one if the offering is competitive and zero otherwise. *Log(Size)* is the natural logarithm of the amount issued in the offering. *Log(Personal Income per Capita)* is the natural logarithm of the personal income per capita in the county where the bond was issued. *Property Tax / Total Revenue* is the proportion of the local government's revenue raised from property taxes. *Liabilities / Assets* is the ratio of assets to liability of the local government. *Bank Qualified* is equal to one if the bond offering was bank-qualified and zero otherwise. *Revenue Bond* is equal to one if the bond offering is a revenue bond and zero if it is a general obligation bond. Continuous variables are standardized to have a mean of zero and a standard deviation of one.

Logistic Regression Predicting Rating (Rated=1, Unrated=0)

	Revenue Bonds		General Obligation		Bank Qualified		Not Bank Qualified	
	Estimate	p-Value	Estimate	p-Value	Estimate	p-Value	Estimate	p-Value
Competitive Offering	0.75	0.00	0.18	0.00	0.25	0.00	0.35	0.00
Log(Size)	0.81	0.00	1.22	0.00	1.71	0.00	0.75	0.00
Log(Personal Income Per Capita)	0.16	0.00	0.16	0.00	0.08	0.00	0.30	0.00
Property Tax / Total Revenue	0.02	0.30	0.04	0.05	0.05	0.01	-0.01	0.59
Liabilities / Assets	-0.01	0.54	-0.11	0.00	-0.08	0.00	-0.02	0.24
Bank Qualified	-0.18	0.00	0.17	0.00				
Revenue Bond					-0.79	0.00	-0.64	0.00
Quarter Fixed Effects	Yes		Yes		Yes		Yes	
State Fixed Effects	Yes		Yes		Yes		Yes	
Use of Funds Fixed Effects	Yes		Yes		Yes		Yes	
Unrated Observations	12,608		17,801		16,311		14,098	
Rated Observations	32,074		50,220		32,508		49,786	
McFadden's Pseudo R-Squared	22%		32%		34%		20%	
% Correctly Classified with 0.5 Threshold	78%		82%		80%		81%	

Table 2-8: Standardized Difference of Rated and Unrated Bond Offerings Before and After Inverse Probability Weighting

Table 2-8 shows the standardized differences of covariates before and after applying the inverse probability weights. *Competitive Offering* is equal to one if the offering is competitive and zero otherwise. *Log(Size)* is the natural logarithm of the amount issued in the offering. *Log(Personal Income per Capita)* is the natural logarithm of the personal income per capita in the county where the bond was issued. *Property Tax / Total Revenue* is the proportion of the local government's revenue raised from property taxes. *Liabilities / Assets* is the ratio of assets to liability of the local government.

Revenue Bonds

Covariate	Before IPW	After IPW
Bank Qualified	-0.26	0.02
Competitive Offering	0.24	0.08
Liabilities / Assets	0.18	0.00
Log(Personal Income Per Capita)	0.13	0.01
Log(Offering Size)	0.79	-0.03
Property Tax / Total Revenue	-0.04	-0.03

Bank Qualified

Covariate	Before IPW	After IPW
Revenue Bond	-0.11	-0.06
Competitive Offering	-0.01	0.02
Liabilities / Assets	-0.02	-0.05
Log(Personal Income Per Capita)	0.03	0.00
Log(Offering Size)	1.04	-0.06
Property Tax / Total Revenue	0.18	-0.02

General Obligation Bonds

Covariate	Before IPW	After IPW
Bank Qualified	-0.36	0.19
Competitive Offering	-0.13	0.16
Liabilities / Assets	-0.12	-0.02
Log(Personal Income Per Capita)	0.07	-0.01
Log(Offering Size)	0.93	-0.25
Property Tax / Total Revenue	0.28	0.07

Not Bank Qualified

Covariate	Before IPW	After IPW
Revenue Bond	-0.20	-0.08
Competitive Offering	0.21	0.12
Liabilities / Assets	-0.07	0.02
Log(Personal Income Per Capita)	0.06	0.01
Log(Offering Size)	0.68	-0.02
Property Tax / Total Revenue	0.18	-0.01

Table 2-9: IPWRA Regression Predicting Yield Spread

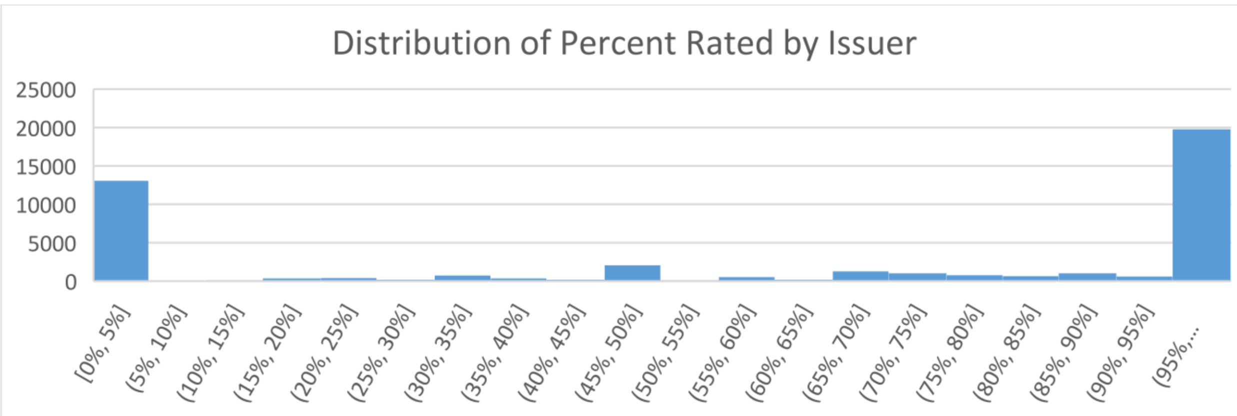
Table 2-9 shows the predicted yields if the bonds in the sample were rated, unrated, and the difference based on a regression of municipal bond offering yields on whether the bond gets a rating and other explanatory variables matching those used in Table 2-6. Standard errors are adjusted for clustering at the bond issue level.
Panel A shows the results for the entire sample while Panel B shows the results for a sample including only GO bonds issued by county-level entities.

	Inverse Probability Weighted Regression Model			
	Revenue Bonds	General Obligation	Bank Qualified	Not Bank Qualified
Panel A: Main Specification				
Average Rated Yield Spread	0.28	0.10	0.16	0.17
Average Unrated Yield Spread	0.75	0.59	0.76	0.59
Average Treatment Effect	-0.47***	-0.49***	-0.60***	-0.42***
Number of Observations	215,722	407,585	287,638	335,669
Panel B: County-Level GO Bonds				
Average Rated Yield Spread		0.15		
Average Unrated Yield Spread		0.67		
Average Treatment Effect		-0.52***		
Number of Observations		147,388		

Table 2-10: IPWRA Regression for Yield Spread Only Including Bonds from Issuers with Exclusively Rated or Unrated Bonds

Panel A of Table 2-10 shows the distribution of issuers by percentage of rated issues. Panel B of Table Y shows the predicted yields if the bonds in the sample were rated, unrated, and the difference based on a regression of municipal bond offering yields on whether the bond gets a rating and other explanatory variables matching those used in Table 2-6. Standard errors are adjusted for clustering at the bond issue level. The sample includes only bonds from issuers who issued either entirely rated or entirely unrated bonds.

Panel A



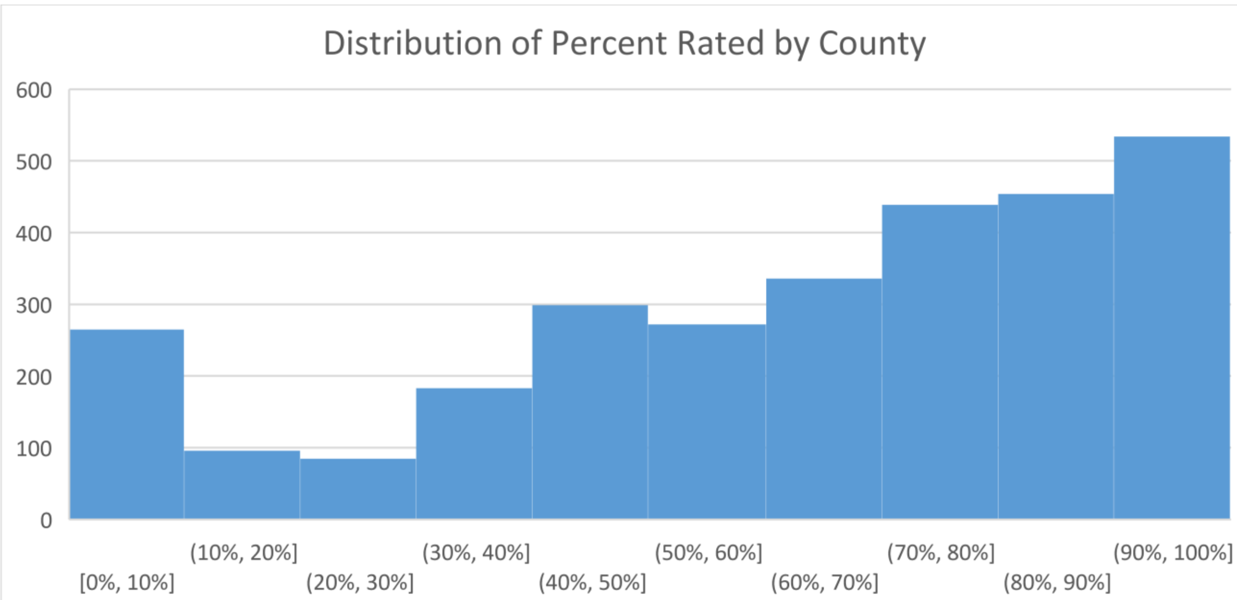
Panel B

Inverse Probability Weighted Regression Model - Issuers That Exclusively Issue Rated or Unrated Bonds

	Revenue Bonds	General Obligation	Bank Qualified	Not Bank Qualified
Average Rated Yield Spread	0.27	0.12	0.15	0.20
Average Unrated Yield Spread	0.92	0.76	0.89	0.79
Average Treatment Effect	-0.65***	-0.65***	-0.74***	-0.60***
Number of Observations	131,905	187,406	161,737	157,574

Table 2-11: IPWRA Regression for Yield Spread Only Including Bonds from Issuers in Counties that Issued Mostly Rated or Unrated Bonds

Panel A of Table 2-11 shows the distribution of counties by percentage of issued bonds that are rated. Panel B of Table 2-11 shows the predicted yields if the bonds in the sample were rated, unrated, and the difference based on a regression of municipal bond offering yields on whether the bond gets a rating and other explanatory variables matching those used in Table 2-6. Standard errors are adjusted for clustering at the bond issue level. The sample includes only bonds from issuers in counties where either fewer than 20% or more than 80% of bonds were rated.
Panel A:



Panel B:

Inverse Probability Weighted Regression Model - Counties with >80% or <20% Rated Issues

	Revenue Bonds	General Obligation	Bank Qualified	Not Bank Qualified
Average Rated Yield Spread	0.27	0.16	0.21	0.18
Average Unrated Yield Spread	0.78	0.76	0.80	0.61
Average Treatment Effect	-0.51***	-0.60***	-0.59***	-0.43***
Number of Observations	100,476	197,815	137,610	160,681

Table 2-12: IPWRA Regression Predicting Effect of Rating on Yield Spread of Rated and Unrated Bonds

Table 2-12 shows the predicted yields if the bonds in the sample were rated, unrated, and the difference based on a regression of municipal bond offering yields on whether the bond gets a rating and other explanatory variables matching those used in Table 2-6. Standard errors are adjusted for clustering at the bond issue level.

Panel A shows the results from a regression using the inverse probability weights from equation 4 in order to estimate the effect of a rating on savings for unrated bonds. Panel B shows the results from a regression using the inverse probability weights from equation 5 in order to estimate the effect of a rating on savings for rated bonds.

	Inverse Probability Weighted Regression Model			
	Revenue Bonds	**General Obligation**	**Bank Qualified**	**Not Bank Qualified**
Panel A: Average Treatment Effect on Rated Bonds				
Average Rated Yield Spread	0.27	0.10	0.14	0.17
Average Unrated Yield Spread	0.80	0.62	0.82	0.63
Average Treatment Effect	-0.53	-0.52	-0.69	-0.46
Number of Observations	215,722	407,585	287,638	335,669
Panel B: Average Treatment Effect on Unrated Bonds				
Average Rated Yield Spread	0.31	0.11	0.20	0.18
Average Unrated Yield Spread	0.78	0.49	0.58	0.65
Average Treatment Effect	-0.48	-0.37	-0.39	-0.47
Number of Observations	215,722	407,585	287,638	335,669

Table 2-13: Estimated Dollar Value of Counterfactual Savings from Obtaining a Rating

Table 2-13 shows estimates of the dollar value of savings from obtaining a rating.The dollar value of savings is estimated by assuming every unrated bond has a fixed coupon payment and is issued at par, with coupons reduced by the estimated reduction in yield spread. Savings are discounted back to the year of issue at the risk-free rate and then adjusted for inflation using the CPI to 2015 values.

	GO	RB
Unrated Dollars Issued (IA)	$237,324,386,037	$357,050,595,879
Yield Reduction	0.49%	0.47%
Dollar Savings (IA)	$4,167,581,328	$18,318,857,111
% Savings	1.76%	5.13%

Table 2-14: Estimated Dollar Value of Counterfactual Savings from Obtaining a Rating using Annual Estimates

For each year in the sample, this table shows the estimated decrease in the yield spread from obtaining a rating, the dollar amount of unrated bonds issued, the dollar savings of interest expenses adjusted to 2015 dollars, and the dollar savings as a percentage of the amount issued adjusted to 2015 dollars.

	Savings from Rating		Unrated Dollars Issued (Inflation Adjusted)		Dollar Savings (Inflation Adjusted)		% Savings	
Year	GO	RB	GO	RB	GO	RB	GO	RB
1998	0.09%	0.24%	$10,688,560,041	$28,265,471,920	$53,812,756	$747,209,424	0.5%	2.6%
1999	0.11%	0.28%	$5,191,454,770	$21,235,937,430	$26,006,117	$636,841,900	0.5%	3.0%
2000	0.18%	0.28%	$4,540,568,334	$16,888,526,832	$49,093,460	$506,641,198	1.1%	3.0%
2001	0.32%	0.58%	$5,738,816,393	$18,266,405,333	$60,724,705	$1,075,156,017	1.1%	5.9%
2002	0.33%	0.59%	$14,732,755,648	$23,405,417,496	$216,675,609	$1,516,355,585	1.5%	6.5%
2003	0.36%	0.63%	$6,823,974,018	$20,492,330,691	$115,697,998	$1,289,476,441	1.7%	6.3%
2004	0.29%	0.56%	$18,904,576,682	$24,328,156,706	$114,527,497	$1,323,538,529	0.6%	5.4%
2005	0.23%	0.34%	$16,658,616,872	$30,653,392,849	$117,131,306	$1,018,260,004	0.7%	3.3%
2006	0.22%	0.36%	$18,994,340,996	$36,139,877,747	$128,571,608	$1,189,136,383	0.7%	3.3%
2007	0.28%	0.34%	$18,189,485,595	$44,832,324,817	$177,962,508	$1,428,911,024	1.0%	3.2%
2008	0.61%	0.44%	$14,616,742,592	$16,148,254,238	$411,984,743	$886,297,224	2.8%	5.5%
2009	0.78%	0.26%	$12,818,301,666	$5,916,817,005	$176,103,685	$139,844,719	1.4%	2.4%
2010	0.68%	0.64%	$11,036,558,333	$7,496,392,793	$141,621,536	$522,199,471	1.3%	7.0%
2011	0.63%	0.68%	$9,951,085,386	$6,516,136,648	$144,379,384	$504,522,600	1.5%	7.7%
2012	0.35%	0.76%	$11,217,885,773	$8,344,989,923	$114,680,330	$783,783,194	1.0%	9.4%
2013	0.32%	0.59%	$11,802,861,348	$7,694,727,633	$105,597,320	$554,295,121	0.9%	7.2%
2014	0.32%	0.52%	$11,468,147,844	$7,006,461,525	$113,723,106	$494,021,735	1.0%	7.1%
2015	0.25%	0.27%	$12,571,034,665	$11,749,957,564	$80,079,927	$393,989,180	0.6%	3.4%
2016	0.19%	0.09%	$10,830,348,816	$9,675,375,349	$50,950,996	$118,238,590	0.5%	1.2%
2017	0.13%	0.06%	$10,548,270,266	$11,993,641,384	$29,601,191	$86,210,455	0.3%	0.7%
Total			**$237,324,386,037**	**$357,050,595,879**	**$2,428,925,782**	**$15,214,928,795**	**1.0%**	**4.3%**

Table 2-15: Logistic Regression Predicting Rating with Underwriter Fixed Effects

Table 2-15 shows the results of a logistic regression that predicts whether a bond offering gets a rating. *Competitive Offering* is equal to one if the offering is competitive and zero otherwise. *Log(Size)* is the natural logarithm of the amount issued in the offering. *Log(Personal Income per Capita)* is the natural logarithm of the personal income per capita in the county where the bond was issued. *Property Tax / Total Revenue* is the proportion of the local government's revenue raised from property taxes. *Liabilities / Assets* is the ratio of assets to liability of the local government. *Bank Qualified* is equal to one if the bond offering was bank-qualified and zero otherwise. *Revenue Bond* is equal to one if the bond offering is a revenue bond and zero if it is a general obligation bond. Continuous variables are standardized to have a mean of zero and a standard deviation of one. The model includes fixed effects for the lead underwriter of the issue.

	Logistic Regression Predicting Rating (Rated=1, Unrated=0)							
	Revenue Bonds		**General Obligation**		**Bank Qualified**		**Not Bank Qualified**	
	Estimate	**p-Value**	**Estimate**	**p-Value**	**Estimate**	**p-Value**	**Estimate**	**p-Value**
Competitive Offering	0.70	0.00	0.01	0.00	0.09	0.00	0.30	0.00
Log(Size)	0.70	0.00	1.34	0.00	1.82	0.00	0.68	0.00
Log(Personal Income Per Capita)	0.10	0.00	0.14	0.00	0.03	0.00	0.21	0.00
Property Tax / Total Revenue	0.02	0.00	0.06	0.00	0.04	0.00	0.03	0.00
Liabilities / Assets	-0.03	0.00	-0.06	0.00	-0.03	0.00	-0.03	0.00
Bank Qualified	-0.03	0.00	-0.12	0.00				
Revenue Bond					-0.75	0.00	-0.73	0.00
Lead Underwriter Fixed Effects	Yes		Yes		Yes		Yes	
Quarter Fixed Effects	Yes		Yes		Yes		Yes	
State Fixed Effects	Yes		Yes		Yes		Yes	
Use of Funds Fixed Effects	Yes		Yes		Yes		Yes	
Unrated Observations	10,940		15,524		14,437		12,027	
Rated Observations	30,323		48,492		31,294		47,521	
McFadden's Pseudo R-Squared	**33%**		**49%**		**48%**		**33%**	
Without Underwiter FE	23%		32%		34%		21%	
Improvement	10%		17%		15%		12%	
% Correctly Classified with 0.5 Threshold	**83%**		**88%**		**86%**		**85%**	
Without Underwiter FE	78%		82%		80%		81%	
Improvement	4%		6%		6%		4%	

Table 2-16: Logistic Regression Predicting Rating With Underwriter Market Share

Table 2-16 shows the results of a logistic regression that predicts whether a bond offering gets a rating. *UW Decile* indicates the decile of market share of the lead underwriter in the offering year. *Competitive Offering* is equal to one if the offering is competitive and zero otherwise. *Log(Size)* is the natural logarithm of the amount issued in the offering. *Log(Personal Income per Capita)* is the natural logarithm of the personal income per capita in the county where the bond was issued. *Property Tax / Total Revenue* is the proportion of the local government's revenue raised from property taxes. *Liabilities / Assets* is the ratio of assets to liability of the local government. *Bank Qualified* is equal to one if the bond offering was bank-qualified and zero otherwise. *Revenue Bond* is equal to one if the bond offering is a revenue bond and zero if it is a general obligation bond. Continuous variables are standardized to have a mean of zero and a standard deviation of one.

	Logistic Regression Predicting Rating (Rated=1, Unrated=0)							
	Revenue Bonds		General Obligation		Bank Qualified		Not Bank Qualified	
	Estimate	p-Value	Estimate	p-Value	Estimate	p-Value	Estimate	p-Value
UW Decile	0.19	0.00	0.22	0.00	0.19	0.00	0.20	0.00
Competitive Offering	0.73	0.00	0.18	0.00	0.26	0.00	0.32	0.00
Log(Size)	0.75	0.00	1.11	0.00	1.59	0.00	0.69	0.00
Log(Personal Income Per Capita)	0.14	0.00	0.15	0.00	0.06	0.00	0.29	0.00
Property Tax / Total Revenue	0.02	0.43	0.04	0.03	0.05	0.01	-0.01	0.74
Liabilities / Assets	-0.01	0.61	-0.10	0.00	-0.07	0.00	-0.02	0.21
Bank Qualified	-0.14	0.00	0.18	0.00				
Revenue Bond					-0.79	0.00	-0.63	0.00
Quarter Fixed Effects	Yes		Yes		Yes		Yes	
State Fixed Effects	Yes		Yes		Yes		Yes	
Use of Funds Fixed Effects	Yes		Yes		Yes		Yes	
Unrated Observations	12,608		17,801		16,311		14,098	
Rated Observations	32,074		50,220		32,508		49,786	
McKelvey-Zavoina	0.68		0.79		0.82		0.65	

Table 2-17: Logistic Regression Predicting Rating With Dual Underwriter/Advisor Indicator

Table 2-17 shows the results of a logistic regression that predicts whether a bond offering gets a rating. *Competitive Offering* is equal to one if the offering is competitive and zero otherwise. *Log(Size)* is the natural logarithm of the amount issued in the offering. *Log(Personal Income per Capita)* is the natural logarithm of the personal income per capita in the county where the bond was issued. *Property Tax / Total Revenue* is the proportion of the local government's revenue raised from property taxes. *Liabilities / Assets* is the ratio of assets to liability of the local government. *Bank Qualified* is equal to one if the bond offering was bank-qualified and zero otherwise. *Revenue Bond* is equal to one if the bond offering is a revenue bond and zero if it is a general obligation bond. Continuous variables are standardized to have a mean of zero and a standard deviation of one.

Panel A: Logistic Regression Predicting Rating (Rated=1, Unrated=0) for Competitive Offerings

	Revenue Bonds		General Obligation		Bank Qualified		Not Bank Qualified	
	Estimate	p-Value	Estimate	p-Value	Estimate	p-Value	Estimate	p-Value
Dual Underwriter	-1.20	0.00	-0.87	0.00	-0.75	0.00	-1.44	0.00
Log(Size)	1.15	0.00	0.98	0.00	1.43	0.00	0.68	0.00
Log(Personal Income Per Capita)	0.16	0.00	0.21	0.00	0.14	0.00	0.35	0.00
Property Tax / Total Revenue	0.07	0.39	0.11	0.00	0.13	0.00	-0.03	0.64
Liabilities / Assets	0.07	0.32	-0.14	0.00	-0.07	0.02	-0.19	0.00
Bank Qualified	-0.38	0.00	0.06	0.11				
Revenue Bond					-0.35	0.00	-0.83	0.00
Quarter Fixed Effects	Yes		Yes		Yes		Yes	
State Fixed Effects	Yes		Yes		Yes		Yes	
Use of Funds Fixed Effects	Yes		Yes		Yes		Yes	
Unrated Observations	1,205		8,389		6,539		3,055	
Rated Observations	7,141		24,357		15,432		16,066	
McFadden's Pseudo R-Squared	39%		33%		32%		37%	
% Correctly Classified with 0.5 Threshold	90%		82%		79%		88%	

Panel B: Logistic Regression Predicting Rating (Rated=1, Unrated=0) for Non-Competitive Offerings

	Revenue Bonds		General Obligation		Bank Qualified		Not Bank Qualified	
	Estimate	p-Value	Estimate	p-Value	Estimate	p-Value	Estimate	p-Value
Dual Underwriter	-0.43	0.07	-0.33	0.14	-0.20	0.35	-0.79	0.00
Log(Size)	1.01	0.00	1.10	0.00	1.28	0.00	0.99	0.00
Log(Personal Income Per Capita)	0.22	0.00	0.19	0.00	0.14	0.02	0.24	0.00
Property Tax / Total Revenue	0.08	0.16	0.07	0.29	0.05	0.47	0.06	0.24
Liabilities / Assets	0.05	0.35	-0.10	0.07	-0.09	0.14	0.10	0.03
Bank Qualified	0.29	0.00	-0.14	0.12				
Revenue Bond					-0.82	0.00	-1.69	0.00
Quarter Fixed Effects	Yes		Yes		Yes		Yes	
State Fixed Effects	Yes		Yes		Yes		Yes	
Use of Funds Fixed Effects	Yes		Yes		Yes		Yes	
Unrated Observations	2,098		1,130		1,236		1,992	
Rated Observations	9,464		10,041		5,252		14,253	
McFadden's Pseudo R-Squared	30%		36%		36%		30%	
% Correctly Classified with 0.5 Threshold	86%		92%		86%		90%	

Figures

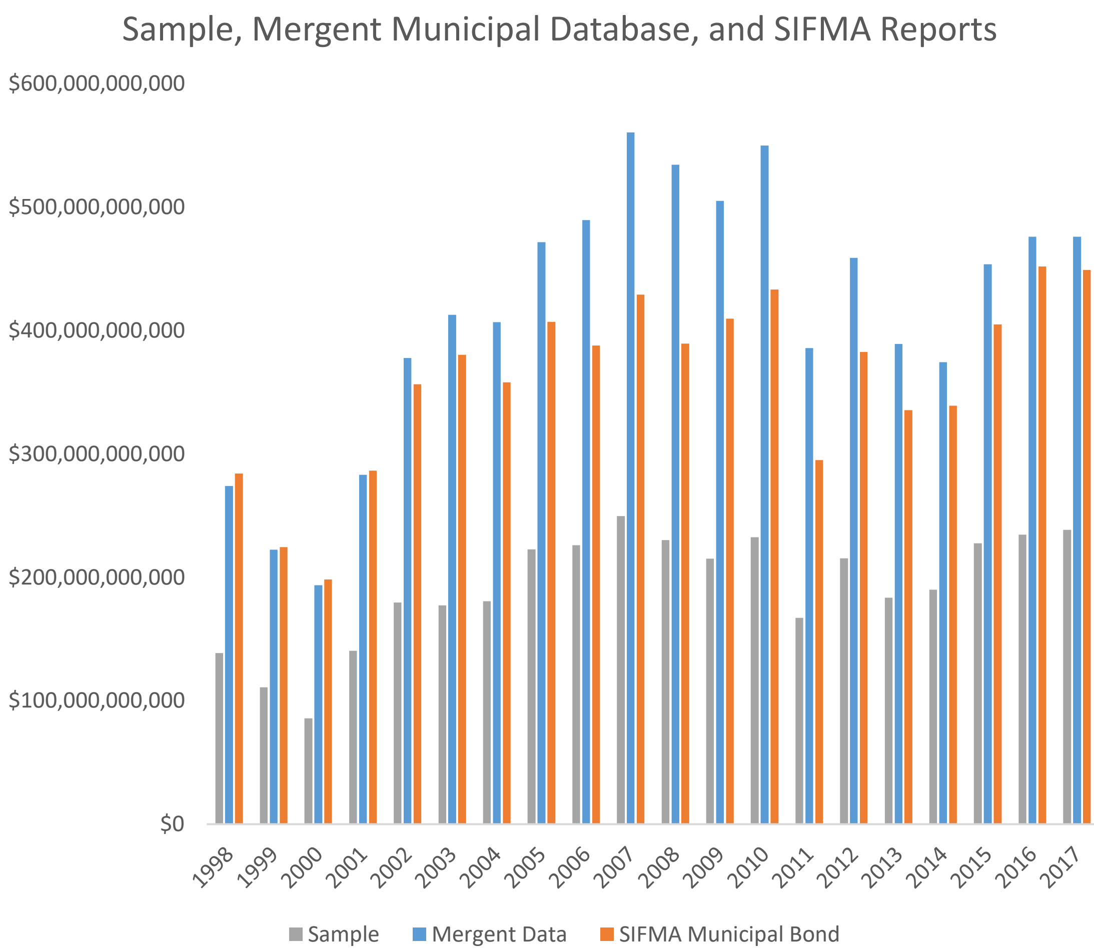
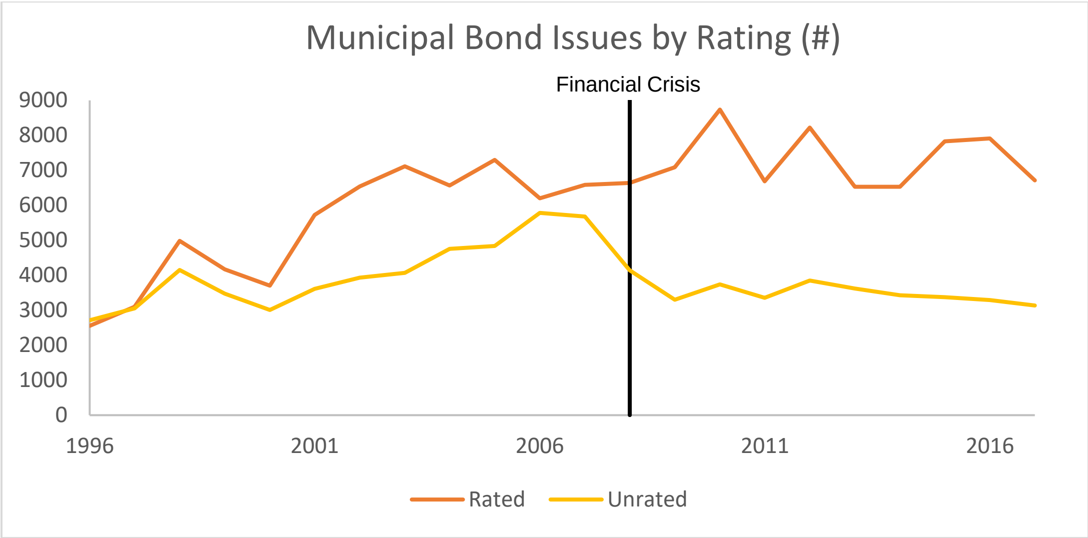


Figure 2-1. Figure shows the dollar amount of municipal bonds issued each year according to the SIFMA issuance reports in the total Mergent data and after applying filters to create our sample.



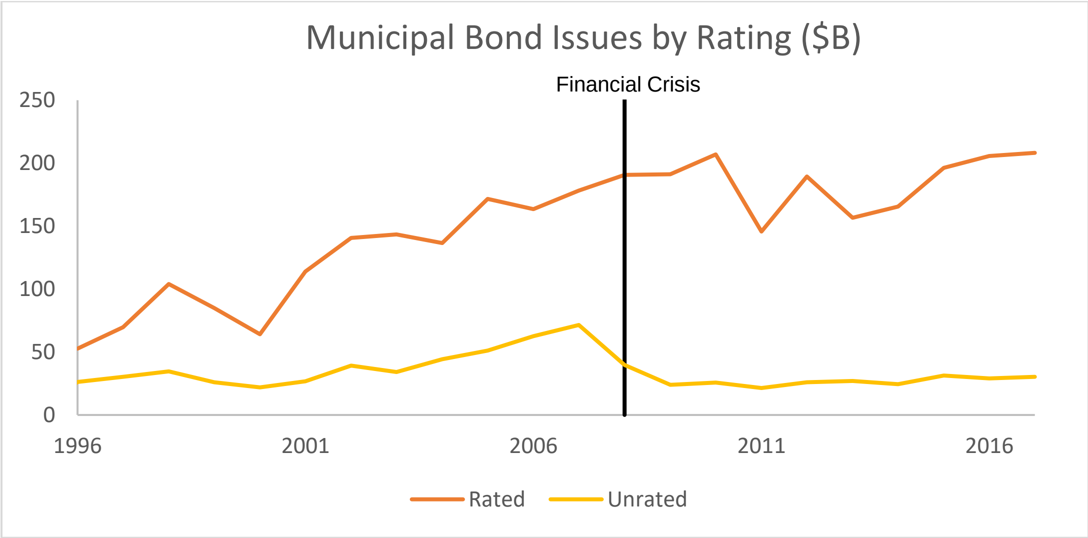


Figure 2-2. Figure shows the number of municipal bond issues each year classified by whether they received a rating or no rating.

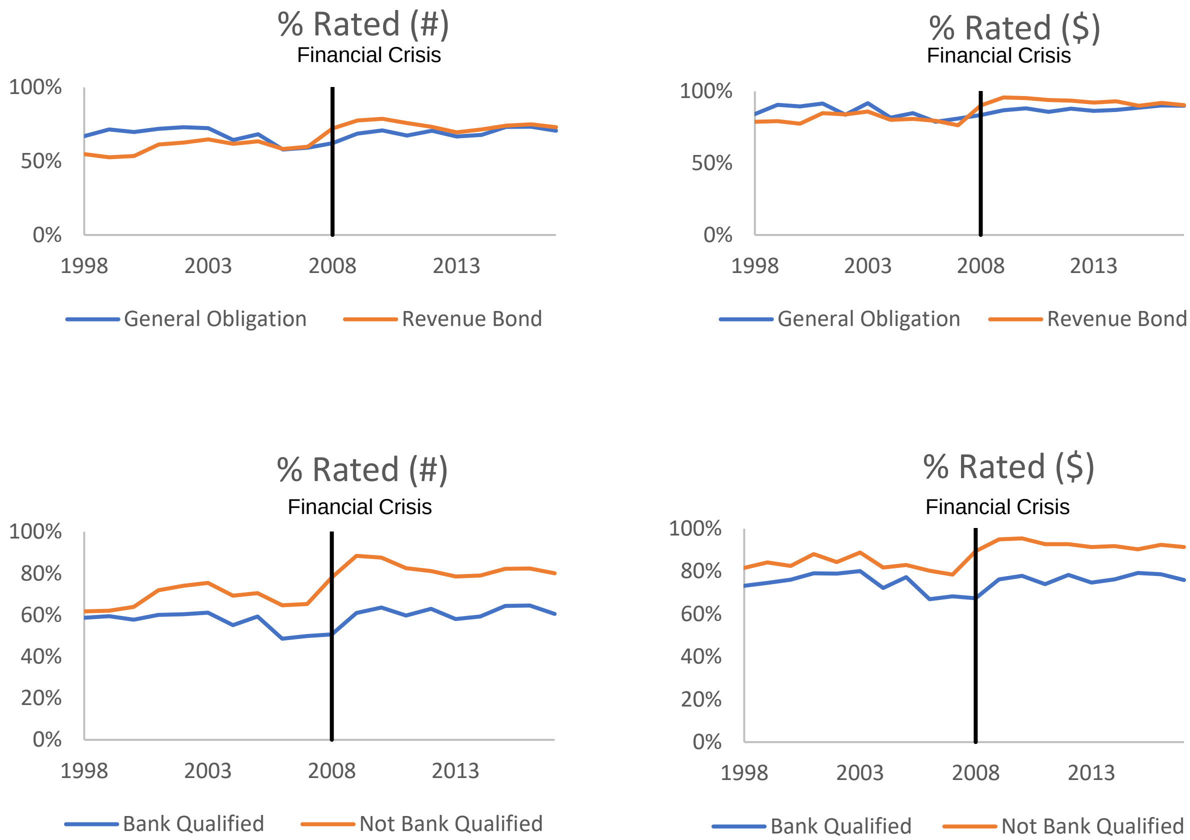


Figure 2-3. The time series of ratings separately for general obligation and revenue bonds and bank-qualified and nonbank-qualified bonds.

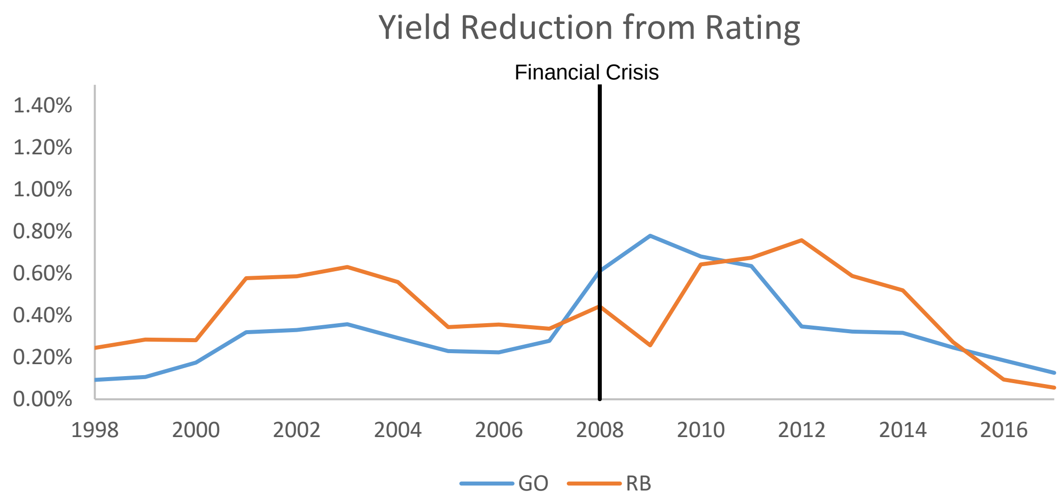


Figure 2-4. Figure shows the annual estimates of the value of obtaining a rating in terms of a reduction in the offering yield spread. Estimates are obtained using the model specified in equation 3 with the indicator variable for rating replaced by an interaction between the rating and year indicator variables. The estimated savings is the negative of the coefficient for the interaction term for the year. *Property Tax / Total Revenue* and *Liabilities / Assets* are omitted as the data was unavailable prior to 2004.

Chapter 3: Alternative Trading Systems in the Corporate Bond Market

Joint work with Matthew Kozora, Bruce Mizrach, Or Shachar, and Jonathan Sokobin [6]

Summary

We investigate the trading of corporate bonds on alternative trading system (ATS) platforms. Most ATS provide at least one of the two most common electronic trading protocols. The first is the request-for-quote (RFQ) protocol in which platforms solicit bids and offers which counterparties can meet. The second type are automated matching systems which provide immediately executable liquidity. We refer to this method as the electronic communication network (ECN) protocol. The usage of these electronic trading protocols, which have not been comprehensively studied before in the context of the corporate bond market, can improve pre-trade transparency and price discovery in the corporate bond market. In this paper, we assess the types of securities that trade more frequently on ATS platforms and in each type of protocol, and estimate the impact of ATS platforms on transaction costs.

Adoption of electronic trading in corporate bonds has been slower in the U.S. than for other asset classes, as noted by the BIS (2016). In this paper, we first analyze the corporate bond transactions on electronic platforms that are registered as an ATS in the U.S. Trades on these platforms are flagged in FINRA's Trade Reporting and Compliance Engine (TRACE), but TRACE does not collect information on the protocol used. As of December 2017, 16 ATS platforms reported corporate bond trades to TRACE. On average, the monthly trading volume

[6] Matthew Kozora and Jonathan Sokobin are affiliated with FINRA. Bruce Mizrach is associated with FINRA and Rutgers University. Or Shachar is affiliated with the Federal Reserve Bank of New York. The views expressed in this paper are those of the authors and do not necessarily reflect the views of FINRA or of the authors' colleagues on FINRA staff, the position of the Federal Reserve Bank of New York, or the Federal Reserve System. The authors gratefully acknowledge the helpful comments provided by Patrick Geraghty, staff from FINRA's Office of General Counsel, staff from FINRA's Transparency Services Department, Bill Vulpis, Ted Bragg, Kristen Maher, and seminar participants of the 2017 FINRA Economic Advisory Committee Meeting.

on ATS platforms represents 2.1% of the total corporate bond market volume and 16.1% of trades. The percentage of dealers (40.5%) and bonds (56.4%) trading on ATS platforms, however, suggest that ATS platforms cover a large segment of traded bonds.

ATS platforms primarily facilitate smaller trades. The median trade size reported on ATS platforms is $15,000, compared to $35,000 across all reported trades. In addition, only 2.0% of trades on ATS platforms are $1 million or more, compared to 14.5% in the total market. Investment grade bonds are more likely to trade on an ATS platform, as well as older, less actively traded bonds from smaller issues. Bonds traded by more dealers, or bonds with higher inventory levels, are also more likely to trade on an ATS platform. Bonds with these characteristics are also more likely to trade on ATS platforms that have received an exemption from some reporting obligations under Rule 6732 than ATS platforms that have not received such an exemption.

Comparing customer-to-customer bond transaction chains that include at least one interdealer trade while controlling for other bond and trade characteristics, we find that dealer participation on ATS platforms is associated with lower customer transaction costs of between 24 and 32 basis points, depending on the specification of the regression model.

Introduction

In the last 20 years, electronic trading networks have evolved to bring together market participants, facilitate price discovery, and provide liquidity across a variety of asset classes. Relative to other asset classes, market participants have been slow to adopt the new technologies for the trading of corporate bonds, and they continue to trade predominantly on bilateral voice over-the-counter (OTC) markets (BIS (2016)).[7] In this paper, we first describe the different types of electronic trading protocols available to participants in the current corporate bond market. Then we focus on trading on ATS platforms, where we can measure trading probability conditioned on characteristics of the corporate bond, and the impact on transaction costs.

Electronic trading takes many forms. The majority of electronic corporate bond volume is pursuant to request-for-quote (RFQ) protocols.[8] Similar to voice OTC trading, RFQ protocols enable participants seeking liquidity to broadcast, usually anonymously, buying or selling interest to select other participants. The quotes participants submit in response to the request are for the soliciting party only, and expire at the end of the session. The quotes may or may not be binding depending on the specifics of the trading protocol (SIFMA (2016)).

Alternatively, market participants may utilize other protocols offered by ATS platforms that aggregate and match the orders of multiple buyers and sellers using established, non-discretionary methods for matching. Electronic limit order books, with firm quotes where participants can receive an immediate execution, are a prominent subset of such protocols. As these protocols are similar to the ECNs in the U.S. equity and Treasury markets, we will refer to this subset of protocols as ECN protocols. It has been suggested that the protocols, which have not been comprehensively studied before, have the potential to improve pre-trade transparency and price discovery in the corporate bond market through the consolidation and display of orders (Harris, Kyle, and Sirri (2015)).

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[7] Internationally, BIS (2016) reports that approximately 40% of investment grade corporate bonds and over 20% of high yield corporate bonds trade electronically. Corporate bonds had the least amount of electronic trading of any of the security classes considered in the report (e.g., U.S. Treasuries).

[8] *See infra* note 19 and related discussion. This finding relies on self-reported figures for volume on non-ATS electronic platforms.

Electronic trading platforms' offerings are not limited to one type of trading protocol, and many trading platforms offer more than one trading protocol. For example, electronic platforms can offer both RFQ trading protocols and ECN trading protocols (SIFMA (2016)).

The predominance of RFQ protocols over other protocols may reflect the potential for additional costs for participants if they were to seek liquidity through an ECN protocol. Participants seeking liquidity may have additional exposure to information leakage and adverse selection when routing orders pursuant to an ECN protocol. The costs depend on the characteristics of the trading protocol, including the number of participants that can view or execute the order and the length of time that the orders are actionable. For these reasons, market participants seeking liquidity may prefer to route orders using an RFQ protocol rather than an ECN protocol.

We first investigate trading activity at the level of the electronic ATS platform. For this analysis, we use the information reported to TRACE. With the TRACE data, we can identify all corporate bond trades on registered ATS platforms, but not the type of the trading protocol through which the trade was executed. This analysis focuses on the market shares of competing platforms over time. The sample period begins in August 2016 after the second of two regulatory changes that enable us to identify all trades on ATS platforms. The sample period ends in December 2017.

As of December 2017, 16 ATS platforms report corporate bond trades to TRACE. Trading on ATS platforms represents 2.1% of the average monthly trading volume and 16.1% of average monthly trades in the corporate bond market, with the majority of trades between dealers. The number of dealers and bonds that trade on ATS platforms, however, suggest that ATS platforms cover a large segment of the overall market. For example, 353.9 dealers (40.5%)

and 11,719.5 bonds (56.4%) that trade in a given month have at least one trade executed and reported on an ATS platform. Dealers who trade on an ATS platform are larger, with reported trading volume 18.9 times greater than dealers not reporting an ATS trade. Trading on ATS platforms, however, is not dominated by large dealers; the ten largest dealers account for a smaller share of ATS platform trading volume (42.3%) than OTC market trading volume (58.7%). A dealer is more likely to trade on an ATS platform when the aggregate dealer inventory for the bond being traded has recently increased, suggesting ATS platforms are used to manage excess inventory. Bonds trading on an ATS platform have on average 2.7 times greater trading volume than bonds not trading on an ATS platform.

Although ATS platforms may reduce search costs by providing easier access to other traders, market participants may also face a higher risk of information leakage and adverse selection when attempting to trade on these venues. As a result of this trade-off, market participants should be more likely to trade on an ATS platform in situations where these risks are less important. Consistent with this view, we find that proxies of such risks are associated with less trading on ATS platforms. For example, information leakage is likely less of a concern for the liquidity seeker when attempting to make a smaller trade. We find that the median trade size on ATS platforms is $15,000 and only 2.0% of trades are $1 million or more. In addition, Han and Zhou (2013) show that information asymmetry and adverse selection are larger for high yield than for investment grade bonds. We find that 73.4% of corporate bonds that trade on ATS platforms are investment grade, compared to 66.2% of the total market. A multivariate analysis confirms investment-grade bonds are more likely to trade on ATS platforms controlling for other characteristics.

Search costs are higher when investors have more difficulty finding counterparties. ATS platforms can reduce search costs by providing easier access to more counterparties. Empirically, we find that bonds of smaller issue size and older vintage are more likely to trade on an ATS platform. This is true both unconditionally and when controlling for other characteristics. Controlling for other characteristics, bonds with lower recent trading volume are more likely to trade on ATS platforms. Together, these results suggest that ATS platforms are particularly useful for bonds where finding a counterparty is more difficult.

The size of trades and the characteristics of the bonds differ between ATS platforms that have received an exemption from some of their TRACE reporting obligation under FINRA Rule 6732 (6732 ATSs) and those ATS platforms that have not received an exemption (non-6732 ATSs). Where an exception has been granted, a 6732 ATS does not have a reporting obligation for trades that meet the conditions in the rule.[9] An exemption under FINRA Rule 6732 simplifies the reporting obligations for an ATS platform, lowering the regulatory burden of reporting trades and so requesting an exemption may be more worthwhile for a platform with a larger number of trades. As of the end of 2017, four ATS platforms have filed for and received an exemption under this Rule. Platforms that have received exemption may not rely on it for the majority of their trades.

The four 6732 ATSs facilitate the majority of trades on ATS platforms, and the trading patterns we observe across all ATS platforms predominantly reflect the trades on 6732 ATSs. 6732 ATSs differ along a number of dimensions from non-6732 ATSs. For example, a larger

[9] Trades subject to the exemption must be between FINRA members, not pass through any ATS account, not involve the ATS exchanging securities or funds on behalf of subscribers, and the ATS must not take either side of the trade for clearing or settlement purposes. The ATS must provide FINRA data on exempted trades on a monthly basis, remit to FINRA a transaction reporting fee for the exempt trades, and enter into written agreements with the members trading requiring them to report the trade and identify it as taking place on the ATS. *See* https://www.finra.org/rules-guidance/rulebooks/finra-rules/6732.

number of dealers and bonds trade on 6732 ATSs than non-6732 ATSs. Similarly, trades on 6732 ATSs are smaller, with a median trade size of $15,000 compared to a median trade size on non-6732 ATSs of $500,000.[10] The clientele of the platforms also appear to differ. For example, nearly all trading by discount retail brokerages on ATS platforms is on 6732 ATSs.

Next, we estimate the potential gains to customers from dealer participation on ATS platforms. Using a methodology similar to Li and Schürhoff (2018), we identify sequences of trades that begin with a customer sale and end with a customer purchase (i.e., trade chains). For the trade chains with an interdealer trade, we compare customer transaction costs between the chains that include and do not include a dealer transaction on an ATS platform. Holding the length of the trade chain constant, we estimate that a trade on an ATS platform is associated with lower customer transaction costs of between 24 and 32 basis points. As a way to assess the relative importance of the difference in transaction costs, the average customer transaction cost in our sample is 115 basis points.

Overall, the results of this paper indicate the economic importance of and trade-offs associated with ATS platforms and the protocols they offer in today's market. ATS platforms seem to be a preferred venue when information leakage is a lesser concern, such as for small trades in investment grade corporate bonds. Market participants may prefer other venues where the costs associated with information leakage are more significant. These result are similar to Hendershott and Madhavan (2015). In contrast to Hendershott and Madhavan (2015), however, our results indicate that ATS platforms are more likely to facilitate trades for older, smaller issues where locating a counterparty may be more difficult.

[10] In the analysis measuring customer costs, we are able to identify few trade chains with a trade on a non-6732 ATS. The reduction in customer costs, therefore, reflect the trades on 6732 ATSs.

Our sample incorporates a larger number of electronic trades in our analysis than the study by Hendershott and Madhavan (2015) due to the larger number of platforms in our sample and the increase in electronic trading that has occurred over time. Hendershott and Madhavan (2015) study approximately 29,000 electronic trades per month between January 2010 and April 2011. With the TRACE data, we study approximately 225,000 electronic trades on ATS platforms per month. Our sample also encompasses platforms offering ECN protocols more similar to electronic trading for equities than the RFQ platform studied by Hendershott and Madhavan (2015).

The remainder of the paper is organized as follows. In Section 2, we provide background describing electronic trading in corporate bonds and TRACE reporting obligations of FINRA members. We describe the sample data in Section 3 and demonstrate the effect of recent regulatory changes on our ability to identify the trades on ATS platforms in the TRACE data. We examine the trading on ATS platforms in Section 4, and we examine the relationship between ATS platform use and customer transaction costs in Section 5. Section 6 concludes.

Background

In this section, we describe the different venues for the trading of corporate bonds (i.e., voice OTC markets, RFQ protocols, and ECN protocols), and the factors that may influence its selection by market participants. We also describe the reporting obligations of FINRA members to TRACE.

Choice of Trading Venue

Corporate bonds trade in both voice OTC and electronic markets. The choice of trading venue may impact the likelihood of a transaction, the price obtained, the broker-dealers' costs to identify a counterparty, the amount of information leakage, and the exposure to adverse selection. Market participants may be particularly sensitive to the choice of venue due to the large number and heterogeneity of corporate bonds, and the infrequency in which many corporate bonds trade.

Traditionally, corporate bonds trade in voice OTC markets. In these markets, participants solicit bids, including trade size and price, from one or more participants to purchase or sell a bond. Participants incur costs to conduct the bilateral and sequential solicitation of other participants (Duffie, Gârleanu, and Pedersen (2005)). With the bilateral and sequential solicitation, however, participants can limit the disclosure of their trading intentions and potentially reduce the costs associated with information leakage.

Corporate bonds also trade in electronic markets.[11] A majority of electronic corporate bond volume is executed pursuant to RFQ protocols.[12] An RFQ protocol is the electronic equivalent of a voice OTC market. Participants seeking liquidity (initiators) can solicit bids or offers, including trade size and price, to purchase or sell a bond from other participants (respondents). Unlike the voice OTC markets, initiators can broadcast buying or selling to more than one participant simultaneously. Although initiators reduce their costs to search for a trading counterparty, the simultaneous broadcast can increase the amount of information leakage. Respondents are under no obligation to respond to a solicitation, and the quotes respondents submit are for the soliciting party only. Quotes can be open for negotiation, and expire at the end

[11] Electronic trading in the corporate bond market greatly increased in the early 2000s. See http://www.algomi.com/bond-market/brief-history-of-electronic-bond-platforms. See SIFMA (2016) for a description of the existing electronic platforms for the trading of U.S. corporate and municipal securities.
[12] See infra note 19 and related discussion.

of the session. Initiators have discretion over whether or not to trade after receiving quotes, and respondents generally make a binding second commitment before confirmation.[13]

Hendershott and Madhavan (2015) model the choice of trading venue between RFQ protocols and voice OTC markets. Their model describes the choice of venue as a tradeoff between an increase in dealer price competition and an increase in the cost of information leakage. Although an RFQ protocol increases dealer competition, resulting in better bond prices, the simultaneous disclosure of trading intentions to multiple participants increases the cost from information leakage. They find empirical results consistent with their model; RFQ protocols facilitate the trades of corporate bonds when participants are more likely to respond to a request and participants are likely to incur fewer costs from information leakage.

ATS platforms offer a variety of protocols that bring together the orders of multiple buyers-and-sellers and use established, non-discretionary methods to match those orders. The majority of trading on the most active ATS platforms takes place via ECN protocols that involve a live and executable order book.[14]

Participants seeking liquidity via ECN protocols may have additional exposure to information leakage but may also benefit from increased price competition when placing orders. Participants who place non-marketable limit orders provide a free option to the other participants to trade at the posted quote (Hendershott and Madhavan (2015)). The cost of the free option increases with the number of participants that may execute the order and the length of time the orders are live and executable. The additional exposure to information leakage and the cost of

[13] An initiator that executes a trade may receive information regarding the second best price (i.e., the "cover price"). The disclosure of the cover price, however, may be dependent on the parties to the trade. For example, *see* https://www.reuters.com/article/us-pimco-marketaxess/marketaxess-allows-pimco-to-trade-by-its-own-rules-idUSKBN1I528W.
[14] Conversations with several of the four 6732 ATSs indicate a majority of their trades are pursuant to such protocols.

keeping quotes for many instruments current are possible explanations for the predominance of electronic trading executed pursuant to RFQ protocols.

Another protocol offered by some ATS platforms is session trading where orders are submitted, matched, and then executed. Session trading is generally not continuously available, occurring at pre-defined times or triggered by a trade through another protocol, and typically occurs at prices provided by a third party or at a midpoint of indications of interest.

Trading protocols can also vary among other dimensions which can impact the potential costs to trade. For example, protocols may offer the ability of participants to specify who receives a request-for-quote or views their orders. This feature may reduce the likelihood of transaction or the probability that best price is received, but also can reduce the potential adverse selection of the participants seeking liquidity. Trades may also be subject to a "last look" where the liquidity provider has a final opportunity to confirm or deny an attempt to trade at a price it quoted. This reduces the risk of adverse selection for the liquidity provider but may increase the risk of adverse selection and information leakage for the responding party. Some platforms set a minimum size requirement for trades.

The method of trading, as well as the information, bargaining power, and preference for immediacy and anonymity, will factor into a participant's choice of trading venue. Another factor is the amount of available liquidity. Pagano (1989) shows that because the depth and liquidity of a market depends on the entry decisions of all potential participants, and when transaction costs are otherwise equal, trading will tend to concentrate where participants expect others to send their orders. The selection of trading venues with more liquidity by market participants is consistent with the empirical evidence; although the total number and market share of electronic platforms have increased over time, trading appears to concentrate on few platforms. The success of electronic trading platforms is dependent on gaining traction among participants. Electronic trading platforms that enter the market may attempt to compete for market share with the existing platforms by offering new technology innovation or targeting a specific segment of the market.

TRACE Reporting

TRACE facilitates the mandatory reporting and dissemination of OTC market transactions in order to assist price discovery and improve execution quality. Securities eligible for TRACE reporting are U.S. dollar-denominated debt securities issued by a domestic or foreign private issuer (other than restricted securities that are not sold pursuant to Rule 144A), issued or guaranteed by an executive agency or Government-Sponsored Enterprise, or issued by the U.S. Department of Treasury.[15]

Each FINRA member that is a party to a reportable transaction in a TRACE-eligible security has a reporting obligation.[16] Member firms that act as an introducing or executing broker-dealer are considered a party to a transaction, and therefore have a reporting obligation. Non-members, including customers and non-member affiliates of member firms, do not have a reporting obligation. A trade report includes the security identifier, date, time, size (par value), and price of the transaction. A report also identifies the member firm's side of the transaction (buy or sell), their capacity as a principal or agent, and the other parties to the transaction. The required reporting time varies between categories of TRACE-eligible securities. Member firms

[15] See FINRA Rule 6710.

[16] A transaction in a TRACE-eligible security is reportable unless an exception applies. Exceptions include the sale from an issuer to an underwriter or initial purchaser, a transfer for the sole purpose of creating or redeeming an instrument (e.g., an exchange-traded fund), and a transaction resulting from the exercise or settlement of an option or a similar instrument. See FINRA Rule 6730.

must report a secondary corporate bond transaction as soon as practicable, but no later than within 15 minutes of the time of execution.

Electronic platforms may or may not have a reporting obligation. The reporting obligation of an electronic platform is dependent on whether the platform is a party to the trade. Some electronic platforms are registered as ATSs.[17] An ATS platform is a party to all transactions executed through its system, and therefore has a reporting obligation.[18] An ATS platform is a party to every trade regardless of whether the trade is pursuant to an ECN protocol or to another protocol (e.g., RFQ protocol).

An electronic platform that is not an ATS is not necessarily a party to all trades executed through its system so may not always have a reporting obligation.[19] One circumstance where an electronic platform that is not an ATS would be a party to a trade through its platform and thus have a reporting obligation is if the platform takes a side to a trade. This may occur when counterparties on the platform remain anonymous through execution and the platform acts as a riskless counterparty to both sides of the trade. In order to facilitate this type of interaction on an

[17] In general, a trading platform that meets the SEC's functional definition of an "exchange" must register as a national securities exchange or comply with Regulation ATS, which requires registration as a broker-dealer. See Securities and Exchange Commission, Regulation of Exchanges and Alternative Trading Systems, Release No. 34-40760.

[18] See FINRA Regulatory Notice 14-53. For a trade between two counterparties, an ATS separately reports a purchase of securities from the first counterparty and a sale of securities to the second counterparty. An ATS may also involve a third-party intermediary that provides clearance and settlement services. The third-party intermediary is a party to the trade and also has a reporting obligation. The presence of a third-party intermediary, however, does not absolve the ATS from its reporting obligations.

[19] Two such electronic platforms are operated by Bloomberg L.P. (Bloomberg) and MarketAxess Corporation (MarketAxess). Bloomberg's electronic fixed-income trading platforms are operated outside of its registered broker-dealer, Bloomberg Tradebook LLC, which was previously subject to Regulation ATS but not for trading of corporate bonds and ceased operating its ATS in September 2016. MarketAxess is registered as a broker-dealer and subject to Regulation ATS, but not for the trading of corporate bonds. In the fourth quarter of 2017, MarketAxess reported that trades on its system accounted for 17.6% of U.S. high-grade trading volume as reported to TRACE. MarketAxess offers all-to-all trading through the RFQ protocol for the trading of corporate bonds, see http://investor.marketaxess.com/static-files/f432852c-be4e-4799-8782-3973f69f3014. MarketAxess has announced that it will offer an ECN protocol in the second half of 2019, see https://www.thetradenews.com/marketaxess-outlines-plans-open-trading-live-order-book/.

RFQ platform, the operator would be required to establish a FINRA-registered broker-dealer to serve as the riskless counterparty. The intermediating broker-dealer would have TRACE reporting requirements.

Two recent changes to the TRACE reporting obligations of ATSs greatly increased our ability to identify trades on electronic platforms. We discuss the regulatory changes in further detail in the next section, and demonstrate their effect on our ability to identify trades on ATS platforms.

Data

We use the supervisory version of TRACE data to document the extent of trading on ATS platforms, the characteristics of the bonds that trade on them, and the differences in transaction costs between trade chains that involve an ATS platform trade and those that do not. We also compare the trades on ATS platforms to the trades off ATS platforms.

Overview

The primary dataset that we use in the analysis is the supervisory version of TRACE data. Similar to the academic version of TRACE data, the supervisory version identifies FINRA members with a unique identifier.[20] The supervisory version, however, identifies member firms uniquely with their Market Participant Identifier (MPID). Non-member affiliates of member firms (affiliates) are identified with an "A," and customers of member firms are identified with a "C." The academic version also provides transaction-level data on a 36-month delayed basis, whereas the supervisory version does not have a similar delay.

[20] We supplement the trade data with bond characteristic information (e.g., type, rating, issue date, and issue size) from TRACE bond master files. This information is sourced from Thompson Reuters Datascope.

The supervisory version also does not censor the total par value of the trade. The real-time public version of TRACE data disseminates investment grade bond trades greater than $5 million as "5MM+," and high-yield or unrated bond trades greater than $1 million par value as "1MM+." The total par value of these trades are publicly available after an 18-month delay.

There are two limitations to analyzing all electronic trading using these data. The first limitation is the inability to identify all trades on electronic platforms. Specifically, we do not observe all trades that were executed on an electronic platforms that are not registered as an ATS platform. Instead, we are only able to identify the trades on non-ATS electronic platforms when the platform takes a side to the trade.[21] Table 3-1 summarizes the trades on electronic platforms that we are able to identify in the TRACE data depending on the classification of the platform, the trading protocol, and whether the platform takes a side to the trade.

Table 3-1

Electronic Platform Reporting Obligations			
ATS Platform	**Limit Order Book Trading Protocol**	**Takes a Side to the Trade**	**Identifiable on TRACE**
Yes	Yes	Yes	Yes
		No	Yes
	No	Yes	Yes
		No	Yes
No	Yes[22]	N/A	N/A
		N/A	N/A
	No	Yes	Yes
		No	No

[21] See supra note 19 and related discussion. Our results regarding trades on ATS platforms may not generalize to non-ATS electronic platforms. Some market participants have expressed that the clientele and trade characteristics may differ.

[22] Under the framework of this paper, an electronic platform that offers an ECN trading protocol would likely need to either register as a national securities exchange or comply with Regulation ATS. We should therefore not encounter trades on electronic platforms that do not register as an ATS but offer ECN trading protocols.

The second limitation is the absence of information that identifies the trading protocol within an ATS platform. Electronic platforms may utilize more than one protocol to facilitate trading (SIFMA (2016)). To our knowledge, there are no discernable patterns in the data to distinguish between trades pursuant to different trading protocols within a platform (e.g., ECN protocol and RFQ protocol). The trades on ATS platforms that we identify in the TRACE data, therefore, relate to the ECN protocol as well as other protocols offered by the platform. As a result of this limitation, we are unable to examine only those trades that are pursuant to an ECN protocol. We are also unable to accurately compare trades occurring on different protocols.

The second limitation is the absence of information that identifies the trading protocol within an ATS platform. Electronic platforms may utilize more than one protocol to facilitate trading (SIFMA (2016)). To our knowledge, there are no discernable patterns in the data to distinguish between trades pursuant to different trading protocols within a platform (e.g., ECN protocol and RFQ protocol). The trades on ATS platforms that we identify in the TRACE data, therefore, relate to the ECN protocol as well as other protocols offered by the platform. As a result of this limitation, we are unable to examine only those trades that are pursuant to an ECN protocol. We are also unable to accurately compare trades occurring on different protocols.

We obtain data from August 2012 to December 2017. We clean the data for corrections and cancellations. Electronic platforms generally facilitate secondary market trades. We therefore exclude primary market trades from the sample. We also account for multiple trade reports for the same trade. We include each trade in our analysis only once regardless of whether the trade is between dealers or on an electronic platform. We discuss our procedure to account for multiple trade reports in the Appendix.

Regulatory Changes to TRACE Reporting

The limitations of TRACE aside, the data allow us to study corporate bond trades on ATS platforms. In particular, the data allow us to study corporate bond trades on ATS platforms following the second of two regulatory changes. The two regulatory changes allowed us to identify previously unidentifiable ATS platforms and ATS platform trades in the TRACE data.

The first regulatory change is amendments to FINRA rules requiring that ATS platforms obtain a single, unique MPID that is exclusive to the platform for the purposes of TRACE reporting.[23] A FINRA member that operates an ATS platform cannot use more than one MPID for a single ATS platform, and cannot use a single MPID for more than one ATS platform. Prior to the effective date, a member firm could use the same MPID for transactions executed in operation of an ATS platform and for other purposes. This limits our ability to attribute trades to a single ATS platform prior to the effective date. The effective date of the regulatory change was February 2, 2015.

The second regulatory change is the adoption of FINRA Rule 6732.[24] Under the rule, an ATS platform can file for an exemption from its TRACE reporting obligations for certain trades between FINRA members. Although a 6732 ATS would not have a reporting obligation, the member firms that are parties to these trades would identify the ATS platform when reporting. The rule adoption did not change the reporting obligations for non-6732 ATSs. The rule adoption, however, did clarify the reporting obligations for all ATS platforms and therefore may have increased the number of trades on non-6732 ATSs that are identifiable in the TRACE data. The effective date of the rule adoption was July 18, 2016.

[23] For a description of the rule, see FINRA Regulatory Notice 14-07 and FINRA Rules 6160, 6170, 6480, and 6720.
[24] For a description of the rule, see FINRA Regulatory Notice 16-15 and FINRA Rule 6732.

Four ATS platforms received an exemption under FINRA Rule 6732 prior to the end of the sample period in December 2017.[25] A platform that has received an exemption may not necessarily rely on the exception for the majority of its trades. An exemption would have a greater effect on simplifying compliance with TRACE reporting obligations for ATS platforms that facilitate a greater number of trades. Whether an ATS platform has been granted an exemption, therefore, may relate to the amount of trading activity on its system. In the analysis below, we separately examine the trades on 6732 ATSs and non-6732 ATSs to account for this potential difference.

Identification of ATS Platforms and Time-Series Summary

We identify trades on ATS platforms by MPID. We use FINRA lists to identify the MPIDs of ATS platforms.[26] The lists include, at a point in time, the active ATS platforms in all OTC fixed-income markets. Using the FINRA lists we are able to identify 20 MPIDs in the TRACE data that relate to ATS platforms within the sample period.

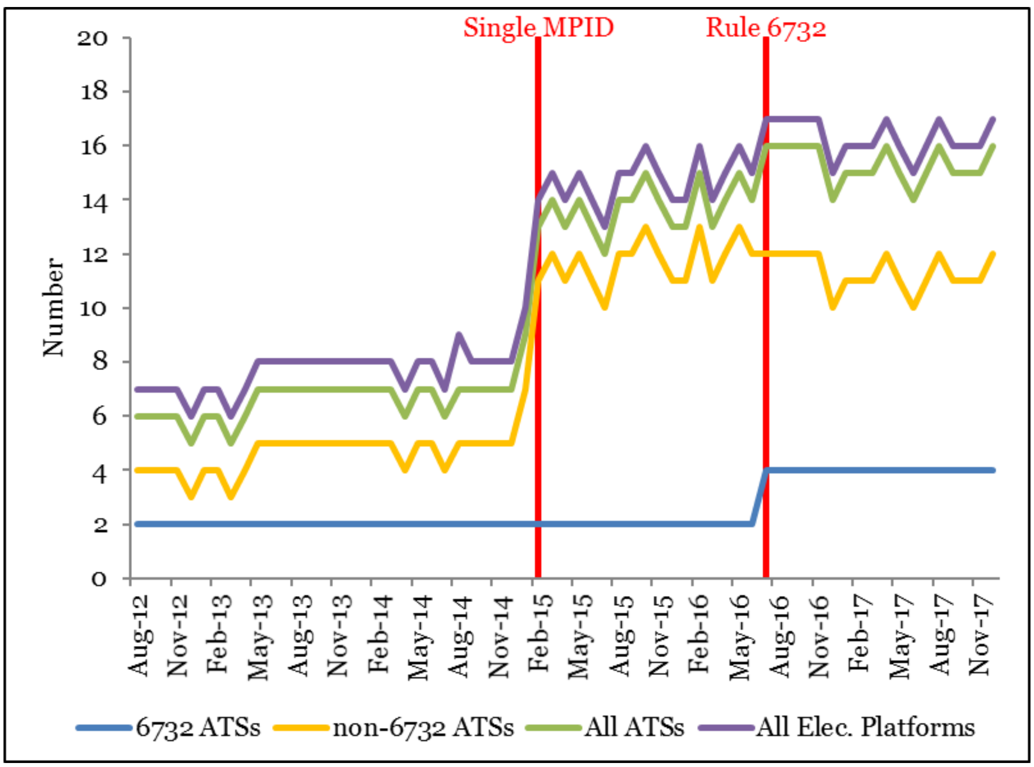
We present a time-series summary of the trading activity on ATS platforms that we are able to identify in the TRACE data. The summary describes the current amount of trading activity on ATS platforms, as well as the effects of the two regulatory changes on the reporting of electronic trades. The two regulatory changes split the sample into three time periods: August 2012 to January 2015, February 2015 to July 2016, and August 2016 to December 2017.

[25] The four ATSs are ICE BondPoint, TMC Bonds LLC, TradeWeb Direct LLC, and Trumid ATS. A fifth ATS platform, Euronext Synapse LLC, has since been granted an exemption. The dates at which each ATS was granted an exemption can be found at https://www.finra.org/rules-guidance/guidance/exemptive-letters.
[26] The lists are publicly available on the FINRA website. *See* https://www.finra.org/filing-reporting/otc-transparency/finra-equity-ats-firms-list. FINRA first posted the lists in February 2015.

Our measures of trading activity include the number of ATS platforms as well as the percentage of bonds traded, the percentage of total market volume (both overall and by trade size), and the percentage of dealer trades and customer or affiliate trades on ATS platforms. We separately report the trading activity on all ATS platforms, 6732 ATS platforms, and non-6732 ATSs. We also report the trading activity on all electronic platforms, including those platforms that do not offer an ECN protocol for the trading of corporate bonds, to the extent it can be identified in TRACE.[27] We present the time-series summary with a series of figures.

Figure 3-1 presents the number of ATS platforms over the sample period that we are able to identify in the TRACE data.

Figure 3-1: Number of Identifiable ATS Platforms



[27] We identify the additional electronic platforms by MPID in TRACE. We obtain the MPIDs from a recent survey (SIFMA (2016)). We may not identify all trades on these platforms. See supra note 19 and related discussion.

The figure demonstrates that 16 platforms facilitated corporate bond trades as of December 2017. The figure also permits us to infer the impact of the unique MPID requirement on our ability to identify ATS platforms in the TRACE data. The number of ATS platform MPIDs in the TRACE data increase from nine prior to the regulation to fourteen after the regulation. Many of the MPIDs in the FINRA lists were not present prior to the regulatory change. This suggests that the increase in the number of MPIDs is a consequence of the new reporting requirement.

The next two figures, Figure 3-2 and Figure 3-3, present the percentage of total monthly trading volume on ATS platforms and the percentage of total monthly trading volume on ATS platforms by trade size.

Figure 3-2: Percentage of Monthly Trading Volume on ATS Platforms

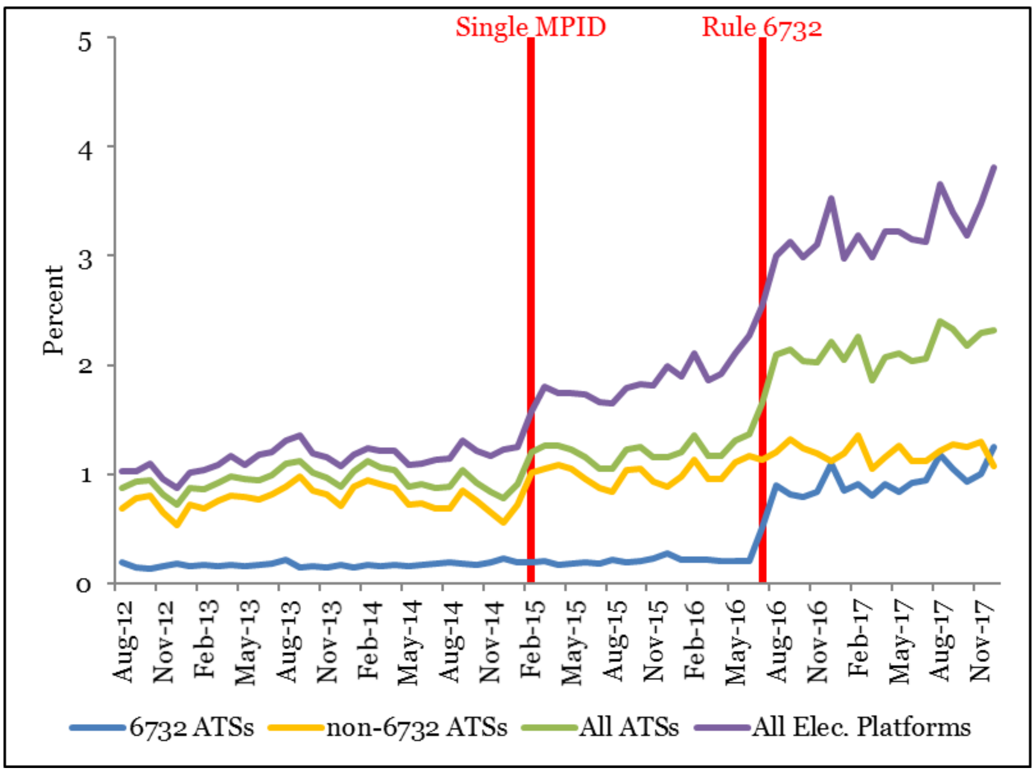


Figure 3-3: Percentage of Monthly Volume on ATS Platforms by Trade Size

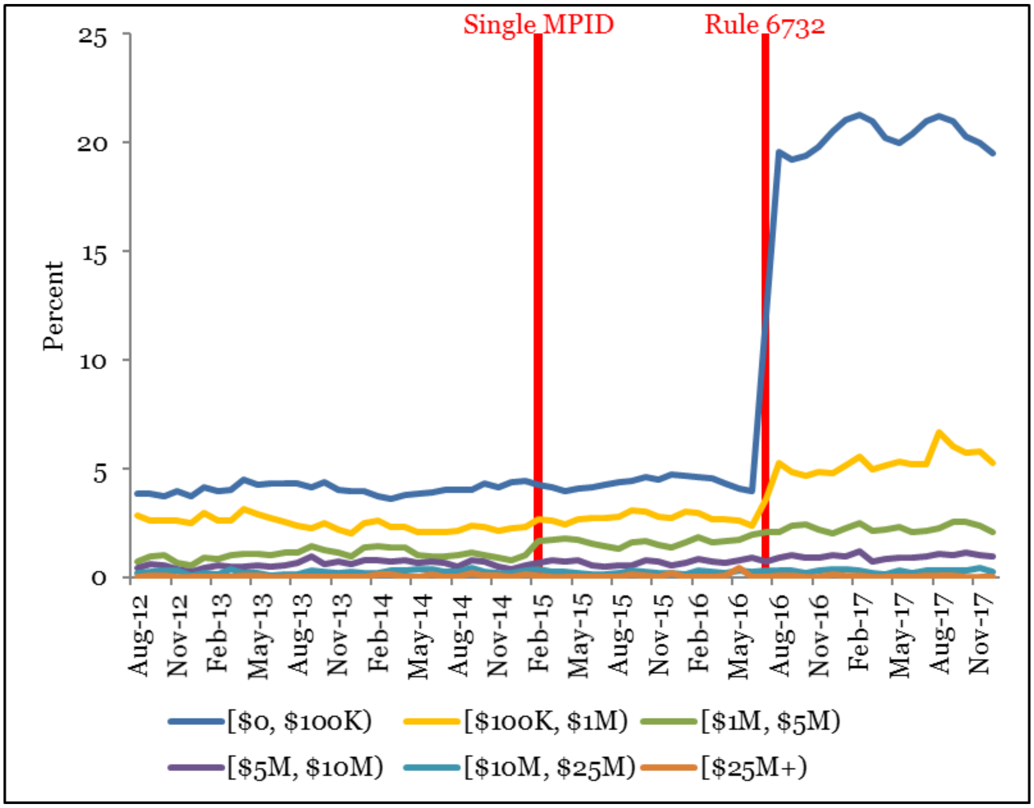


Figure 3-2 shows that the total trading volume on ATS platforms is small relative to the total market. Figure 3-3 shows, however, that the relative volume of small trades is material and important. As of December 2017, only 2.3% of the total trading volume is on ATS platforms. For trades less than $100,000, however, 19.5% of the trading volume is on ATS platforms. Figure 3.3 also shows that the adoption of FINRA Rule 6732 greatly increased our ability to identify small trades on ATS platforms. Prior to the rule adoption, the percentage of trading volume that we are able to identify for small trades is less than five percent.

Finally, Figure 3-4 presents the percentage of all dealer trades on ATS platforms, and Figure 3-55 presents the percentage of all customer or affiliate trades on ATS platforms.

Figure 3-4: Percentage of Dealer Trades on ATS Platforms

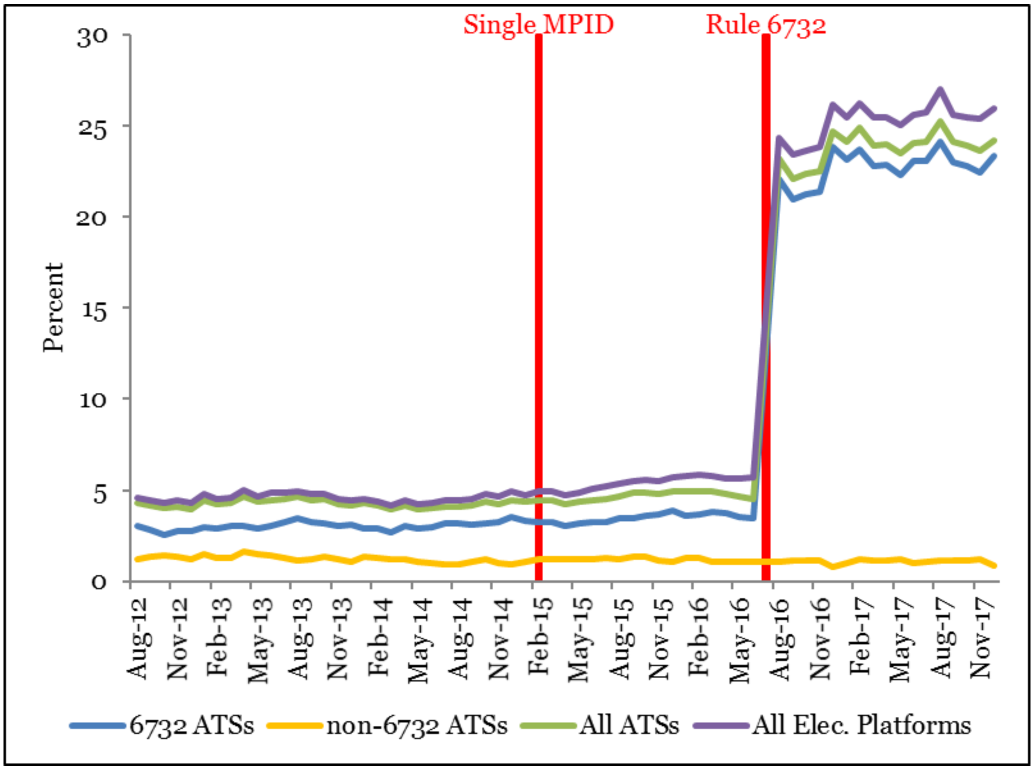


Figure 3-5: Percentage of Customer or Affiliate Trades on ATS Platforms

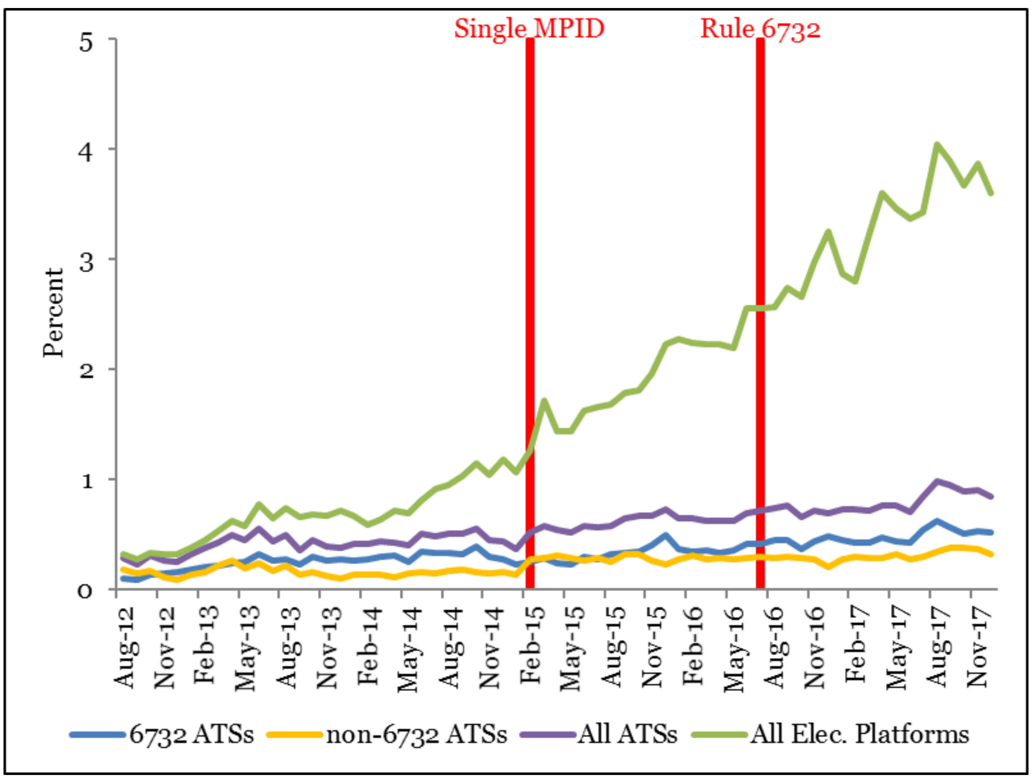


Figure 3-4 shows that ATS platforms facilitate a large percentage of dealer trades, and Figure 3-5 shows that ATS platforms directly facilitate few customer or affiliate trades.[28] This is indicative of ATS platforms as primarily dealer markets. From August 2016 to December 2017, dealers represent 98.3% of the total number of counterparties that trade on ATS platforms. As of the end of the sample period, 24.2% of dealer trades are on an ATS platform.[29] The majority of dealer trades on an ATS platform (96.4%), however, are on a 6732 ATS. Similar to the increase in the volume of small trades on ATS platforms, the adoption of FINRA Rule 6732 increased our ability to identify dealer trades on ATS platforms, and in particular on 6732 ATSs.

In sum, the two regulatory changes increased our ability to identify trades on ATS platforms. The unique MPID requirement increased the number of ATS platforms that we are able to identify in the TRACE data, and FINRA Rule 6732 increased the number of trades on ATS platforms that we are able to identify. The increase in the number of trades on ATS platforms in the latter part of the sample period, however, is driven by an increase in small dealer trades on 6732 ATSs.

Trading on ATS Platforms

In this section, we examine the trades on ATS platforms using the TRACE data. We use the TRACE data to describe the overall trading on ATS platforms. The sample period of the TRACE is data is from August 2016 to December 2017.

[28] Figure 3.5 also shows that the percentage of customer trades on all electronic platforms steadily increased over the sample period. The increase is the result of trades on the other electronic platforms that do not offer an ECN protocol for the trading of corporate bonds. Some dealers, including discount brokerages, display quotes from ECN protocols to their customers. These customers may initiate some of the dealer traders on these platforms.

[29] In addition, over half (52.7%) of the interdealer trades reported to TRACE are on an ATS platform. This measure includes multiple reports relating to the same trade.

We examine several measures of trading activity on ATS platforms. The measures include the amount of trading volume, the number and trading activity of dealers, the number and trading activity of bonds, and trade size. We also examine the characteristics of the bonds that trade on ATS platforms. Finally, we estimate models describing the choice of trading venue.

Market Coverage

Table 3-2 presents the amount of trading volume on all ATS platforms, and separately on 6732 ATSs and non-6732 ATSs. As a comparison, the table also presents total market volume over the corresponding sample periods. The table describes trading volume with monthly averages.

Table 3-2: Volume on ATS Platforms

Volume ($B)			
ATS Platform	6732 ATSs	non-6732 ATSs	Total Market
15.0	6.5	8.5	699.4

The TRACE data indicate that ATS platforms facilitate a small percentage of overall corporate bond volume. On average, the monthly volume on ATS platforms represents 2.1% of the total market volume ($15.0 billion of $699.4 billion). A relatively large percentage of trading volume is on 6732 ATSs. Although 6732 ATSs account for approximately one-fourth of the number of ATS platforms, the average volume per month on 6732 ATSs is 43.6% of the total volume on all ATS platforms ($6.5 billion of $15.0 billion).

Trading volume may not reflect the full economic significance of the trading on ATS platforms. ATS platforms facilitate a higher proportion of trades (16.1%) than trading volume. Because ATS platforms offer pre-trade transparency, participants trading in the broader corporate bond market may still benefit from the price discovery on ATS platforms. As noted by

Alan and Schwartz (2013), prices are a public good and can be used for non-trading purposes such as marking-to-market. Wider market coverage may also indicate the value of ATS platforms as an outside option for those with access to the platforms, and evidence that the potential growth of these platforms may not be constrained by the infeasibility of trading certain bonds electronically. The extent of these benefits is affected by the market coverage of ATS platforms. We measure market coverage by the number and trading activity of the dealers and bonds that trade on ATS platforms. Similar to Table 3-2, Table 3-3 presents the number of dealers that trade on ATS platforms. The table describes the number of dealers with monthly averages.

Table 3-3: Dealers Trading on ATS Platforms

Number of Dealers			
ATS Platform	**6732 ATSs**	**non-6732 ATSs**	**Total Market**
353.9	316.8	118.9	874.5

The TRACE data indicate that 40.5% of the active dealers trade on an ATS platform (353.9 of 874.5 dealers). The dealers that trade on ATS platforms, however, engage in more trading activity than dealers not trading on ATS platforms. For example, dealers that trade on at least one ATS platform per month have 18.9 times the amount of trading volume ($2,080.2 to $109.9 million) and trade 11.7 times more bonds (601.2 to 51.4) than dealers that do not trade on an ATS platform. The dealers that trade on ATS platforms, therefore, are the large more active dealers. However, the ten largest dealers account for a smaller proportion of ATS platform volume (41.9%) than OTC volume (59.6%). On average, dealers that trade on at least one ATS platform trade on 2.8 ATS platforms, including 1.6 6732 ATSs, and dealers that trade on multiple ATS platforms trade more actively than dealers that trade on one ATS platform.

The majority of dealers that trade on ATS platforms trade on 6732 ATSs (316.8 of 353.9 dealers, or 89.5%). A smaller percentage of dealers (33.6%) trade on non-6732 ATSs. This difference is consistent with the percentage of dealer trades between 6732 ATSs and non-6732 ATSs (e.g., Figure 3.4).

The dealers that trade on ATS platforms include discount retail brokerages. In the aggregate and on average, these discount brokerages trade $2,432.2 million per month. Approximately one-third of their total corporate bond volume ($817.9 million) is reported as occurring on ATS platforms, with nearly all of the volume on 6732 ATSs. Retail investors are likely able to observe and access the quotes displayed on ECN protocols.[30] Dealers anticipating participation by less-informed investors will generally reduce spreads to reflect the lower risk of adverse selection by informed traders. In OTC markets, however, dealers may charge less favorable prices to uninformed traders (whether retail or institutional) who not only lack private information about the prospects of the security but also knowledge of the prices available to trade (Green, Hollifield, and Schurhoff (2007)). The last effect is less likely on ATS platforms because pricing information is easier to obtain.

Similar to Table 3-3, Table 3-4 presents the number of bonds that trade on ATS platforms. The table describes the number of bonds with monthly averages.

Table 3-4: Bonds Traded on ATS Platforms

Number of Bonds			
ATS Platforms	6732 ATSs	non-6732 ATSs	Total Market
11,719.5	11,039.6	3,074.5	20,765.1

[30] For example, see https://www.sec.gov/spotlight/fixed-income-advisory-committee/bondsavvy-comment-letter-pre-trade-transparency-for-retail-investors-in-the-us-corporate-bond-market.pdf.

The TRACE data indicate that 56.4% (or 11,719.5 of 20,765.1) of the bonds that trade each month trade on an ATS platform. The bonds that trade on an ATS platform, however, have more reported trading activity than bonds that do not trade on an ATS platform. For example, bonds that trade on at least one ATS platform each month have 3.6 times more trading volume ($46.4 to $17.2 million) and are traded by 2.7 times more dealers (20.4 to 5.6) than bonds that do not trade on an ATS platform. On average, bonds that trade on at least one ATS platform each month trade on 2.4 ATS platforms. The majority of the 2.4 ATS platforms (2.0), however, are 6732 ATSs.

Among the 11,719.5 bonds that trade each month on an ATS platform, 94.2% trade on a 6732 ATS. A smaller percentage of bonds (26.2%) trade on a non-6732 ATS. The number of bonds that trade on a 6732 ATS relative to a non-6732 ATS is consistent with the difference in the number of trades between the two classifications.

In sum, the evidence indicates that although only a small proportion of trading volume takes place on ATS platforms, a much larger proportion of bonds are traded on ATS platforms. The price discovery on these platforms may also benefit the broader market.

Trade Size

Although greater dealer participation on 6732 ATSs may lead to greater price competition, it may result in the dealers seeking liquidity to incur greater costs from information leakage. Dealers can reduce this risk by decreasing order size (Hendershott and Madhavan (2015)). Table 3-5 presents the size of trades on ATS platforms. The table describes trade size with averages and percentiles over the sample periods. Table 3-6 presents the percentage of block trades on ATS platforms. The table describes the percentage of block trades from $1 to $5 million, $5 to $10 million, $10 to $25 million, and greater than $25 million over the sample periods. As a comparison, the tables also present the size and percentage of block trades among all trades.

Table 3-5: Distribution of Trade Size

	Size ($K)					
Category	**Avg.**	**p5**	**p25**	**p50**	**p75**	**p95**
ATS Platforms	82.5	2.0	8.0	15.0	40.0	250.0
6732 ATS	37.9	2.0	8.0	15.0	30.0	135.0
non-6732 ATS	918.4	9.0	121.0	500.0	1,000.0	3,500.0
Total Market	618.6	3.0	10.0	35.0	250.0	3,000.0

Table 3-6: Percentage of Block Trades

	Blocks (%)				
Category	**$1-5M**	**$5-10M**	**$10-25M**	**$25M+**	**Total**
ATS Platforms	1.8	0.1	0.0	0.0	2.0
6732 ATS	0.2	0.0	0.0	0.0	0.2
non-6732 ATS	32.4	2.7	0.4	0.0	35.5
Total Market	11.0	2.3	1.0	0.1	14.5

The TRACE data indicate that the median trade size on ATS platforms is $15,000. The median trade size, however, relates to trades on 6732 ATSs and not non-6732 ATSs. For example, whereas the median trade size on 6732 ATSs is $15,000, the median trade size on non-6732 ATSs is $500,000. The TRACE data also indicate that 6732 ATSs facilitate few block trades; 2.0% of trades on 6732 ATSs are block trades, whereas approximately one-third of trades on non-6732 ATSs (35.5%) are block trades.

Bond Characteristics

Table 3-7 presents the characteristics of the bonds that trade on ATS platforms. The table categorizes bonds by credit rating (investment grade, IG, or high yield, HY), vintage (less than two years, New, or two years or greater, Old), and issue size (less than $500 million, Small, or $500 million or greater, Large). As a comparison, the table also presents the characteristics of all bonds that trade over the corresponding sample periods. The table presents bond characteristics with the percentage of trades per category.

Table 3-7: Characteristics of Bonds

	Credit Rating %		Vintage %		Issue Size %	
Category	**IG**	**HY**	**New**	**Old**	**Small**	**Large**
ATS Platforms	73.4	26.6	27.7	72.3	27.0	73.0
6732 ATS	74.6	25.4	26.8	73.2	27.8	72.2
non-6732 ATS	49.1	50.9	44.1	55.9	9.8	90.2
Total Market	66.2	33.8	34.3	65.7	22.0	78.0

The TRACE data indicate that a greater percentage of bonds that trade on ATS platforms (relative to the total market) are investment grade, older vintage, and of smaller issue size. The TRACE data also indicate that the characteristics of the bonds that trade on 6732 ATSs are different than the bonds that trade on non-6732 ATSs. For example, whereas approximately three-quarters (74.6%) of the bonds that trade on 6732 ATSs are investment grade, just less than half (49.1%) of the bonds that trade on a non-6732 ATS are investment grade. A greater percentage of bonds that trade on 6732 ATSs have been trading for two years or longer (73.2% to 55.9%) and of larger issue size (27.8% to 9.8%) than bonds that trade on non-6732 ATSs.

We formally test for the relationship between bond characteristics and trading venue with two models. Each model describes a different choice of trading venue. The first model describes the trading activities occurring on or off an ATS platform. The second model describes the trading activities occurring on a 6732 or non-6732 ATS.

We measure the choice of trading venue for each bond and trade date. The measure, Venue, is equal to 1 if the bond traded on an ATS or 6732 ATS depending on the specification and 0 otherwise. We include four variables controlling for bond characteristics. The variables are intended to capture differences in the credit rating of the bond (InvGrade), the issue amount (IssueSize), the days since issuance (Age), and the days until maturity (Maturity). InvGrade is an indicator variable equal to one if the bond is investment grade, and zero otherwise. The set of bond characteristics we include in our model is consistent with Hendershott and Madhavan (2015).

We also include three variables to control for recent bond trading activity. The variables are the trading volume of the bond (Volume), the number of unique dealers trading the bond (Dealers), and the absolute value of the aggregate change in dealer inventory (Inventory). We measure the variables over intervals of twenty trading days prior to the trade date. Inventory controls for dealer risk capacity. The variable has been found in other contexts to describe the risks of market makers (e.g., Comerton-Forde et al. (2010)).

We specify the following regression to model the choice of trading venue:

$$Prob(Venue) = f(InvGrade, IssueSize, Age, Volume\ , Maturity\ , Dealers, Inventory)$$

We estimate the model using a general linear model with a binomial error distribution to account for the truncated dependent variables. Table 3-8 presents the coefficient estimates and marginal effects (dy/dx) for these models.[31] The t-statistics are presented in parentheses below the coefficient estimates.

[31] We standardize the marginal effects at the average of the dependent variable, so our estimates are the percentage change in the dependent variable needed to increase the probability by 1%.

Table 3-8: Regression Predicting Trade Venue

	on ATS = 1 off ATS = 0		6732 ATS = 1 non-6732 ATS = 0	
	Aug. 2016 - Dec. 2017		Aug. 2016 - Dec. 2017	
	Coeff. Est.	ME	Coeff. Est.	ME
Constant	0.291		0.219	
	(143.70)		(6.14)	
InvGrade	0.065	9.07%	0.195	11.53%
	(214.88)		(33.81)	
IssueSize ($ par)	-0.0347	-2.19%	-0.046	-6.58%
	-(237.69)		-(17.85)	
Age (Days)	0.0193	8.22%	0.045	13.88%
	(152.64)		(19.00)	
Volume ($ par)	-0.0024	-24.61%	-0.012	-19.63%
	-(28.32)		-(6.84)	
Maturity (Days)	-0.0010	-137.70%	-0.040	-13.58%
	-(7.17)		-(19.65)	
Dealers (#)	0.0042	11.49%	0.004	36.53%
	(411.42)		(23.29)	
Inventory ($ par)	0.0023	30.66%	0.002	180.11%
	(34.06)		(1.08)	
Pseudo-R^2	0.36		0.21	

For all explanatory variables, the results are directionally consistent between the two models. Investment grade bonds, older bonds, less active bonds, bonds closer to maturity, with larger dealer networks, and larger changes to dealer inventories are more likely to trade on an ATS platform or on a 6732 ATS.

Investment grade bonds are more likely to trade on an ATS rather than off, and, conditional on trading on an ATS platform, on a 6732 rather than a non-6732 ATS. The marginal effect for investment grade bonds range from 9.1% to 11.5%. This suggests that a bond portfolio with 10% more investment grade bonds will be 1% more likely to trade on an ATS. As documented by Han and Zhou (2013), microstructure measures of adverse selection are larger for high yield than for investment grade bonds. The sign and significance of investment grade bonds is consistent with market participants trading on ATS platforms and 6732 ATSs when such risks are less relevant.

The previous summary findings indicate that corporate bonds trading on at least one ATS platform are traded by more dealers. Consistent with this finding, we find that the variable Dealers is positively related to trading on an ATS platform. This suggests that trading on ATS platforms is positively influenced by the potential level of dealer participation. Participation by other dealers may relate to greater price competition (Hendershott and Madhavan (2015)), and is consistent with positive effects of network externalities.[32] The economic significance of Dealers is similar to credit rating.

ATS platforms also appear to facilitate the trading of corporate bonds when the level of those bonds in aggregate dealer inventory has risen. This suggests that dealers utilize ATS platforms to reduce excess inventory, and with the increase in trading on these platforms (e.g., Figure 3.2), that ATS platforms are becoming a potentially more important source of liquidity.

The need for new sources of liquidity in the corporate bond market has likely grown because of changes in the capital commitment of dealers. Bessembinder et al. (2018) find a 33% reduction in the daily capital commitment of bank affiliated dealers. Bao, O'Hara, and Zhou (2016) note that since the implementation of the Volcker Rule in 2014, the dealers affected by the regulation have decreased their corporate bond inventories. The marginal effect of Inventory, however, is weak. In the first model (describing the trading on and off ATS platforms), a 30.7% increase from average inventories only increases the probability a trade takes place on an ATS platform by 1%.

[32] Research by Hendershott et al. (2017), however, suggests that transaction costs may increase once a dealer network reaches a certain threshold (e.g., twenty dealers).

Smaller and older issues with lower levels of recent trading activity are more likely to trade on an ATS platform or a 6732 ATS. This result contrasts with Hendershott and Madhavan (2015), who find that larger and newer issues are more likely to trade electronically. Finding a counterparty may be more difficult for smaller, older, and thinly traded bonds so this result suggests ATS platforms are particularly valuable in situations where search costs are high.

Customer Trading Costs

Lastly, we examine the relationship between dealer participation on ATS platforms on customer transaction costs. Customers compensate dealers for order processing costs, the risk of adverse selection, and inventory risk (Huang and Stoll (1997)). In OTC markets, customers also compensate dealers for search costs (Duffie, Gârleanu, and Pedersen (2005)). Participation on ATS platforms may lower dealer costs to intermediate orders, which could reduce customer transaction costs.

To measure customer transaction costs, we identify sequences of trades that begin with a customer sale and end with a customer purchase (i.e., trade chains). We measure customer transaction costs as the difference between the price of the initial customer sale and the price of the final customer purchase. The difference between the sale price and purchase price from the same trade chain captures the total (shared) costs to customers to purchase and sell the bond. How those costs are shared between buyer and seller are not a part of this analysis.

In this framework, customer transaction costs compensate dealers for the risk of market making, providing intermediation services, and the return from purchasing and selling the bond. We compare the difference in transaction costs between chains that include a dealer transaction on an ATS platform and chains that do not include a dealer transaction on an ATS platform.

This comparison provides an indication of the relationship between dealer participation on ATS platforms and the costs they collectively incur to intermediate trades.

Methodology

We use the TRACE data from August 2016 to December 2017 for this analysis. We identify trade chains using a similar algorithm as Li and Schürhoff (2018), who apply it to the municipal bond market. Each trade chain starts with a customer sale to a dealer. For each of these transactions, starting from the earliest, we then match the initial dealer purchase to the subsequent dealer sale.[33] We match purchases to sales by dealer MPID, bond CUSIP, and par value (size) of the trade.

If the dealer sale is to another dealer, then we match the second dealer purchase to the subsequent dealer sale. A trade chain ends if the first dealer sale, or any other subsequent dealer sale, is to a customer. The trade chain also ends if we are not able to match a dealer purchase to a subsequent sale, or in the rare case where the chain exceeds seven trades. After a trade is identified as part of one complete trade chain, it may not be included in another.

Our algorithm differs from that of Li and Schürhoff (2018) in three respects. First, we only match trades within the same day, and we exclude trade chains that span more than two hours. Li and Schürhoff (2018) include trade chains that span up to thirty days. We use this more restrictive approach to minimize the effects of intraday price changes on our measure of customer trading costs. We also use this more restrictive approach to minimize the effects from matching unrelated trades. To the extent that short holding periods are anticipated by dealers,

[33] We do not impose strict chronological ordering on the chains. A trade that occurs earlier in the identified chain may take place up to 15 minutes after the subsequent trade in the chain to account for the possibility of a delay in reporting or a dealer arranging the sale of a bond before its purchase.

however, a smaller component of transaction costs may be attributable to inventory risk. We do include trade chains that span up to thirty days in a separate analysis as a robustness check.

Second, we require all trades in a chain to have the same par value. Li and Schürhoff (2018) include "split" chains where the final dealer in a chain sells less than the full par value to a customer.[34] Trade size has also been found by other researchers to be a significant determinant in bond transaction cost (e.g., Edwards, Harris, and Piwowar (2007)). By including trade chains with the same par value, we reduce the variation in customer costs that relates to trade size although this assumption reduces the number of trade chains analyzed.

Third, to account for potential reporting discrepancies, we restrict the next trade in a chain to have a report time no less than fifteen minutes prior to the report time of the prior trade. Li & Schürhoff (2018) match dealer purchases to dealer sales that may have been executed ten days prior. This may incorporate short sales into their analysis and introduce reporting discrepancies into their sample.

We calculate customer transaction costs as:

$$CustomerCost = 10^4 \cdot \frac{(P^{DC} - P^{CD})}{P^{CD}}$$

Where P^{CD} is the price of the initial customer sale, and P^{DC} is the price of the final customer purchase. We measure CustomerCost in basis points. CustomerCost measures the combined transaction costs of the two customers purchasing and selling the bond. We do not attempt to allocate the cost between the customers.

We apply a series of additional requirements for us to include a trade chain as part of the final sample. We first require trade chains to include at least one interdealer trade. Choi and

[34] Li and Schürhoff (2018) report median customer costs that are 30 basis points greater for split chains than for non-split chains. Sirri (2014) also includes chains where a dealer splits one purchase into multiple subsequent sales.

Huh (2017) note that the customer purchase price is significantly lower when a dealer purchases a bond from one customer and sells to another in a short period of time. The authors argue that this result is due to “customer liquidity provision” where one of the customers effectively acts as a dealer. We exclude trade chains without at least one interdealer trade to control for these instances.

Second, we require broker-dealers to be reported as trading in a principal capacity in the initial purchase from the customer and the final sale to the customer of each trade chain. Trades where dealers act in an agency capacity may relate to advisory accounts, and customers may not be charged a commission on a per trade basis. In such cases, the measure of customer transaction costs would not reflect total dealer compensation.

Third, we require CustomerCost to be greater than zero and less than 500 basis points. Otherwise, trade chains may relate to mismatched trades or to reporting discrepancies. Fourth, we require bond characteristic information to be available. Finally, we require that the trade chain span less than two hours. There are 17,299 trade chains in the final sample. Table 3-9 presents the effect of each restriction on the number of observations in the final sample.

Table 3-9: Trade Chain Sample Filters

Sample Restriction	Total	Trade on ATS Platform	No Trade on ATS Platform
Same Trade Size	343,632		
One Interdealer Trade	73,714	52,042	21,672
Principal Trades	27,150	17,613	9,537
Customer Costs Less than 500bp	26,284	17,213	9,071
Information Available	23,246	17,112	6,134
Less than Two Hours	15,438	11,426	4,012

Table 3-10 describes the trade chains in the final sample including CustomerCost, chain length (ChainLength), trade size (TradeSize), and the amount of time in minutes from the start to the completion of the chain (Time). The table also describes the characteristics of the bonds (InvGrade, IssueSize, Age, Volume, and Dealers).[35]

Table 3-10: Trade Chain Sample Characteristics

	Avg.	P5	P25	P50	P75	P95
CustomerCost (bp)	115.2	10.4	29.2	82.0	172.3	332.9
ChainLength	3.6	3.0	3.0	3.0	4.0	5.0
TradeSize ($K)	427.9	4.0	10.0	20.0	50.0	2,000.0
Time (minutes)	34.5	0.0	1.8	21.2	60.8	105.8
InvGrade	0.6	0.0	0.0	1.0	1.0	1.0
IssueSize ($K)	871.8	5.4	250.0	500.0	1,000.0	2,850.0
Age (days)	2,193.7	233.5	902.9	1,572.7	2,621.8	7,031.6
Maturity (days)	23,123.0	139.6	779.4	1,769.4	3,394.6	10,293.4
Volume ($M)	87.0	0.0	2.3	29.0	99.3	349.6
Dealers	34.5	1.0	12.0	29.0	51.0	87.0

The average trade chain has a customer transaction cost of 115.2 basis points and a median of 82.0 basis points. The average chain in the sample involves between three and four trades, or one or two interdealer trades and two customer trades. Fifty percent of the chains in the sample were completed within 21.2 minutes. The distribution of trade size is heavily skewed; although the size of the median trade chain is $20,000, the size of the average trade chain is approximately $427,900.

Table 3-11 further describes the length of the trade chains in the final sample. The table separately describes the length of the trade chains dependent on whether the chain includes a trade reported on an ATS platform (ATSP = 1) or does not include a trade reported on an ATS platform (ATSP = 0).

[35] See previous section for a description of these measures.

Table 3-11: Trade Chain Length, Duration, and Customer Transaction Costs

			Time (minutes)		*CustomerCost* (bp)	
Length	***ATSP***	**Number**	**Avg.**	**Median**	**Avg.**	**Median**
3	0	2,932	30.7	14.6	88.1	52.9
	1	4,875	28.8	10.3	109.6	76.2
4	0	1,024	45.9	38.5	146.2	116.3
	1	4,715	33.8	19.5	118.3	85.5
5	0	52	43.0	40.0	148.1	112.1
	1	1,506	50.1	45.6	147.0	118.8
6	0	4	39.0	17.4	126.0	106.0
	1	328	56.6	53.7	145.9	105.7
7	0	0	n/a	n/a	n/a	n/a
	1	2	78.3	78.3	169.7	169.7

The number of trade chains with or without a trade reported on an ATS platform are similar. In general, chains with a trade reported on an ATS platform are completed in a shorter period of time than chains without a trade reported on an ATS platform. Chains without a trade reported on an ATS platform, however, may be more likely to span more than two hours and therefore not be included in the sample. In unreported tests, the time span for chains with three or four trades is significantly shorter at the ninety-nine percent confidence level if at least one of the trades is reported on an ATS platform.

Multivariate Analysis

We formally test for differences in customer transaction cost between trade chains with a trade reported on an ATS platform and trade chains without a trade reported on an ATS platform. We regress CustomerCost on ATSP and control variables. The control variables include ChainLength, TradeSize, InvGrade, IssueSize, Age, Maturity, Volume, and Dealers. Previous research finds that bond rating, issue size, and bond vintage are significant determinants of transaction cost (e.g., Edwards, Harris, and Piwowar (2007); and Li and Schürhoff (2018)). Dealer networks and volume control for recent bond trading activity.

We specify the following regression to model customer transaction cost:

$$CustomerCost = \propto + \beta 1 \cdot ATSP + \beta 2 \cdot ChainLength + \beta 3 \cdot TradeSize + \beta 4 \cdot Log(TradeSize) + \beta 5 \cdot InvGrade + \beta 6 \cdot IssueSize + \beta 7 \cdot Age + \beta 8 \cdot Maturity + \beta 9 \cdot Volume + \beta 10 \cdot Dealers$$

We use an ordinary least squares model to estimate parameters. We cluster the standard errors by bond and trade date. Table 3-12 presents the regression results.

Table 3-12: Customer Transaction Cost Regressions

	CustomerCost			
	Coeff. Est.			
	Two Hours	**One Day**	**Thirty Days**	**Commonly Traded**
Constant	218.500	245.800	260.000	175.000
	(22.81)	(19.93)	(36.89)	(11.74)
ATSP	-24.190	-31.150	-32.030	-30.380
	(9.94)	(10.05)	(19.78)	(9.21)
Chain Length	11.430	19.990	23.310	12.360
	(10.11)	(14.18)	(31.46)	(6.69)
TradeSize ($M)	0.000	0.000	0.000	0.000
	(4.48)	(3.15)	(6.86)	(4.90)
Log(TradeSize)	-12.580	-14.110	-10.590	-10.920
	(19.70)	(16.93)	(20.53)	(10.93)
InvGrade	-1.720	-28.150	-80.960	9.068
	(0.95)	(11.70)	(56.76)	(3.34)
IssueSize ($M)	-19.350	-20.610	-35.720	-17.840
	(19.26)	(16.44)	(53.24)	(14.10)
Age	0.001	0.003	0.006	0.003
	(3.15)	(4.88)	(19.53)	(4.81)
Maturity	0.000	0.000	0.000	0.000
	(22.84)	(17.95)	(22.98)	(18.81)
Volume ($B)	7.159	11.970	99.650	-1.598
	(1.22)	(1.64)	(25.99)	(0.22)
Dealers	0.445	0.294	0.607	0.788
	(12.35)	(6.25)	(21.87)	(15.66)
# Obs.	15,438	23,240	138,771	6,431
Adj. R^2	0.12	0.08	0.09	0.15

The first column of Table 3-12 presents the regression results with the test sample. The results indicate that customer transaction costs are 24 basis points lower if at least one trade is on an ATS platform. This is suggestive of the potential decrease in dealer costs to intermediate trades when trading on an ATS platform, holding constant the characteristics we previously showed as correlated with the likelihood of ATS trading.

The results for variables we include as controls are also consistent with the previous literature. For example, the results indicate that each additional interdealer trade is associated with an 11 basis point increase in customer costs. Li & Schürhoff (2018) and Sirri (2014) also find that longer chains are associated with higher customer costs. In addition, consistent with Edwards, Harris, and Piwowar (2007), larger trades, trades of investment grade bonds, and trades of bonds with larger issue sizes are associated with lower customer costs. Larger dealer networks and trading volume both positively relate to customer transaction costs. Although both variables would suggest lower dealer search costs, these variables could instead relate to longer intermediation chains and therefore greater total customer costs. Trading volume is also only marginally statistically significant.

We believe the two-hour requirement limits the extent to which other factors could influence the measurement of customer costs used in these tests. This includes the risk premium for dealers to hold bonds in inventory, changes in bond price, and the possibility that we falsely identify two unrelated trades as part of the same chain. This requirement, however, reduces the size of the final sample and may introduce a selection bias. As a robustness check, we re-estimate the regressions using trade chains that span less than one day and, similar to Li and Schürhoff (2019), trade chains that span less than thirty calendar days. The second and third columns of Table 3-12 present the results. The results remain substantively the same. For the one day sample, a trade on an ATS platform is associated with lower customer costs by 31 basis points; and for the thirty day sample, a trade on an ATS platform is also associated with lower customer costs by 32 basis points.

An alternative explanation can be that the lower transaction costs reflect the unobservable characteristics of order flow, i.e., the characteristics of order flow uncorrelated with our control variables. For example, the trades on ATS platforms may reflect when attractive quotes are available via the ATS. It is possible that the regression results relate to systematic differences, not accounted for by the control variables, between the bonds that trade on and do not trade on ATS platforms. To address this possibility, we restrict the test sample to include only those bonds with at least one trade chain involving an ATS and one trade chain not involving an ATS. After the additional restriction we find that a trade on an ATS platform is associated with lower customer costs of 30 basis points, similar to the previous estimates.

Conclusion

In this paper, we analyze the impact of electronic trading technology in the corporate bond market through the trading activity on ATS platforms. Although the trading volume pursuant to ECN protocols is small relative to RFQ protocols (or voice OTC markets), the market coverage of ATS platforms suggests that participants likely benefit from the pre-trade transparency and price discovery that ECN protocols provide.

This paper demonstrates the importance of dealer reporting obligations for analyzing securities markets. Two recent regulations increased not only the number of ATS platforms but also the number of trades on ATS platforms that we are able to identify with the TRACE data. With this information, we are able to investigate the current role of ATS platforms to facilitate corporate bond trades and their economic implications.

Our results show that not all trades are equally likely to occur on ATS platforms. Consistent with investors avoiding ATS platforms for trades where adverse selection and information leakage are important considerations, trades on ATS platforms are smaller and more likely to involve investment-grade bonds. Consistent with investors preferring ATS platforms for trades where search costs are substantial, trades on ATS platforms are also more likely for older, less actively traded bonds from smaller issues and for bonds traded by more dealers where inventory is high.

We also demonstrate substantial heterogeneity within the category of ATS platforms we study. We show that the same characteristics which influence a bond trading on an ATS platform rather than in the OTC market also have similar effects on whether a bond trades on 6732 ATS or non-6732 ATS.

Finally, we estimate the gains to customers from dealer participation on ATS platforms. We identify sequences of trades that begin with a customer sale and end with a customer purchase (i.e., trade chains). For the trade chains with an interdealer trade, we compare customer transaction costs between the chains that include and do not include a dealer transaction on an ATS platform. Controlling for other observable trade characteristics, trade chains involving a trade on an ATS platform are associated with between a 24 and 32 basis point reduction in customer transaction costs.

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