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Author(s): Chris Downing and Frank Zhang

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Trading Activity and Price Volatility in the Municipal Bond Market

CHRIS DOWNING and FRANK ZHANG*

ABSTRACT

Utilizing a comprehensive database of transactions in municipal bonds, we investigate the volume–volatility relation in the municipal bond market. We find a positive relation between the number of transactions and a bond’s price volatility. In contrast to previous studies, we find a *negative* relation between average deal size and price volatility. These results are found to be robust throughout the sample. Our results are inconsistent with current theoretical models of the volume–volatility relation. These inconsistencies may arise because current models fail to account for the effects of overall market liquidity on the costs of large transactions.

THE RELATION BETWEEN THE VOLUME OF TRADE in a security and its price volatility has probably always been of interest to market practitioners. More recently, with the availability of large databases of individual transactions, the volume–volatility relation has received significant attention from the academic community, as well. Previous studies across a wide range of securities markets, including the markets for corporate equity, financial and commodities futures, and foreign exchange, have documented a positive relation between price volatility and the volume of transactions (see Karpoff (1987) for a review of early theoretical and empirical research). More recent empirical studies have used intraday data to examine the distinct roles played by different players on the market, and the elements of total trade volume. For example, Daigler and Wiley (1999) test whether the volume–volatility relation in the futures market depends on the type of trader, concluding that the “general public”—less informed individuals far away from the trading floor—drives the positive volume–volatility relation found in previous studies. Jones, Kaul, and Lipson (1994) find that, after controlling for the number of transactions, trade size offers no additional explanatory power for equity price volatility.¹ Despite the attention that these issues have received in the academic literature, however, there are relatively few studies of the volume–volatility relation in the

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¹ Other recent empirical studies include Chan and Fong (2000), Bessembinder and Seguin (1993), Foster and Viswanathan (1993), Gallant, Rossi, and Tauchen (1992), and Schwert (1989).

fixed income markets, and none that we are aware of for the municipal bond market.

The object of this article is to make the first comprehensive examination of the volume–volatility relation in the municipal (muni) bond market. The question of the relation between trade volume and price volatility is of interest in and of itself.² But perhaps more importantly, the municipal bond market offers a different market structure against which to compare and contrast the results on the volume–volatility relation in other markets. In at least three important respects, the muni market is different from the other markets in which the volume–volatility relation has been studied. These differences stem principally from the fact that the muni market is an over-the-counter market, much like the market for corporate bonds. First, the municipal bond market is less transparent than the equity and futures markets in terms of the availability of basic information on trading activity. For instance, information on individual municipal bond transactions has not been publicly disclosed until very recently. Even now, comprehensive trade volume and price data are only publicly available after a two-week lag. This stands in stark contrast to the other markets, where transaction disclosure occurs just seconds after the completion of a deal. Second, the municipal bond market is less transparent in terms of information about the bond issuers, because muni bond issuers are not subject to the same financial disclosure requirements as are publicly traded corporations. While publicly traded corporations are required to maintain a quarterly data feed on their activities (10-Q and 10-K reports), most municipal bond issuers typically only release detailed financial information when they float a bond. For smaller muni bond issuers, who tap the credit markets infrequently, official information concerning their financial situation can be very scant, indeed. Finally, the muni bond market is very illiquid compared to the equity, futures, and foreign exchange markets. As we shall discuss in detail later in this paper, even the largest muni bonds are only traded a few times after issuance, while it is not uncommon for shares of a widely held corporation to trade millions of times a day, for example.

The scarcity of information on muni bond trading activity and on the bond issuers implies that information asymmetries between traders on the muni market may be more pronounced than in other markets.³ Large institutional investors are likely to be much better informed about prices and market volume than are individual investors, since they conduct a larger share of the transactions, and are active in the market on a daily basis. Furthermore, the relatively high costs of acquiring information on bond issuers confers further

² In this paper, we measure trade volume in three ways. We measure the number of trades in a given bond, the total par amount traded in a given bond, and the average size of each trade in a bond.

³ The relative scarcity of information on municipal bond issuers is to some extent mitigated by the high credit quality of most municipal bonds. Nevertheless, there have been a number of defaults on municipal bonds since the mid-1970s. Of the municipal bonds issued between 1977 and 1998, 1,765 issues eventually defaulted, with a combined face value of \$24.9 billion, out of a total of 253,850 issues with a total face value of \$375.7 billion (Litvack and Rizzo (1999)).

informational advantages on large institutional investors, who are more likely to have the resources to analyze the credit quality of individual issuers. Hence these investors will be better situated to determine if a transaction is related to a change in fundamental value (e.g., a deterioration in the credit quality of a bond issuer) or if a transaction is being carried out for reasons unconnected to fundamental value (a liquidity trade, such as to rebalance a portfolio). Finally, in a thin market like muni bonds, liquidity is more of a concern to traders than in the other, more liquid, markets. Institutional investors conducting large trades for liquidity reasons may prefer to trade with other equally informed institutional investors on the market, in order to minimize transaction costs and the price impact of the deal. This may help to explain why large investors tend to maintain a broad set of dealer contacts, in order to maximize the probability of finding matching orders for large trades with minimal price impact.

Utilizing a newly developed comprehensive database of secondary market transactions in municipal bonds, we investigate the weekly cross-sectional relation between price volatility, the number of trades, and average trade size. Our results differ in important ways from previous studies. As in many previous studies, we find a positive relation between the number of trades in a bond and the bond's weekly price volatility. In contrast, however, we find a *negative* relation between average trade size and price volatility, and we find that average trade size retains its explanatory power even after controlling for the number of trades in a particular bond.⁴ These results are found to be robust throughout various strata in the data sample, as well as across different time periods and different measures of price volatility.

A rough taxonomy of the theoretical models on the volume–volatility relation consists of three classes of models: (1) competitive, (2) strategic, and (3) models built on the mixture of distributions hypothesis. Models in the competitive class assume that agents differ in their beliefs or information (Shalen (1993), Harris and Raviv (1993), Kim and Verrecchia (1991), Holthausen and Verrecchia (1990), Grundy and McNichols (1989), and Pfleiderer (1984), among others). In these models, the over-response of uninformed investors to an observed increase in trading activity generates a positive volume–volatility relation. The strategic models also incorporate asymmetric information across agents, but assume that a single informed investor, or small group of informed investors, are able to collude to disguise their trades by making several small-sized trades (see Holden and Subrahmanyam (1992), Foster and Viswanathan (1990), Admati and Pfleiderer (1988), and Kyle (1985), among others). Like the competitive models, the strategic models also predict a positive volume–volatility relation. The third class of models are primarily statistical, built on the mixture of distributions hypothesis (Harris (1987), Tauchen and Pitts

⁴ It should be noted that the results of Jones et al. (1994) are not necessarily inconsistent with what we find here. In that paper, the authors applied a strong prior that average trade size should have a positive effect on price volatility, as reflected in their use of *one-tailed* *t*-tests on the coefficients of average trade size. In fact, for a large number of the firms in their sample, average trade size has a negative coefficient, as we find here. However, based on the information provided in the paper, it is not possible to determine if the negative coefficients are statistically significant.

(1983), and Epps and Epps (1976)). These models predict that, when price volatility is conditioned on average trade sizes and the number of transactions, average trade sizes should have no effect on price volatility (since the number of trades reflects the number of daily information arrivals, the mixing variable). These models have been criticized on the grounds that they are primarily statistical models, as opposed to equilibrium models of economic behavior (see Jones et al. (1994)).

Our results are at odds with the predictions of the competitive and strategic models, in that we find larger average trade sizes depress price volatility. This result is somewhat surprising, given that the structure of the muni market suggests that the asymmetries of information between investors are likely to be even more pronounced than in other markets. However, as we have touched on earlier, the muni market is a very illiquid market. It is relatively costly to break up a large block of bonds and search for buyers for each piece (costly both in terms of the direct transaction costs and the time it takes to find all of the individual bids). Hence, in order to carry out large liquidity-based transactions quickly and at low cost, institutional investors might find it cheaper to transact with other institutional investors. Since both sides to these transactions are informed, the trades in and of themselves would produce little price impact. Moreover, given the long lags in the dissemination of information about the trades to the rest of the market, uninformed investors would not see the trades and thus would not react. To investigate this conjecture, we split the sample into quartiles based on the trade volume of a bond in a given week (this turns out to be roughly equivalent to splitting the sample based on trade sizes). We find that the negative volume–volatility relation exists only among transactions in the uppermost quartile of the trade size distribution—big trades by institutional investors of about \$1 million or more in size each—in line with our conjecture. In the lower quartiles, we find that our results are much more consistent with the results found in the equity and futures markets.

When comparing our empirical results with those obtained in the equity, futures, or foreign exchange markets, it is important to bear in mind that our methodology differs somewhat from that typically used in studies of those more actively traded securities. Because muni bonds are traded relatively infrequently, we are unable to construct an unbroken time series of prices for virtually all of the bonds in our raw data sample. Hence, we are forced to use repeated cross-sectional regressions, as opposed to the time-series regressions used in most previous studies.⁵ This affects our results along at least two important dimensions. First, we are unable to examine the full cross-sectional variation in the volume–volatility relation. We estimate a single coefficient on our volatility variables, as opposed to a coefficient for each issuer (or firm (equities) or class of security (futures, foreign exchange)), as is typical in the other markets. Second, we are unable to control for any persistence in volatility that might be present at the issuer level. This means that, to a certain extent, the

⁵ Lo and Wang (2000) and Brennan and Subrahmanyam (1998) study the cross-sectional properties of trading volume in a different context.

significance of our coefficients ought to be interpreted with care, although the large size of our data sample (numbering in the thousands for each weekly regression) mitigates this issue to some extent. Despite these caveats, our findings add to the empirical literature on the volume–volatility relation by shedding additional light on the differences in the volume–volatility relation across markets, with implications for the growing theoretical literature on this important topic.

Our paper is organized as follows. Section I discusses the data set at some length and details the construction of the variables that we use in our empirical investigation. Section II presents our empirical results. Section III evaluates the robustness of our empirical findings, and Section IV concludes.

I. Data Description

A. MSRB Data

Since 1997, the municipal bond industry has operated under a mandatory transaction reporting regime overseen by the Municipal Securities Rulemaking Board (MSRB).⁶ All dealer-to-dealer and dealer-to-customer muni bond transactions are reported to the MSRB after the close of business each day. The MSRB assimilates the daily reports, and after two weeks have passed, releases electronic files containing the information.⁷ Our data are drawn from the comprehensive reports for the period July 2000 through February 2002.

The MSRB transaction reports contain the data fields shown in Table I. Of particular interest to this study are the date information (date of each trade, and for each bond the date of issue and date of maturity), the par amount traded, and the price at which the par amount is traded. The raw files contain a total of 12,309,409 transaction records. However, a defining feature of the muni bond market is that it is a very illiquid market. Figure 1 displays some basic information on trading activity in the muni market. Panel A shows a histogram of the number of trades observed for each bond.⁸ As can be seen from the figure, approximately one-third of the bonds trade only once over the entire period. The bulk of the remaining bonds trade two or three times, with a very long right tail into which fall bonds with many more transaction records.

The very illiquid nature of the muni market suggests that a daily observation interval, as is typically used in studies of price volatility in the equity and futures markets, may prove problematic. Indeed, fully 75 percent of the transactions are on single-trade days—that is, on days when the bond trades only once. On these days, one cannot compute a meaningful measure of the intra-day price volatility of the bond in question. A weekly measurement interval

⁶ Full details on the system are available at <http://www.msrb.org/>.

⁷ This lag was imposed at the request of the major muni bond dealers, purportedly in order to preserve liquidity in smaller issues. It is questionable whether the reporting lag preserves liquidity. In fact, the MSRB has been releasing the comprehensive data with shorter and shorter lags (at initiation, the lag was one month), suggesting that the concerns about liquidity were overblown.

⁸ This graph is based on trades that are sales to customers on the secondary market.

Table I
MSRB Comprehensive Transaction Reports Data Record Items

Variable	Description
CUSIP	CUSIP of issue traded.
Security description	Description of issue traded.
Dated date	Dated date of issue.
Coupon	Interest rate of issue.
Maturity date	Maturity date of issue.
When-issued indicator	Indicator of a trade occurring before the syndicate settlement date.
Assumed settlement date	For issues with unknown syndicate settlement date, a date 15 business days after the trade date.
Trade date	Date trade was effected.
Time of trade	Time of trade execution.
Par traded	Par amount of trade.
Dollar price (sale to customer)	If trade is a sale to customer, the dollar price (i.e., trades at the dealer's ask price).
Yield (sale to customer)	The yield-to-maturity (not always reported).
Dollar price (purchase from customer)	If trade is purchase from customer, the dollar price (i.e., trades at the customer's ask price).
Yield (purchase from customer)	The yield-to-maturity (not always reported).
Dollar price (inter-dealer)	If the trade was between dealers, the dollar price.
Yield (inter-dealer trade)	The yield-to-maturity (not always reported).

improves the situation somewhat, but we are still forced to exclude most of the transactions. As shown in panel B of Figure 1, a little over 65 percent of the transactions occur in weeks during which the bond trades just once. Despite this fact, we select the weekly measurement interval, as it seems to strike a reasonable balance between our need for multiple price observations in order to compute a measure of price volatility, and the requirement that the prices going into the volatility measure be conditioned on nearly the same information set.

In constructing the data sample used in our subsequent empirical analysis, we impose the following screening criteria. First, we restrict our attention to transactions that are sales to customers (trades that occur at the dealers' ask prices), in order to eliminate the possibility of bid-ask bounce effects. Second, we eliminate trades that occur on or before the underwriting syndicate settlement date (i.e., keeping only secondary market trades), focusing exclusively on arms-length transactions between dealers and investors. These restrictions reduce the number of data records to 5,616,779. Third, since we are interested in price volatility, we discard those bonds that are traded only once.⁹

⁹ It should be noted that, in principle, one could also examine *classes* of bonds in order to bring these single-trade bonds under consideration. However, this approach raises a host of issues concerning the comparability of different bond structures, so we focus instead on bonds for which we have multiple observations. Another alternative is to examine portfolios, but this requires unbroken price series for the securities in the portfolios, making it an unsuitable technique for bond price data.

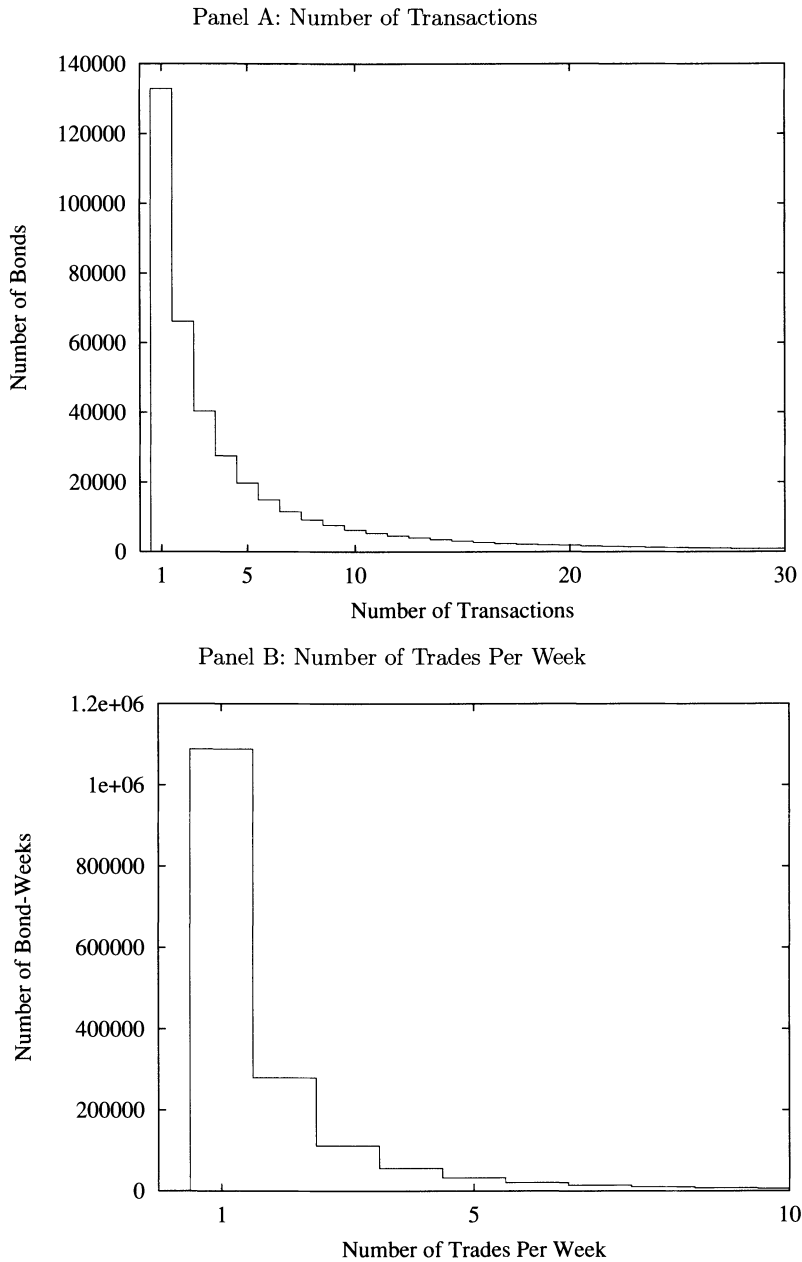


Figure 1. Histograms of trading activity. The upper panel displays a histogram of the number of transactions in each bond. The vertical bars indicate the number of bonds in the sample that are observed to trade the number of times given on the horizontal axis. The lower panel shows a histogram of the number of trades per week for each bond. The vertical bars indicate the number of bond-week observations where in a given week the bond is observed to trade the number of times given on the horizontal axis.

Fourth, in order to improve the signal-to-noise ratio in our volatility measure, we impose the requirement that a bond trade at least four times during the week. This results in our regressions having higher R^2 measures relative to regressions including data constructed with fewer observations per week, but does not otherwise change our basic results.¹⁰ Fifth, bonds maturing in less than one year are also discarded. Finally, to each of the data records, we match additional descriptive information obtained from Bloomberg. For each CUSIP, we add the rating of the bond when it was issued, information on the structure of the bond (e.g., whether the bond is callable or contains sinking fund provisions, or if the bond is insured), the issue size, and data on the nature of the issuer (e.g., if the security is a general obligation or a revenue bond). After applying our screening filters, and match-merging the descriptive information that is available from Bloomberg, our final estimation data set contains 219,902 bond-week observations.

B. Univariate Statistics

Since the goal of this article is to study the relation between price volatility and trading volume on the muni market, the first task at hand is to construct a measure of price volatility. In the subsequent empirical exercises, the primary measure of price volatility that we use is the scaled price range: The difference between the highest and the lowest prices during a week divided by the weekly average price. Range-based measures of price volatility have a long history in the finance literature (see Garman and Klass (1980), Parkinson (1980), Beckers (1983), and Ball and Torous (1984), among others). Intuitively, the price range is a better measure of intraweek price volatility than variables derived from closing prices or returns, since it can better capture the price variation within the week. Range is also less noisy than many other volatility measures, such as those based on returns, because there are less restrictions involved in constructing the measure.

More formally, let $P_i^{max}(t)$ and $P_i^{min}(t)$ denote the maximum and minimum observed prices for bond i during week t , respectively, and let $\bar{P}_i(t)$ denote the average price. Our dependent variable is given by

$$S_i(t) = \frac{100}{\bar{P}_i(t)} (P_i^{max}(t) - P_i^{min}(t)). \quad (1)$$

We scale the price ranges by the inverse of average price so that a given price change will be given greater weight if the bond is discounted, and vice versa.

¹⁰ We have carried out extensive sensitivity analysis of the choice of this threshold. We have re-run our analysis using cutoffs ranging from two to 10 trades, and none of our results change in a material way. In addition, we repeated all of our calculations using daily and bi-weekly observation intervals. For the daily intervals, given that so few bonds trade more than twice per day, we re-ran our regressions on bonds that trade twice or more in a given trading session. For the bi-weekly regressions, we included bonds that traded four or more times over the period. We found that none of our results are sensitive to these changes in the length of the observation interval.

The other weekly variables in our study are constructed based on the daily series for each variable. Specifically, weekly trading volume and the number of trades per week are defined as the sums of their respective daily counterparts, and the weekly average trade size is given as the weekly trading volume divided by the number of trades during the week.

The first row of Table II displays the unconditional means and standard deviations for the variables used in our analysis, where we have pooled all of the weekly data. The first column displays the univariates for our dependent variable. As the table indicates, on average, the proportional change in price is 1.360 percent with a standard deviation of 1.983 percent, showing that there is a significant degree of cross-sectional and time-series variation in price volatility. We observe an average of 10 trades per week on each bond, with substantial variation reflecting the long right tail illustrated in panel B of Figure 1. The average par amount traded is \$2.886 million per week, with a standard deviation of \$11.87 million, and the average size of each deal is \$0.429 million, with a standard deviation of \$1.739 million. The relatively small average deal size is indicative of the presence of “general public” (i.e., individual) investors, who tend to execute smaller trades than institutional buyers. The small average deal size also reflects the fact that municipal issues tend to be smaller than corporate or agency issues, for example, implying smaller block-sizes in secondary market trading.

The average maturity of the bonds in our sample is almost 18 years, with a standard deviation of 8.8 years, indicating that there is significant variation in the maturity dimension. However, the average bond is just 3.8 years old, with a standard deviation of 3.6 years, suggesting that a large proportion of the observations are trades occurring close to the date on which the bond was issued—which is in line with the conventional wisdom in the muni market that individual investors in muni bonds tend to follow buy-and-hold investment strategies. We observe bonds with a wide range of ratings from BBB (lowest investment-grade) up to AAA, but the majority of the bonds carry the highest rating.¹¹ The fact that so many muni bonds carry an AAA rating reflects the prevalence of bond insurance in the muni market; in fact, almost all of the AAA bonds in the sample are insured.¹²

In order to examine the characteristics of our sample in detail, we stratify the sample along several dimensions. First, we break the sample down into two groups—one containing trades that occur within three months of issue, and the other containing trades that occur later. As can be seen from Table II, the recently issued bonds trade more actively and with smaller average deal sizes than the seasoned bonds. Though there is substantial variation in both variables for each group, these results suggest that general public investors tend to most actively trade in a bond shortly after it is issued.

¹¹ We convert the alphabetic rating scales to numeric scales with AAA ratings assigned a value of 1, AA and A ratings a value of 2, and BBB ratings a value of 3. We exclude unrated and lower-rated bonds.

¹² For recent studies of the effects of insurance on muni bond yields, see Quigley and Rubinfeld (1991) and Hsueh and Chandy (1989).

Table II
Univariate Statistics

This table summarizes the characteristics of the weekly variables of the municipal bond data used in the empirical study stratified along the dimensions of age, maturity, rating, type, and optionality. For each subsample, the mean value of each variable and its standard deviation (in parenthesis) are reported. The label "All" refers to the whole sample; "Short" refers to the bonds with maturities between one and seven years; "Medium" refers to bonds with maturities between seven and 15 years; and "Long" refers to bonds with maturities longer than 15 years. The label "GO" refers to general obligation bonds; "S" denotes the spread between weekly high and low prices divided by average price; "N" denotes number of trades; "Avs" denotes the average trade size (in millions); "Vol" denotes the weekly trading volume (in millions); "Issue" denotes the issue size (in millions); "Maturity" denotes the years to maturity; "Age" denotes years since issuance; "Rating" denotes the bond rating (coded AAA = 1; AA/A = 2; BBB = 3); "Coupon" denotes the coupon rate; and "Nobs" is the number of observations.

Subsample	S	N	Avs	Vol	Issue	Maturity	Age	Rating	Coupon	Nobs
All	1.360 (1.983)	10.314 (16.022)	0.429 (1.739)	2.886 (11.871)	2.302 (3.755)	17.989 (8.824)	3.768 (3.586)	1.398 (0.598)	4.226 (2.142)	219,902
Age > 3 Months	1.369 (1.981)	9.905 (14.972)	0.438 (1.698)	2.890 (11.082)	2.434 (3.885)	18.071 (8.879)	4.357 (3.524)	1.405 (0.609)	4.225 (2.191)	189,442
Age ≤ 3 Months	1.301 (1.993)	12.862 (21.253)	0.374 (1.977)	2.864 (15.925)	1.382 (2.480)	17.481 (8.460)	0.105 (0.063)	1.354 (0.521)	4.233 (1.809)	30,460
Short	0.617 (1.033)	6.583 (5.848)	0.327 (1.714)	2.253 (15.057)	2.654 (4.059)	4.856 (2.084)	4.601 (4.539)	1.436 (0.569)	4.170 (2.076)	32,001
Medium	1.111 (1.932)	7.411 (6.580)	0.246 (1.152)	1.492 (6.034)	2.138 (3.465)	11.666 (2.053)	4.052 (4.275)	1.390 (0.581)	4.294 (2.075)	46,889
Long	1.611 (2.107)	12.127 (19.208)	0.513 (1.895)	3.493 (12.454)	2.278 (3.770)	23.072 (6.385)	3.485 (3.006)	1.391 (0.610)	4.216 (2.177)	141,012

AAA	1.399 (1.883)	10.943 (17.802)	0.350 (1.596)	2.442 (11.220)	2.262 (4.001)	18.204 (8.921)	3.562 (3.316)	1.000 (0.000)	4.212 (2.057)	145,448
AA/A	1.093 (1.461)	8.743 (11.442)	0.689 (2.160)	4.394 (14.189)	2.416 (2.935)	17.136 (8.720)	4.003 (4.003)	2.000 (0.000)	4.008 (2.297)	61,469
BBB	2.187 (3.967)	10.715 (12.711)	0.080 (0.328)	0.719 (2.352)	2.220 (4.270)	19.610 (7.792)	4.959 (4.066)	3.000 (0.000)	5.411 (1.922)	12,985
GO	1.164 (1.324)	9.013 (12.031)	0.302 (1.450)	1.995 (9.694)	2.229 (3.078)	14.979 (7.602)	3.102 (3.257)	1.353 (0.497)	4.181 (2.001)	69,459
Revenue	1.450 (2.216)	10.915 (17.529)	0.487 (1.855)	3.297 (12.730)	2.335 (4.022)	19.378 (9.001)	4.076 (3.687)	1.418 (0.638)	4.247 (2.203)	150,443
Not callable	0.949 (2.294)	7.096 (7.135)	0.305 (1.654)	2.092 (13.735)	2.886 (4.795)	8.460 (6.289)	3.506 (3.630)	1.368 (0.551)	3.419 (2.417)	40,864
Callable	1.453 (1.892)	11.049 (17.343)	0.457 (1.757)	3.067 (11.395)	2.174 (3.471)	20.164 (7.820)	3.828 (3.573)	1.404 (0.608)	4.410 (2.029)	179,038

We next explore the potential interaction of maturity and the volume–volatility relation with a stratification by maturity. We divide the sample into three subsamples: “short” maturity bonds, with maturities from one to less than seven years; “medium” maturity bonds, with maturities from seven to less than 15 years; and “long” maturity bonds, with maturities greater than or equal to 15 years. As shown in Table II, the short maturity bonds have an average maturity of 4.8 years, the medium maturity bonds have an average maturity of 11.7 years, and the long maturity bonds have an average maturity of 23.1 years. As we would expect based on their lower durations, the average price volatility of the short maturity bonds is much lower than that of the medium- and long-maturity bonds. Interestingly, the long-term bonds trade more actively, with a higher average number of trades per day, and with higher average trade volumes.

As noted earlier, one way the municipal bond market is distinguished from the other fixed income markets is by the prevalence of bond insurance. Some have suggested that the prevalence of bond insurance “commodifies” the muni market to a certain degree, raising the possibility that there might be an important interaction between credit quality, and the volume–volatility relation. In order to explore this possibility, we stratify the sample based on rating. The univariate statistics in Table II provide some evidence of liquidity differences among bonds of different credit quality. The lowest rated (“BBB”) bonds appear to be the least liquid, trading in quite small blocks relative to the rest of the market, with an average trade size of just \$0.08 million, relative to \$0.689 million for “AA” and “A” rated bonds, and \$0.350 million for “AAA” rated bonds. The lowest-rated bonds trade an average 10.7 times per day, compared to 8.7 times per day for “AA” and “A” rated bonds, and 10.9 times per day for “AAA” rated bonds.

The muni market is further distinguished from the other fixed income markets by the distinction between general obligation (GO) bonds, which are backed by the full faith and credit of a state or local government (making insured GO bonds close substitutes to Treasury securities, excepting their liquidity differences), and revenue bonds, which more closely resemble corporate bonds in that they are secured by specific revenue streams (e.g., the revenues generated by a toll road).¹³ General obligation bonds are generally viewed as fundamentally more secure than revenue bonds, and account for about a third of outstanding municipal debt. As shown in Table II, GO bonds trade with lower average price volatility than revenue bonds, and with somewhat lower average deal sizes and trade volumes. In addition, GO bonds have an average maturity of 15 years, while revenue bonds have a longer average maturity of 19 years.

Our final stratification separates out bonds that are callable from bonds that are not callable. It is fairly standard in the muni market for bonds with maturities greater than 10 years to contain call provisions, most often with 10 years of call protection and an initial strike price of \$101 or \$102 per \$100 of principal.

¹³ Some bonds are both GO and revenue bonds—so-called “double-barreled” bonds. These account for only a tiny fraction of the market, and are excluded from our sample.

As illustrated in Table II, the average maturity of the “Not Callable” bonds is less than 10 years. Moreover, the callable bonds carry higher average coupons, and trade with higher average price volatility, both reflecting the presence of embedded call options.¹⁴

II. Estimation Procedures and Empirical Results

In this section, we study the relation between price volatility and trading activity in the muni market. We first discuss the estimation methodology, and then present a general picture of the cross-sectional relation between price volatility and trading activity variables such as the number of trades, average trade size, and trading volume. We also examine the volume–volatility relation in the context of a set of corresponding pooled regressions, and test the constancy of the structural relation over the sample period. Lastly, we explore the potential interaction of the volume–volatility relation and bond characteristics by running separate regressions in subsamples along the dimensions of age, maturity, rating, revenue-backing, and optionality.

A. Estimation Methodology

To examine the cross-sectional relation between the scaled price range and variables measuring trading activity and bond characteristics, we estimate a series of regressions of the following form:

$$S_i(t) = \gamma + \sum_{j=1}^J \alpha_j Z_{i,j}(t) + \sum_{k=1}^K \beta_k X_{i,k}(t) + \varepsilon_i(t), \quad (2)$$

where i ranges over all of the bond issues and t indexes the weeks covered by our sample. In the regression specification (2), $S_i(t)$ is the scaled price range for bond i at week t , and the $Z_{i,j}(t)$ are variables measuring the trading activity in bond i , such as the number of trades, the average trade size, and the par volume traded. The $X_{i,k}(t)$ are controls for bond structure, including issue size, maturity, rating, age, and coupon. Cross-sectional regressions of the general form (2) are repeated each week under different sets of the $Z_{i,j}(t)$, resulting in a set of nested regressions.

The incremental statistical and economic significance of each explanatory variable can be gauged with the following battery of measures: (i) the proportion of weeks in which the variable is statistically significant in the weekly cross-sectional regressions, (ii) the Fama–MacBeth t -statistics, given by the ratio of the average of the weekly coefficient estimates and the corresponding standard error, which is defined as the standard deviation of the weekly parameter estimates divided by the squared-root of number of weeks (see Fama and Macbeth (1973)), and (iii) the incremental improvement in the adjusted- R^2

¹⁴ Duffee (1998) studies the effects of call options on corporate bond yields.

when an explanatory variable is added to the right-hand side of the regression equation. The first two measures examine the statistical significance of an explanatory variable, while the third measure assesses the economic significance of the relation between the scaled price range and the explanatory variable.

B. Empirical Results

As noted above, we use a series of nested regressions to test the cross-sectional relation between bond price volatility and the number of trades, average deal size, and trading volume. Each regression differs in the set of trading activity variables included on the right-hand side of the regression. We run a total of five regressions. In the first, only the number of trades (N) is included in the specification, in addition to the controls for different bond structures. In the second regression, trade volume (Vol) replaces the number of trades on the right-hand side of the regression equation. In the third regression, we add average size (Avs) to the first specification, in order to test whether it has any additional information beyond that incorporated in the number of trades. In the fourth regression, average size is replaced by trading volume, and in the fifth regression, all three variables—the number of trades, average trade size, and trade volume—are included.

Table III reports our main results. One result that stands out is that, as shown by the proportion of weeks that the indicator $1_{t_N > 2}$ equals 1 in the weekly regressions, the number of trades is significantly positive in 100 percent of the weekly regressions in the four specifications in which it is included as an explanatory variable. Moreover, the coefficient on N has a Fama–MacBeth t -statistic of 38 in all four regressions, with a coefficient estimate averaging close to 0.023 in all four regressions. These results are in line with the previous findings on the positive volatility–number of trades relation in other markets. When the number of trades variable is added to the regression specification containing trade volume, the adjusted- R^2 jumps from 10.5 to 14.8 percent, underscoring the important link between the number of trades and price volatility.

Another interesting result is that when trade volume is the sole trading activity variable on the right-hand side of the regression equation, it is negative and significant in 98.8 percent of the weekly regressions, with a Fama–MacBeth t -statistic of -27.9 . This result contradicts the positive volume–volatility relation found in the equity and futures markets (see Karpoff (1987)). This rather surprising result suggests that the volume–volatility relation is quite different in the fixed income markets than in the equity markets. This may be due to the different trading mechanisms in the equity and fixed income markets. While equity trading takes place in both exchange and dealer markets, the vast majority of trading in the muni bonds are carried out in a dealer market, which is much less transparent and not as liquid compared to equity markets, as we discussed at the outset.

The average trade size is found to be significantly negatively related to volatility when it appears as an additional explanatory variable alongside the number of trades. The coefficient estimates on average trade size have a mean value

Table III
Weekly Regression Results

This table reports the weekly regression results for the whole sample under five different regression specifications. The dependent variable is the price range, defined as the difference between the highest and lowest prices during the week divided by the average price. The explanatory variables are number of trades (N), average trade size (Avs) and/or trade volume (Vol), along with issue size (Issue), maturity, age, rating (coded AAA = 1; AA/A = 2; BBB = 3), and coupon. For each regression specification, the first row reports the average value of the coefficient estimates from the weekly cross-sectional regressions. The numbers in parentheses are Fama-MacBeth t -statistics, computed as the average coefficient estimate divided by the standard deviation of the coefficient estimates (the standard deviation of the weekly cross-sectional coefficient estimates divided by the square root of the number of weeks; see Fama and Macbeth (1973)). The R^2 statistics are adjusted for the degrees of freedom before averaging across the weekly regressions. The counting indicator $1_{N>2}$ is the proportion of weeks in which the t -statistic for the coefficient on variable N is greater than 2; the other counting indicators are defined analogously. The column labeled “Nobs” gives the average number of observations in the weekly regressions.

Const	N	Avs	Vol	Issue	Maturity	Age	Rating	Coupon	$1_{N>2}$	$1_{t_{Avs} < -2}$	$1_{t_{Vol} < -2}$	F	R^2	Nobs
-0.205 (-7.020)	0.023 (38.228)			0.035 (24.039)	0.037 (38.913)	0.012 (7.508)	0.064 (4.910)	0.108 (32.939)	100.0			4.39	13.1	2,467
-0.003 (-0.087)			-0.020 (-27.921)	0.045 (28.846)	0.047 (50.280)	0.006 (3.767)	0.060 (4.576)	0.084 (25.485)			98.8	4.23	10.5	2,467
-0.054 (-1.782)	0.022 (38.252)	-0.152 (-25.548)		0.037 (25.414)	0.040 (41.535)	0.014 (9.240)	0.084 (6.339)	0.064 (18.056)	100.0	98.8		4.32	15.0	2,467
-0.088 (-2.941)	0.024 (38.260)		-0.021 (-27.997)	0.039 (26.177)	0.040 (41.632)	0.014 (8.879)	0.082 (6.112)	0.069 (21.129)	100.0		98.8	3.76	14.8	2,467
-0.054 (-1.762)	0.022 (37.740)	-0.121 (-12.679)	-0.006 (-5.946)	0.038 (25.968)	0.041 (41.547)	0.014 (9.348)	0.085 (6.411)	0.062 (17.847)	100.0	64.7	15.3	4.56	15.1	2,467

of -0.152 over the period, and are significantly negative in 98.8 percent of the weekly regressions. Moreover, the coefficient estimate of the average trade size has a Fama–MacBeth t -statistic of -25.548 . The addition of average trade size on the right-hand side of the regression also improves the explanatory power of the model: The adjusted- R^2 increases from 13.1 percent in the regression where the number of trades is the only trading activity variable to 15.0 percent when both the number of trades and average trade size are included.

When average trade size is replaced by volume, the results are similar. Volume is negative and significant in 98.8 percent of the weekly regressions, with a Fama–MacBeth t -statistic of -27.997 , and the magnitude of improvement in adjusted- R^2 is also similar. These results suggest that the number of trades and the average trade size (or volume) contain distinct information, which contradicts previous findings that the volume–volatility relation disappears when the number of trades is controlled for (see Jones et al. (1994)).

When both average trade size and volume are added to the number of trades, average trade size is still negative and significant in a majority of the weekly regressions. However, volume is no longer significantly negative in many of the weekly regressions. At the same time, the improvement in adjusted- R^2 is minimal. This is not surprising, since average trade size and volume are by construction highly correlated. Taken together, these results show that average trade size and volume are interchangeable, and in later subsample analysis, we will focus on the regression that features the number of trades and average trade size as the trading activity variables.

The coefficient estimates of the control variables in the regressions are also noteworthy. It is interesting that the issue size is positive and significant in all of the regression specifications. This result could suggest that there are more individual investors involved in larger issues, given the evidence that noise trading tends to increase price volatility (see Daigler and Wiley (1999)).

As expected, years-to-maturity is positive and significant, with a Fama–MacBeth t -statistic around 40 in all five regressions. This result is consistent with the notion that bonds with longer maturity tend to have higher durations. Moreover, longer-term bonds have greater sensitivity to credit conditions and other macroeconomic or business cycle factors. Similarly, the coefficient of age has an average estimate around 0.014, and a t -statistic of about eight. Credit worthiness is negatively related to price volatility, as shown by the positive relation between the “rating” variable, which assigns a bigger number to a lesser credit worthy rating. And lastly, the coupon rate is positively and significantly associated with price volatility. This is due to the fact that high coupon bonds usually are also callable, and so their prices tend to fluctuate more than their noncallable counterparts. More detailed analysis of the relation between bond attributes and price volatility will be presented later on.

We also examine if our results on the volume–volatility relation stand when we pool all of the bond transaction records together. The main results from the pooled regressions remain the same as in the weekly regressions.¹⁵ The

¹⁵ To save space, we omit the full details of the results.

number of trades is positive and highly significant with a t -statistic of around 80 in all of the regressions. The coefficient estimate for the number of trades in the pooled regression is around 0.021, which is very close to the average coefficient estimate from the weekly regressions. Trading volume is negative and highly significant in regressions when it is the only trading activity variable or when it is paired with the number of trades. Similarly, the average trade size is negative and highly significant in all regressions. Moreover, as in the case of weekly regressions, adding the number of trades variable greatly enhances the explanatory power of the regression. As in the case of weekly regressions, trading volume or average trade size retain their incremental explanatory power when the number of trades is controlled for. Lastly, just like in the weekly regressions, when average trade size is already in the line-up of the explanatory variables, adding trade volume does not enhance the explanatory power of the regression.

A natural question is whether there are any structural changes in the volume–volatility relation over the sample period. As a first pass at this issue, we test the hypothesis that the coefficients of the explanatory variables in the regressions are the same for all weeks during the sample period. The F -statistics for each regression are reported in Table III. The hypothesis that the coefficient estimates are the same across the weeks is clearly rejected by the F -tests for all five regression specifications.¹⁶ This suggests that the pooled regression approach is overly restrictive.

In summary, we have taken a close look at the volume–volatility relation under five different specifications, in both weekly cross-sectional regressions and in pooled regressions. The most striking finding is that the coefficient estimates on average trade size and volume are negative, and that each retains its explanatory power when the number of trades is controlled for. We rejected the hypothesis that the structural relation between price volatility and our explanatory variables remains constant from week to week over the sample period. Bearing this in mind, in what follows we focus on the weekly cross-sectional regressions.

C. Subsample Evidence

In order to gain further insight into our main results, as well as to check their robustness, we next consider the volume–volatility relation in different strata of the data. We split the sample along the age, maturity, rating, bond type, and optionality dimensions. Table IV presents the empirical results for each subsample.

As noted in Section I, one characteristic of the muni market is that newly issued bonds trade more frequently than seasoned bonds. Since most muni bond issuers only release detailed financial information at the time a bond is issued, *ceteris paribus* the degree of information asymmetry in the market for

¹⁶ Due to the very large sample size, the critical values of the 95 percent F -tests are all approximately 1.0.

Table IV
Subsample Weekly Regression Results

This table reports the weekly regression results for each subsample, where “Short” refers to maturities between one and seven years; “Medium” refers to maturities between seven and 15 years; “Long” refers to maturities longer than 15 years; and “GO” refers to general obligation bonds. The dependent variable is the price range, defined as the difference between the highest and lowest prices during the week divided by the average price. The explanatory variables are number of trades (N), average trade size (Avs) and/or trade volume (Vol), along with issue size (Issue), maturity, age, rating (coded AAA = 1; AA/A = 2; BBB = 3), and coupon. For each regression specification, the first row reports the average value of the coefficient estimates from the weekly cross-sectional regressions. The numbers in parentheses are Fama–MacBeth t -statistics, computed as the average coefficient estimate divided by the standard deviation of the coefficient estimates (the standard deviation of the weekly cross-sectional coefficient estimates divided by the square root of the number of weeks; see Fama and Macbeth (1973)). The R^2 statistics are adjusted for the degrees of freedom before averaging across the weekly regressions. The counting indicator $1_{N>2}$ is the proportion of weeks in which the t -statistic for the coefficient on variable N is greater than 2; $1_{t_{Avs}>-2}$ is defined analogously. The column labeled “Nobs” gives the average number of observations in the weekly regressions.

Subsample	Const	N	Avs	Issue	Maturity	Age	Rating	Coupon	$1_{t_N>2}$	$1_{t_{Avs}<-2}$	R^2	Nobs
Age > 3 Months	-0.118 (-3.763)	0.023 (36.425)	-0.163 (-27.474)	0.037 (25.104)	0.043 (41.544)	0.015 (8.026)	0.095 (6.819)	0.065 (17.665)	100.0	98.8	15.3	2,158
Age ≤ 3 Months	0.288 (3.058)	0.026 (14.460)	-0.125 (-11.557)	0.045 (5.757)	0.025 (22.911)	-0.123 (-0.538)	0.024 (0.650)	0.046 (4.904)	90.6	72.9	21.6	309
Short	-0.129 (-2.307)	0.017 (14.110)	-0.094 (-9.459)	0.026 (11.493)	0.088 (26.417)	0.022 (7.185)	0.071 (3.547)	-0.013 (-2.454)	50.6	50.6	12.0	350
Medium	-0.146 (-1.657)	0.032 (21.515)	-0.177 (-11.772)	0.027 (8.348)	0.067 (15.292)	0.012 (4.069)	0.128 (4.232)	-0.002 (-0.318)	76.5	82.4	7.9	516
Long	0.276 (6.404)	0.022 (36.062)	-0.148 (-26.447)	0.046 (23.770)	0.021 (15.871)	0.006 (2.869)	0.097 (7.177)	0.095 (24.695)	100.0	98.8	13.9	1,600

AAA	0.247 (10.133)	0.021 (33.288)	-0.167 (-22.113)	0.039 (23.564)	0.040 (35.563)	0.013 (8.104)	0.029 (8.176)	100.0	98.8	17.1	1,632
AA/A	-0.191 (-7.424)	0.027 (31.384)	-0.124 (-19.765)	0.049 (26.440)	0.035 (41.412)	0.004 (1.937)	0.097 (21.236)	96.5	97.6	20.8	685
BBB	-0.122 (-0.754)	0.036 (11.073)	1.240 (3.764)	0.014 (2.529)	0.060 (12.640)	0.065 (5.601)	0.062 (2.839)	43.5	0.0	8.6	150
GO	0.318 (10.651)	0.029 (31.648)	-0.175 (-14.619)	0.042 (21.507)	0.040 (42.671)	-0.002 (-0.809)	-0.054 (-3.941)	98.8	97.6	19.9	766
Revenue	-0.143 (-4.213)	0.021 (36.263)	-0.154 (-24.617)	0.040 (23.054)	0.039 (37.740)	0.017 (9.476)	0.117 (7.647)	100.0	96.5	14.6	1,701
Not Callable	0.300 (6.263)	0.025 (13.710)	-0.143 (-10.363)	0.033 (11.338)	0.060 (23.232)	0.019 (5.575)	-0.062 (-15.336)	64.7	63.5	16.7	444
Callable	-0.290 (-7.461)	0.022 (37.180)	-0.132 (-23.541)	0.037 (23.817)	0.038 (35.258)	0.007 (4.089)	0.117 (8.307)	100.0	95.3	15.9	2,022

a particular bond should increase as the bond ages. To explore this possibility, we run our regressions separately for newly issued and seasoned bonds, as defined in Section I. As can be seen in Table IV, the number of trades is significantly positive in both subsamples. Average deal size is significantly negative in all but one (98.8 percent) of the weekly regressions for the seasoned group, while it is significantly negative in 72.9 percent of the regressions for the newly issued group. The stronger negative relation between volatility and average size in the seasoned subsample suggests that as the level of current information available to all investors falls, average deal size increases in importance. In other words, as time goes by, average deal size increases in value as an indicator of the amount of information in the price of a deal. A possible explanation for this result is that institutional (i.e., informed) traders tend to trade seasoned bonds more actively than general public investors. This explanation is also consistent with the generally held view in the muni market that general public investors tend to follow buy-and-hold investment strategies.

We next stratify the data by rating and maturity. The positive relation between volatility and number of trades and the negative association between volatility and average trade size is generally stronger for longer maturity bonds and higher rated bonds. In particular, unlike subsamples of AAA and AA/A bonds, the number of trades is significantly positive in only 43.5 percent of the weekly regressions for BBB bonds. Moreover, for BBB bonds the coefficient on average size has an average value of 1.240, and is not significant in any of the weekly regressions (using a one-sided test for a negative coefficient). However, the small average number of observations for the BBB bonds suggests we should exercise caution when interpreting these results. With respect to maturity, the proportion of weeks that the average trade size is significantly negative is only 50.6 percent for short-term bonds, compared to 82.4 percent for the medium-term bonds, and 98.8 percent for the long-term bonds. But again, the result on average size for the short-term bonds may not be completely comparable to that of the longer maturity bonds due to the differences in sample sizes. Overall, we interpret these results as suggesting that our main result is robust across differences in rating and maturity.

We also split the sample into subsamples of GO bonds and revenue bonds, and into callable bonds and noncallable bonds. There do not appear to be any major differences in the results for GO and revenue bonds. Callable bonds exhibit a stronger positive relation between volatility and the number of trades, as well as a stronger negative relation between volatility and average size. For noncallable bonds, the number of trades is significantly positive in 64.7 percent of weekly cross-sectional regressions, while it is always significantly positive for the callable bonds. And the average deal size is significant and negative in 63.5 percent of the weekly regressions for the noncallable bonds, while it is significant and negative in 95.3 percent of the regressions for callable bonds. Again, we interpret these results as supportive of our overall findings.

In summary, even though there is some variation across different groups of bonds, the subsample results show that our main conclusions are robust: Price

volatility is generally significantly positively related to the number of trades, and significantly negatively related to average trade size.

D. Regression Results by Volume

The regression results from the previous subsections show that, in contrast to the widely documented volume–volatility relations in the equity market, the relation between average deal size (or volume) and price volatility are negative on the muni market. What drives the difference in the volume–volatility relation between the muni market and the equity market?

One possible explanation is that, since the muni market is a very illiquid market, finding opposite matching orders is costly in terms of both time spent and the price impact. For big institutional investors trying to execute large liquidity-based transactions, it might be cheaper to trade with other institutional investors, rather than breaking up the block of bonds into small pieces (in order to trade with small individual investors). Since both sides of these big block transactions are informed investors, the trades would produce little price impact. On the other hand, trades involving small individual investors would increase price volatility, due to overreaction of uninformed individual investors, who cannot differentiate liquidity trades from information-based trades.

To shed some light on the validity of this conjecture, we split the weekly data into three subsamples based on volume: the top quartile, the middle two quartiles, and the bottom quartile. We then analyze the relation between price volatility and volume separately for each subsample. Univariate statistics show that there is substantial variation in the number of trades, trade volumes, and average deal sizes across the three subsamples. For the three subsamples, the average number of trades per week is 19.127, 8.713, and 4.818, respectively. The mean volumes of the three subsamples are 10.678 million, 0.383 million, and 0.086 million, respectively. Similarly, the mean average deal sizes for the top quartile, the middle two quartiles, and the bottom quartile are, respectively, 1.588, 0.053, and 0.018 million. These results are broadly in line with our conjecture that trades in the top quartile are primarily between big institutional investors, while trades in the other subsamples involve more individual investors. It is also interesting to note that there are no big differences in average issue sizes across these three subsamples.

Table V reports the weekly regression results for the three subsamples. The most important result from these regressions is that the average deal size is negative and significant in 85.9 percent of the regressions for the top quartile, while it is negatively significant in only 15.3 percent of the weekly regressions in the middle two quartiles, and it is not negatively significant in any of the weekly regressions for the bottom quartile. Moreover, the sign of the average weekly coefficient of average deal size changes from negative to positive for the bottom quartile. On the other hand, the number of trades remains positively significant in most of the weekly regressions for all three subsamples. Hence the regression results for the middle two and the bottom quartile are similar to what Jones et al. (1994) found on the equity market. Regression results with the number

Table V
Regression Results for Subsamples by Volume

This table reports the weekly regression results for subsamples by quartiles of volume: the top quartile, the middle two quartiles, and the bottom quartile. The dependent variable is the price range, defined as the difference between the highest and lowest prices during the week divided by the average price. The explanatory variables are number of trades (N), average trade size (Avs) and/or trade volume (Vol), along with issue size ($Issue$), maturity, age, rating (coded AAA = 1; AA/A = 2; BBB = 3), and coupon. For each regression specification, the first row reports the average value of the coefficient estimates from the weekly cross-sectional regressions. The numbers in parentheses are Fama-MacBeth t -statistics, computed as the average coefficient estimate divided by the standard deviation of the coefficient estimates (the standard deviation of the weekly cross-sectional coefficient estimates divided by the square root of the number of weeks; see Fama and Macbeth (1973)). The R^2 statistics are adjusted for the degrees of freedom before averaging across the weekly regressions. The counting indicator $1_{N>2}$ is the proportion of weeks in which the t -statistic for the coefficient on variable N is greater than 2; $1_{t_{Avs}}^2$ is defined analogously. The column labeled "Nobs" gives the average number of observations in the weekly regressions.

Volume Quartiles	Const	N	Avs	Issue	Maturity	Age	Rating	Coupon	$1_{N>2}$	$1_{t_{Avs}^2 < -2}$	R^2	Nobs
Top 25%	-0.389 (-5.112)	0.017 (25.858)	-0.084 (-17.022)	0.029 (7.269)	0.041 (29.387)	-0.024 (-7.421)	0.040 (1.310)	0.209 (25.441)	97.6	85.9	38.5	619
Middle 50%	0.189 (4.868)	0.038 (34.711)	-1.102 (-6.060)	0.033 (21.902)	0.049 (40.767)	0.027 (10.977)	0.145 (9.854)	-0.045 (-11.262)	95.3	15.3	13.8	1,203
Bottom 25%	-0.528 (-10.070)	0.113 (19.341)	6.737 (4.528)	0.038 (14.505)	0.040 (27.921)	0.062 (27.600)	0.082 (4.233)	-0.016 (-2.985)	61.2	0.0	8.1	645

of trades and volume as trading activity variables are similar with what we find in Table V. On balance, these results seem to support our conjecture that trades between big informed institutional investors dampen price volatility, while trades involving uninformed individual investors increase volatility.

III. Robustness Tests

In this section, more robustness checks are performed to evaluate the stability of the coefficient estimates. We conduct split-sample tests for time-series stability, we examine alternative regression specifications, and we check the sensitivity of the results to the choice of the price volatility measure. Finally, we look for year-end effects related to the selling of municipal securities for tax reasons.

A. Split-Sample Tests

We first examine the stability of our main results over the time period of our study. The F -test results reported earlier suggested that the coefficient estimates differ significantly across the weeks of our sample. In this subsection, we examine the data more closely to see if the F -test results are an indication that our main results do not hold across subperiods. We split the sample into two equal time periods, one covering the period from July 7, 2000 to May 3, 2001 and the other from May 4, 2001 to February 28, 2002. In each subperiod, we re-estimate the weekly regressions.¹⁷

The regression results for the subperiods are presented in panels A and B of Table IV. The subperiod results confirm our findings for the entire sample period. In both subperiods, the number of trades is always significant and positively related to price volatility. Moreover, the average trade size is, in general, significant and negative, even after number of trades is already included as an explanatory variable. The average size is significant and negative in 97.6 percent of the weekly regressions in the first period, and significant and negative in 100 percent of the regressions in the second period. Just as in the case of the entire sample, adding average size also increases the average explanatory power of the independent variables. For example, the average adjusted- R^2 in the first half increases from 13.4 to 15.4 percent when average size is added to the number of trades.

While our results appear to be robust within the time span of the available data, our sample period is necessarily short, owing to the fact that the MSRB data collection system has only been in existence for a few years. This raises the possibility that our results might be driven by market phenomena specific

¹⁷ We have repeated all of our empirical tests using a somewhat longer, albeit less comprehensive, data set covering the period August 1998 to 2002. The MSRB released less comprehensive transaction reports prior to July 2000 as a precursor to the comprehensive data that are now being disseminated. Unlike our comprehensive data set that starts in 2000, these data consist only of bonds that traded four or more times per day. None of our results change in a material way based on the longer data set.

Table VI
Regression Results for Sub-Periods

Panels A and B report the regression results for the 1st and 2nd halves of the sample period. The dependent variable is the price range, defined as the difference between the highest and lowest prices during the week divided by the average price. The explanatory variables are number of trades (N), average trade size (Avs) and/or trade volume (Vol), along with issue size ($Issue$), maturity, age, rating (coded $AAA = 1$; $AA/A = 2$; $BBB = 3$), and coupon. For each regression specification, the first row reports the average value of the coefficient estimates from the weekly cross-sectional regressions. The numbers in parentheses are Fama–MacBeth t -statistics, computed as the average coefficient estimate divided by the standard deviation of the coefficient estimates (the standard deviation of the weekly cross-sectional coefficient estimates divided by the square root of the number of weeks; see Fama and Macbeth (1973)). The R^2 statistics are adjusted for the degrees of freedom before averaging across the weekly regressions. The counting indicator $1_{N>2}$ is the proportion of weeks in which the t -statistic for the coefficient on variable N is greater than 2; the other counting indicators are defined analogously. The column labeled “Nobs” gives the average number of observations in the weekly regressions.

Const	N	Avs	Vol	Issue	Maturity	Age	Rating	Coupon	$1_{N>2}$	$1_{AAs<-2}$	$1_{Vol<-2}$	R^2	Nobs
Panel A: Regression Results for the First Half (7/7/2000–5/3/2001)													
-0.177 (-4.657)	0.025 (31.252)			0.033 (20.562)	0.040 (26.655)	0.008 (3.313)	0.017 (1.161)	0.108 (22.908)	100.0			13.4	2,633
0.052 (1.209)			-0.020 (-19.287)	0.043 (21.506)	0.048 (30.327)	0.002 (1.029)	0.024 (1.596)	0.084 (18.202)			97.6	11.3	2,633
-0.013 (-0.312)	0.024 (31.287)	-0.158 (-17.307)		0.036 (20.264)	0.043 (26.770)	0.010 (4.370)	0.036 (2.441)	0.064 (12.868)	100.0	97.6		15.4	2,633
-0.049 (-1.228)	0.026 (31.724)		-0.022 (-19.366)	0.037 (20.801)	0.042 (27.062)	0.010 (4.188)	0.034 (2.236)	0.070 (15.649)	100.0		97.6	15.2	2,633
-0.011 (-0.270)	0.025 (30.721)	-0.126 (-8.798)	-0.006 (-4.361)	0.036 (20.840)	0.043 (26.742)	0.010 (4.469)	0.038 (2.525)	0.062 (12.701)	100.0	69.0	23.8	15.5	2,633
Panel B: Regression Results for the Second Half (5/4/2001–2/28/2002)													
-0.056 (-1.589)	0.019 (25.641)			0.030 (10.546)	0.031 (32.373)	0.010 (5.017)	0.066 (3.166)	0.093 (18.440)	100.0			12.3	2,563
0.116 (3.005)			-0.018 (-17.425)	0.042 (13.856)	0.043 (43.471)	0.003 (1.728)	0.049 (2.228)	0.071 (12.280)			100.0	9.1	2,563
0.078 (1.988)	0.019 (26.059)	-0.141 (-14.265)		0.032 (11.463)	0.035 (37.113)	0.012 (6.638)	0.086 (3.960)	0.051 (8.220)	100.0	100.0		14.3	2,563
0.047 (1.241)	0.020 (25.900)		-0.019 (-17.275)	0.034 (11.855)	0.034 (36.661)	0.012 (6.272)	0.083 (3.868)	0.057 (9.785)	100.0		100.0	14.0	2,563
0.077 (1.966)	0.019 (26.821)	-0.115 (-8.016)	-0.005 (-3.550)	0.033 (11.431)	0.035 (37.594)	0.012 (6.681)	0.087 (4.005)	0.050 (8.125)	100.0	64.0	4.0	14.3	2,563

to the period we study. In particular, our sample period features historical lows in interest rates, a phenomenon that might have affected trading on the municipal bond market to the extent that yields on muni bonds shifted relative to other assets, or if the level of rates per se affects holdings of municipal securities. The robustness of our results might also be in question if, over the period we study, the relative holdings of municipal bonds by institutional (relatively informed) and noninstitutional (relative uninformed) investors are out of line with historical experience.¹⁸

Figure 2 plots the ratios of yields on municipal GO and revenue bonds over Treasury and AAA corporate bond yield indices from 1983 to 2002.¹⁹ As can be seen, the ratios of municipal over Treasury yields during our sample period approached 20-year highs, owing at least in part to a “scarcity premium” on Treasury securities stemming from expectations of substantial paydowns of the federal debt early in our sample period, and deteriorations in state and local credit quality later in the period. On the other hand, the ratios of municipal yields over AAA corporate yields are right around their historical average of 80 percent, suggesting little change in relative prices.

Figure 3 plots the percentages of municipal bonds held by households and nonhouseholds from 1945 to 2002, based on Federal Reserve flow-of-funds data. As can be seen, since 1945 there have been sizeable swings in the share of municipal securities held by households, with lows around 20 percent and highs near 50 percent. Importantly, holdings by households in our sample period are right around the historical mean of 35 percent, though individual holdings declined in the early 1990s and then reversed at a point roughly coinciding with strong performance in the equity market. While this analysis is not definitive evidence against the possibility that the volume–volatility relation is a function of the level of prevailing interest rates or other factors (for values outside of those that we observe in our sample), these results do suggest that the shares of municipal securities held by households and nonhouseholds during our sample period were well within the range of historical experience.

B. Time between Price Observations

It is likely that the length of time between transactions is positively related to price volatility, since longer intervals allow more time for information to arrive. If large trades tend to trade over shorter intervals during the week, then the negative coefficient on trade volume could reflect the omission of a control for the length of time between transactions. In the next exercise, we study whether adding the independent variable, hours, defined as the number of hours between the first and last trades during a week, alters our findings.

As shown in panel A of Table VII, our major conclusions do not change with the inclusion of the hours variable. The number of trades is significantly positive

¹⁸ We thank the referee for pointing out this important issue.

¹⁹ It is standard to use ratios instead of spreads when talking about the relative prices of municipal bonds because spreads would be negative, owing to the tax-exemption of municipal bonds.

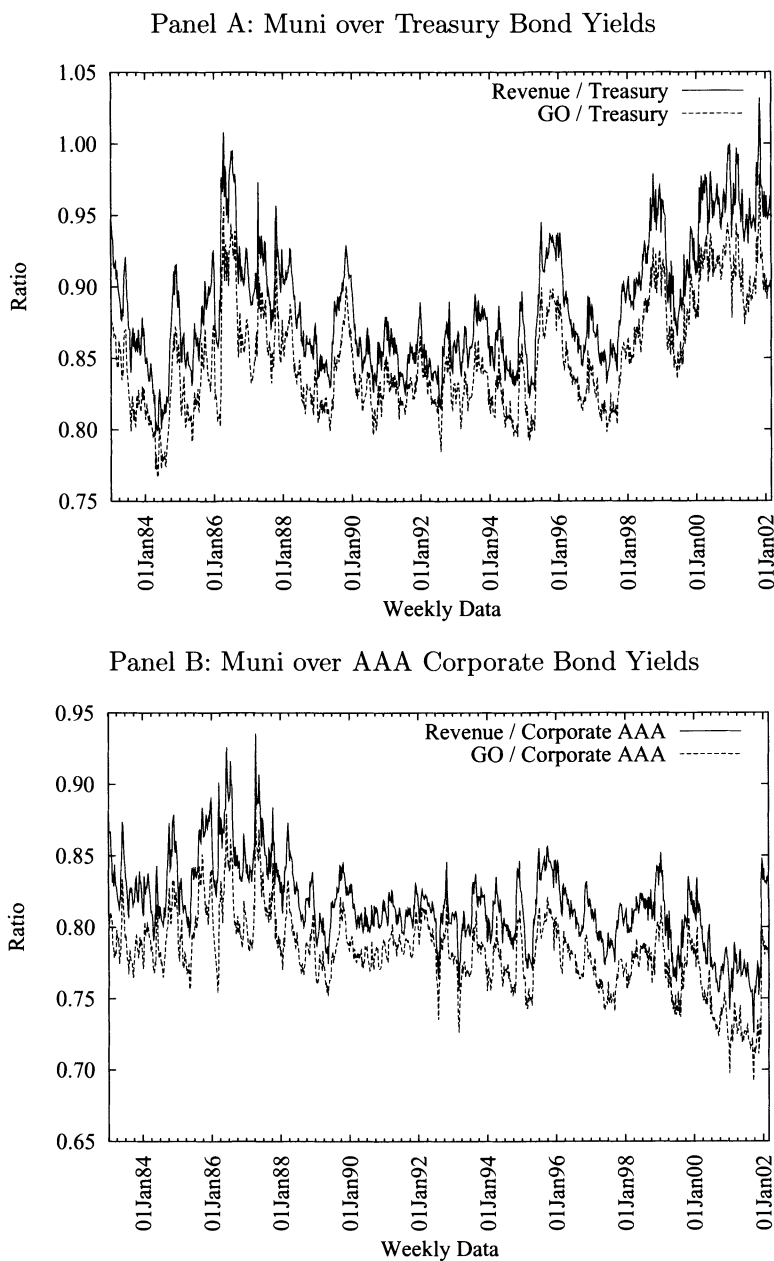


Figure 2. Ratios of municipal bond yields to treasury and corporate bond yields. The upper panel displays the ratio of long-term municipal revenue bond yields to Treasury bond yields (solid line), and the ratio of long-term municipal general obligation bonds to Treasury bond yields (dashed line). The revenue and general obligation bond yield indices are from the Bond Buyer. The Treasury bond yield is the constant maturity series calculated by the Department of the Treasury. The lower panel displays similar ratios, where the denominator is Moody's yield index for seasoned AAA corporate bonds, all industries.

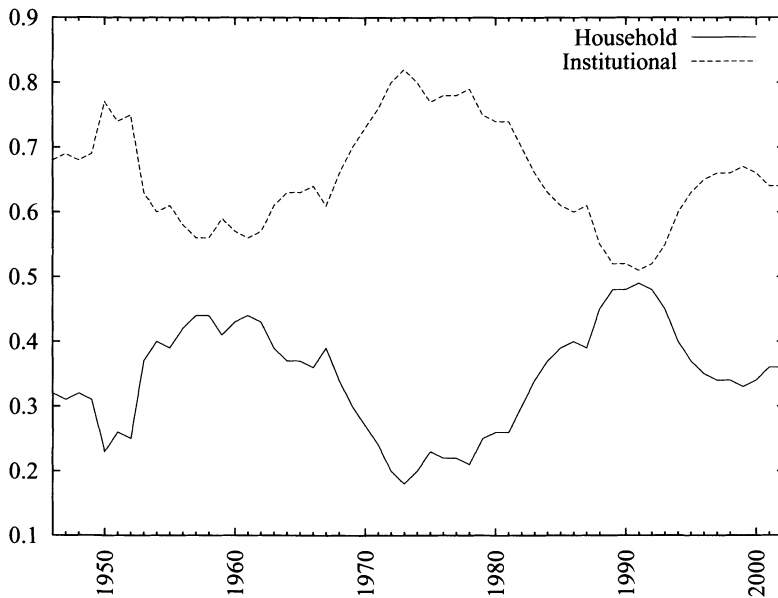


Figure 3. Shares of institutional and household holdings of municipal bonds. The figure displays the shares of all outstanding municipal bonds held by households and all other entities (institutional holders). The data are from the Federal Reserve's flow-of-funds accounts.

in all the weeks for all regressions, and the average deal size or volume is negative and significant in nearly all (98.8 percent) weekly cross-sectional regressions. However, the hours between the first and last trades is positive and significant, and it does improve the explanatory power of the regressions. For example, when hours between the first and last trades is added to the number of trades and the average deal size, the adjusted- R^2 increases from 15 to 18.9 percent. This suggests the length of time between the first and last trades during a week does explain some volatility in bond prices during the week.

C. Alternative Volatility Measure

We next evaluate the sensitivity of our results to the choice of price volatility measure. In a recent article, Alizadeh, Brandt, and Diebold (2002) show that the log range is a measure of price volatility with attractive statistical properties. Principally, the log range appears to be nearly Gaussian, making it a good instrument in quasi-maximum likelihood estimation. In their formulation, the log range is defined as $\log[\log(P^{max}) - \log(P^{min})]$, with P^{max} and P^{min} defined as before. We replicate our regressions using log range defined as above to test whether there are major changes in our results under this alternative price volatility measure.

As shown in panel B of Table VII, our main conclusions are unchanged under this alternative volatility measure. The number of trades is significantly

Table VII
Regression Results under Alternative Specifications

Panel A reports the regression results with the number of hours between the first and last trades during a week as an additional explanatory variable. Panel B reports the results for the whole sample period with log price range as the dependent variable. Log price range is defined as the log of the difference between the log of high price and the log of the low price for the week. The other explanatory variables include the number of trades (N), average trade size (Avs) and/or trade volume (Vol), along with issue size ($Issue$), maturity, age, rating (coded $AAA = 1$; $AA = 2$; $BBB = 3$), and coupon. For each regression specification, the first row reports the average value of the coefficient estimates from the weekly cross-sectional regressions. The numbers in parentheses are Fama-MacBeth t -statistics, computed as the average coefficient estimate divided by the standard deviation of the coefficient estimates (the standard deviation of the weekly cross-sectional coefficient estimates divided by the square root of the number of weeks; see Fama and Macbeth (1973)). The R^2 statistics are adjusted for the degrees of freedom before averaging across the weekly regressions. The counting indicator $1_{N>2}$ is the proportion of weeks in which the t -statistic for the coefficient on variable N is greater than 2; the other counting indicators are defined analogously. The column labeled "Nobs" gives the average number of observations in the weekly regressions.

Const	N	Avs	Vol	Hours	Issue	Maturity	Age	Rating	Coupon	$1_{N>2}$	$1_{Avs<-2}$	$1_{Vol<-2}$	R^2	Nobs
Panel A: Regression Results with Hours Included as an Explanatory Variable														
-0.648	0.017			0.010	0.028	0.030	0.013	0.053	0.110	100.0			17.0	2,467
(-22.220)	(36.084)			(39.730)	(20.824)	(32.244)	(8.954)	(4.359)	(32.547)					
-0.556			-0.020	0.012	0.035	0.037	0.010	0.054	0.082			98.8	16.5	2,467
(-18.622)			(-30.227)	(44.836)	(25.157)	(41.679)	(6.923)	(4.378)	(24.931)					
-0.496	0.016	-0.147		0.010	0.030	0.033	0.015	0.073	0.067	100.0	98.8		18.9	2,467
(-16.314)	(35.700)	(-27.098)		(39.897)	(22.386)	(35.415)	(10.689)	(5.870)	(19.135)					
-0.532	0.018		-0.021	0.011	0.032	0.033	0.015	0.071	0.071	100.0		98.8	18.8	2,467
(-17.786)	(36.277)		(-29.805)	(40.249)	(23.272)	(35.460)	(10.419)	(5.673)	(21.815)					
-0.499	0.017	-0.099	-0.009	0.010	0.031	0.034	0.016	0.074	0.065	100.0	54.1	29.4	19.0	2,467
(-16.399)	(35.131)	(-11.417)	(-8.718)	(40.120)	(23.011)	(35.378)	(10.816)	(5.952)	(18.983)					

Const	N	Avs	Vol	Issue	Maturity	Age	Rating	Coupon	$1_{N>2}$	$1_{Aus<-2}$	$1_{Vol<-2}$	R ²	Nobs
Panel B: Regression Results with Log Price Range as Dependent Variable													
-8.911 (-132.951)	0.038 (33.212)			0.099 (35.171)	0.016 (9.697)	-0.055 (-15.443)	-0.421 (-25.261)	0.595 (66.315)	100.0			17.3	2,467
-8.351 (-128.098)			-0.073 (-24.588)	0.124 (38.900)	0.038 (23.387)	-0.061 (-17.200)	-0.394 (-23.867)	0.485 (55.918)			100.0	19.0	2,467
-8.389 (-125.017)	0.035 (32.707)	-0.536 (-23.644)		0.107 (37.495)	0.028 (17.028)	-0.046 (-13.554)	-0.349 (-20.910)	0.442 (45.365)	100.0	100.0		21.7	2,467
-8.501 (-132.687)	0.041 (33.702)		-0.076 (-24.560)	0.112 (38.038)	0.027 (16.551)	-0.048 (-13.585)	-0.358 (-21.058)	0.461 (52.579)	100.0		100.0	21.2	2,467
-8.388 (-124.308)	0.037 (33.029)	-0.398 (-12.875)	-0.027 (-7.590)	0.109 (38.233)	0.029 (17.591)	-0.046 (-13.348)	-0.345 (-20.676)	0.436 (45.828)	100.0	78.8	41.2	21.9	2,467

Table VIII
Test for Tax-Loss Selling Effects

Panels A and B report the weekly regression results for the December-only and non-December subsamples respectively under five different regression specifications. The dependent variable is the price range, defined as the difference between the highest and lowest prices during the week divided by the average price. The explanatory variables are number of trades (*N*), average trade size (*Avs*) and/or trade volume (*Vol*), along with issue size (*Issue*), maturity, age, rating (coded *AAA* = 1; *AA* = 2; *BBB* = 3), and coupon. For each regression specification, the first row reports the average value of the coefficient estimates from the weekly cross-sectional regressions. The numbers in parentheses are Fama-MacBeth *t*-statistics, computed as the average coefficient estimate divided by the standard deviation of the coefficient estimates (the standard deviation of the weekly cross-sectional coefficient estimates divided by the square root of the number of weeks; see Fama and Macbeth (1973)). The *R*² statistics are adjusted for the degrees of freedom before averaging across the weekly regressions. The counting indicator *1_{N>2}* is the proportion of weeks in which the *t*-statistic for the coefficient on variable *N* is greater than 2; the other counting indicators are defined analogously. The column labeled "Nobs" gives the average number of observations in the weekly regressions.

Const	N	Avs	Vol	Issue	Maturity	Age	Rating	Coupon	<i>1_{N>2}</i>	<i>1_{AAA<-2}</i>	<i>1_{t_{Vol}<-2}</i>	<i>R</i> ²	Nobs
Panel A: Regression Results for the December-Only Subsample													
-0.485 (-7.557)	0.027 (8.249)			0.035 (5.378)	0.050 (19.160)	-0.007 (-0.999)	0.175 (6.424)	0.152 (18.976)	100.0			10.6	1,771
-0.304 (-4.141)	0.026 (8.278)	-0.209 (-8.374)		0.036 (5.430)	0.055 (20.669)	0.002 (0.336)	0.199 (7.356)	0.091 (9.858)	100.0	100.0		12.3	1,771
-0.367 (-5.486)	0.028 (8.500)		-0.026 (-10.295)	0.038 (5.738)	0.054 (22.336)	0.001 (0.116)	0.193 (6.965)	0.103 (15.556)	100.0		88.9	12.0	1,771
-0.304 (-4.120)	0.026 (7.314)	-0.243 (-3.509)	0.005 (0.456)	0.035 (6.173)	0.055 (21.314)	0.003 (0.414)	0.201 (7.423)	0.089 (10.091)	100.0	66.7	0.0	12.5	1,771
-0.243 (-4.426)			-0.023 (-10.117)	0.043 (6.413)	0.059 (25.212)	-0.010 (-1.633)	0.190 (7.141)	0.116 (18.136)			88.9	9.5	1,771
Panel B: Regression Results for the Non-December Subsample													
-0.246 (-8.563)	0.023 (30.509)			0.032 (21.795)	0.039 (47.273)	0.009 (5.231)	0.086 (6.007)	0.120 (34.016)	100.0			12.8	1,675
-0.086 (-2.841)	0.022 (30.230)	-0.167 (-29.385)		0.032 (22.127)	0.043 (52.698)	0.015 (8.184)	0.105 (7.310)	0.070 (17.124)	100.0	98.8		14.9	1,675
-0.119 (-4.028)	0.024 (31.280)		-0.024 (-30.918)	0.033 (22.726)	0.042 (51.720)	0.015 (8.050)	0.103 (7.116)	0.075 (19.642)	100.0		98.8	14.7	1,675
-0.088 (-2.877)	0.022 (30.190)	-0.116 (-12.897)	-0.010 (-9.356)	0.033 (22.360)	0.043 (52.653)	0.015 (8.427)	0.106 (7.364)	0.068 (16.996)	100.0	51.8	22.4	14.9	1,675
-0.029 (-0.934)			-0.022 (-30.301)	0.040 (25.206)	0.050 (65.351)	0.005 (2.826)	0.080 (5.564)	0.089 (22.616)			96.5	10.4	1,675

positive in 100 percent of the weekly cross-sectional regressions under all regression specifications. When average deal size or volume is added to the specification, they are significantly negative in all of the weekly regressions.

D. Tax-Loss Selling

For many securities markets, there are predictable year-end phenomena involving the selling of securities for tax purposes. In the muni market, this is often referred to as “tax-loss selling.” To investigate if tax-loss selling at year-end might have affected trading behavior over the period we study, we split the sample into two subsamples, one containing only December observations and the other containing the rest of our observations. We then replicated our empirical tests for both subsamples. As shown in Table VIII, our results are virtually unchanged, suggesting that tax-loss selling is not an important factor driving our results, at least over the period we study.²⁰

IV. Conclusion

In this paper, we made the first comprehensive test of the volume–volatility relation in the municipal bond market. We found that the number of trades observed over a week is positively associated with the price volatility of a particular bond. However, we found that price volatility is negatively related to the average transaction size, and that the average transaction size retains its explanatory power even when the number of trades is controlled for. These results were found to be robust in different strata of the data, as well as through time. We split the sample into quartiles based on trade volume, and found that the negative volume–volatility relation is driven principally by trades in the upper quartile of trade sizes. In the lower quartiles, our results were similar to those found in the equity and futures markets.

As noted at the outset, our results are at odds with the predictions of competitive and strategic models of the volume–volatility relation. When interpreted in the context of the muni market structure, however, a direction for future modeling approaches is indicated. Our results seem to suggest that models of the volume–volatility relation need to take into account overall market liquidity, and how this affects the costs of carrying out large transactions. If market liquidity is very low, as in the muni market, large informed investors may be forced to trade with one another, perhaps resulting in a very different relation between volume and price volatility than predicted by the models extant in the literature.

In this research we have focused on the relation between trading activity and price volatility. An important related question is what drives trades to market? A natural approach to this question would be to examine the degree to which

²⁰ It should be pointed out that the incidence of tax-loss selling is path-dependent in interest rates. Hence we cannot rule out the possibility that, in the more distant past, there were episodes where tax-loss selling was an important factor driving trading activity at the end of the year.

index-tracking, movements of prices in related markets such as the Treasury and equity markets, and other factors might help explain the intensity of trade arrivals on the municipal borket. We leave this question for future work.

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