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Do Municipal Bond Exchange-Traded Funds Improve Market Quality?

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ABSTRACT

I examine the relationship between exchange-traded funds (ETFs) and the liquidity profiles of municipal bonds. Using data on the bond-level holdings of ETFs from 2010-2020, I find that bonds held by ETFs tend to trade more often than bonds held by mutual funds, but with little or no impact on price dispersion, returns, or systematic risk. However, these effects vary considerably by the type of bond. Lower credit quality bonds held by ETFs tend to trade much more frequently than those with higher credit quality. Market conditions also matter. During the COVID-19 market dislocation of March 2020, bonds held by ETFs traded far less often. These results have implications for regulators' stated concerns about the liquidity differential between ETFs and their underlying holdings, especially during market downturns. My findings suggest that at best ETFs bolster municipal bond liquidity overall, and at worst, bonds held by ETFs are no less liquid than bonds held in mutual funds.

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1. Introduction

In this paper I examine how exchange-traded funds (ETFs) affect the liquidity of municipal bonds. A bond ETF is a tradable security that tracks a bond index. Like mutual funds, ETFs own the underlying bonds and can create and redeem shares in the fund every day. Unlike mutual funds, investors in ETFs can trade in and out of positions throughout the day because ETFs trade like a stock on an exchange. This makes them attractive to investors who want a degree of liquidity not typically available in fixed income over-the-counter markets.

ETFs are, in many ways, an ideal innovation for the municipal bond (i.e. "muni") market. The muni market is fragmented. It is comprised of nearly one million active muni CUSIPs, compared to roughly 35,000 active corporate CUSIPs (Mizrach 2015). It's also comparatively illiquid. Most munis trades a few times over their lifespan, where most corporate bonds trade dozens of times each day (Wu 2018; Downing and Zhang 2004). Unlike publicly traded corporations, state and local government financial disclosure is largely unregulated, so price-relevant information can be costly to obtain (Cuny 2018). This lack of liquidity and high search costs are reflected in mark-ups on muni trades that are often orders of magnitude larger than similar trades in corporates or equities (Wu 2018; Schultz 2012; Edwards, Harris, and Piwowar 2007; Green, Hollifield, and Schurhoff 2007; Harris and Piwowar 2006). The muni market has high barriers to entry, but ETFs are a comparatively low-cost, well-diversified, and richly informed vehicle for investors to access it.

Given those benefits it's not surprising that muni-focused ETFs have grown in scope and scale. According to ETF Exchange, the number of municipal bond focused ETFs has grown from just one in 2006 to 56 in 2020. Figure 1 shows the ten-year trend in ETF, closed-end fund, and mutual fund holdings of municipal bonds. ETF holdings are currently roughly 6% of mutual fund holdings, but they have increased almost exponentially throughout the past decade. Overall trading activity in muni ETFs has also grown considerably. For instance, trading volume in the largest muni ETFs by assets - iShares National Muni Bond ETF (ticker: MUB) - has grown 39% annually since it launched in September 2007.

But despite these benefits, ETFs also raise concerns for regulators and policymakers. Many of those concerns surround liquidity dynamics. Like with many fixed income ETFs, the bonds held by muni ETFs can be considerably less liquid than the ETF itself. That can create a substantial liquidity mismatch where ETF issuers might need to buy (sell) a particular bond at a considerable price premium (discount) when liquidity is scarce. This mismatch can distort the relationship between the ETF's net asset value and its share price. It can also uncouple the ETF from the market index it is designed to track. Regulators like the Municipal Securities Rulemaking Board (Wu and Burns 2018) and the Securities and Exchange Commission (2019) have taken note and have called for more attention to how ETF inclusion affects the liquidity of individual bonds (Wu 2020; Wu and Burns 2018). This paper is a response to that call in the muni context.

Concerns about the liquidity mismatch became strikingly evident during the "COVID-19 Crisis" of March 2020. On March 12, President Trump suspended travel from Europe to the US. That announcement triggered a massive flight to safety across virtually all domestic financial markets. Several large money managers responded by liquidating positions in muni ETFs to free up cash to then redirect to Treasuries and other safe assets. Those liquidations forced a massive dislocation in the muni ETF market. From March 16 through March 27, more than $3.2 billion - or roughly 7% of the sector's assets under management (AUM) - flowed out of muni ETFs. By comparison, the average outflow across all other bond ETFs was about 2.5% of AUM.

Muni ETF share prices and net asset values (NAV) responded in ways consistent with the liquidity mismatch story. For the past several years, MUB's typical daily price/NAV ratio was +/- 10 bps. On March 18, 2020 it was -577 bps. On March 20, 2020 the Fed announced plans to expand its Money Market Fund Liquidity Facility (MMLF) to include a backstop for tax- exempt money market funds (MMFs). That move injected badly needed liquidity into the short end of the muni market. Muni ETFs responded, and by March 26, 2020 MUB's price/NAV ratio had soared to +157 bps. Since then it's settled into a more typical range of +/- 25 bps.

The COVID-19 crisis illustrates an extreme version of how ETFs can exacerbate the price dynamics that follow from the municipal bond market's inherent illiquidity. Fortunately, the data employed in this paper offer some visibility into how ETFs affected individual bond liquidity during this period. At the same time, a more relevant policy question is how ETFs shape individual bonds' liquidity profiles in more typical market conditions? The analysis presented here also addresses that question.

My main finding is that ETFs bolster muni liquidity. When ETFs hold more of a muni, it trades more frequently, at lower price dispersion, and at lower volume-adjusted daily returns. These volume-related effects are especially strong for bonds with lower credit quality. The estimated effect of ETF ownership on bond turnover for BBB-rated and below investment grade bonds is more than three times as large as that effect for other credit quality classes.

However, I also find this relationship is contingent on market conditions. When daily returns are negative the effect is reversed, and bonds with a greater share of ETF ownership trade at higher yields. I also find that during the "COVID Crisis" the ETF liquidity boost was cut in half. These results offer support for regulators' concerns about the ETF liquidity mismatch. It's clear that in certain market conditions ETFs can tighten liquidity, or at a minimum, not impart any particular liquidity advantage relative to other patterns of institutional ownership.

To my knowledge this paper is the first to examine the implications of ETF ownership for individual municipal bonds. Wu and Burns (2018) found that the overall growth in muni ETF AUM did not affect market-wide muni trading volume. Their analysis was based on aggregated market wide data and did not address the liquidity of individual munis. The papers closest to my paper are a trio of recent analyses of the effects of ETF ownership on corporate bond liquidity. The first is Rhodes and Mason (2019), who find that corporate bonds held by ETFs tend to be more liquid but also exhibit more systematic risk. Another is Agapova and Volkov (2018), who also find that ETF ownership improves liquidity and price discovery relative for corporate bonds across all levels of credit quality. In a related paper focused on corporate bond yields, Dannhauser (2017) finds that ETF inclusion had no discernible effect on corporate bond liquidity. My paper employs a similar methodology as these papers and arrives at roughly similar conclusions for munis.

The rest of this paper is organized as follows. In the next section I briefly review mechanics of fixed income ETFs, with special attention to how their arbitrage function and share creation process can amplify the liquidity mismatch. In the third section I describe the data used throughout the analysis and outline a variety of stylized facts about muni ETFs and their holdings. In the fourth section I describe the liquidity and market sensitivity measures, and outline some testable hypotheses about how ETF inclusion affects those measures. The fifth section is a presentation of the main empirical findings, and the sixth section is an overview of a variety of sub-sample analyses and follow-up tests. In the conclusion I discuss these policy and regulatory implications of these findings.

2. ETF Mechanics and Liquidity Dynamics

ETFs blend the core features of mutual funds with the core features of closed-end funds. Like mutual funds, they offer investors an ownership interest in a diversified, index-linked, professionally managed asset portfolio. But unlike mutual funds, they trade on an exchange, they offer intra-day liquidity, and their share price can deviate from their net asset value (NAV). So with respect to liquidity and price transparency, they are much more like closed-end funds.

This hybrid structure is made possible by a unique share creation/redemption mechanism. ETF issuers sanction a group of asset managers - known as Authorized Participants (APs) - to arbitrage away gaps between the fund's share price and its NAV. This process works as follows. When the ETF is trading above its NAV, APs buy a representative basket of the fund's underlying securities, and then offer those securities to the ETF issuer in exchange for blocks of the ETF's shares. APs can then sell those shares in the secondary market for a profit. This process works in reverse when the ETF is trading below its NAV. In that case, APs buy ETF shares in the secondary market, exchange those shares with the issuer for representative securities, and then sell those securities in the secondary market. This arbitrage process is designed to quickly align the share price with the NAV.

Of course, this creation/redemption mechanism is only effective when arbitrage is efficient. When the arbitrage opportunity is slower, as it often the case in fragmented and illiquid fixed income markets, price/NAV deviations can be large and persistent. In fact, it's often said that without efficient arbitrage, ETFs essentially become closed-end funds that trade at a hefty discount.

This is especially true in the municipal market, when contemporaneous prices on individual securities are not nearly as transparent as corporates or Treasuries, and where many bids simply do not find a corresponding ask. It follows that when liquidity is further constrained, such as in a sharp market downturn, APs attempting to sell securities can do so only at a substantial discount. This is the ”liquidity mismatch” of interest to market participants and regulators.

Given these mechanics, there are two competing stories for how ETFs might affect muni bond liquidity. One view is that they increase liquidity because the arbitrage mechanism encourages trading. To successfully arbitrage, APs must regularly buy and sell bonds included in the ETF's related index. Since most bond indices include thousands of individual CUSIPs, ETF trading could span a wide cross-section of otherwise illiquid bonds. As a corollary, bond dealers know that if they buy bonds analogous to those held in an ETF, that the ETFs portfolio manager may be an interested buyer. As a result, APs and bond dealers have a stronger incentive to make a tighter market in bonds held by ETFs. More generally, ETFs allow uninformed investors to better hedge and speculate in an otherwise shallow market. Taken together, these supply-demand dynamics are thought to bolster overall trading volume and increase turnover.

ETFs can also strengthen liquidity by expediting price discovery. Bhattacharya and O'Hara (2018) argued that ETFs increase the level of information across financial markets because uninformed traders in underlying asset markets look to ETFs for price signals from informed traders. They also show this information-sharing process can at times make markets more fragile because it encourages herd trading and runs on assets, but the hypothesized increase in market-wide information is clear. Tucker and Laipply (2013) show that fixed income ETFs are especially efficient as a price discovery mechanism. In fact, they document that corporate bond ETF price movements often lead subsequent bond price movements in the cash market. This clearer and more informative price signal from ETFs, the argument suggests, narrows price dispersion and minimizes returns in the underlying bonds. I employ a series of four proxies to measure these different trade-based and price-based dimensions of liquidity.

However, there are several interrelated views that suggest ETFs constrain liquidity. One view implies that they unintentionally reduce the incentives to trade. When uninformed noise traders use ETFs to capitalize on technical market movements, the informed investors left behind in the cash market are far less likely to trade with each other (Ben-David, et. al. 2017). In her study of corporate bond ETFs, Dannhauser (2017) described this adverse selection effect in the corporate bond market as uninformed investors leaving informed investors "with less camouflage to disguise their trades," and informed investors trading less as a result. This would suggest ETF inclusion reduces trade volume and increases price dispersion.

The ETF share creation/redemption process can also impede liquidity. Recall that when an ETF is trading at a price/NAV premium, APs transfer bonds to the ETF sponsor in exchange for shares. That transfer reduces the supply of those bonds and potentially impedes future liquidity.

A related problem is that APs may not be reliable arbitrageurs. Pan and Zeng (2019) found that when AP's balance sheets are constrained, they withdraw from corporate bond ETF arbitrage. APs must also contend with potential conflicts of interest when they act both as participants in the share creation/redemption process, and as broker/dealers for those shares in the secondary market. A natural extension of this logic is that APs may go so far as to create ETFs not to close price/NAV gaps, but rather to manage the liquidity of their own inventories.

Taken together, these arguments offer compelling ex-ante reasons to believe ETFs might bolster or impede muni liquidity.

3. Data and Overview of ETF Muni Holdings

3.1 Sources and Dataset Construction

The data used in this analysis are from three sources. Data on ETF muni holdings are from Refinitiv. These data are gathered from individual ETFs' N-Q and 10-Q quarterly SEC filings. These data are available from March 31, 2006 through March 31, 2020. The later date is the most recently available set of quarterly filings. The Refinitiv data also include mutual fund and closed-end fund holdings of municipal bonds. I also collect those data and employ them as a comparison group throughout this analysis. The complete data file includes the holdings of 51 ETFs and 628 mutual fund portfolios across this 2006-2020 time period. Some funds manage multiple portfolios, but portfolios do not overlap. All observations of fund holdings are from the last date of each quarter.

Given that the focus here is ETF holdings, I then identified all municipal bonds held in any ETF portfolio during any quarter from 2010-2020. That list included 47,469 unique CUSIPs from 2,895 individual issuers. I then identified mutual fund and closed-end fund holdings of those same bonds during those same quarters. Throughout this analysis I refer to the combined data on mutual funds (i.e. open-end funds) and closed-end funds as simply "mutual funds." The combined dataset of ETF holdings and mutual fund holdings included 369,448 quarterly bond-portfolio observations.

With the fund holdings identified, I then matched those holdings data with secondary market trades from the Municipal Securities Rulemaking Board (MSRB). Even though the fund holdings data are available starting in 2006, I use the MSRB data beginning in 2010. I do this for two reasons. First, the muni market liquidity premium has increased considerably since the Great Recession, due in large part to the collapse of the monoline muni bond insurers (Marlowe 2013; Ang, et. al. 2014), and to a decline in the total number of municipal bond dealers and stronger risk management practices among the dealers that remain. Those changes make it difficult to compare muni liquidity before 2010 with muni liquidity after 2010. Second, the MSRB has changed its secondary market trade reporting requirements several times in the past two decades, but since 2010 those requirements have remained mostly unchanged (see Schultz 2012). With that assumption established, I observe that these 47,469 bonds traded 9,540,963 times in total from January 2010 through March 2020. A total of 5,346,403 of those trades happened when those bonds were held in ETF portfolios. Note also that many of those bonds were also contemporaneously held in mutual fund portfolios. The remaining 4,194,560 trades happened when these bonds were held only in mutual fund portfolios.

As a final step I merged the holdings and trading data with data on individual bonds' credit rating, coupon, maturity date, and other underlying characteristics. Those data are from Mergent's municipal bonds database.

I then applied a variety of filters to focus the analysis on liquidity in fixed rate bonds trading in the buy side of the secondary market. I first removed variable rate bonds and bonds with missing data on rating, coupon, or maturity date. I also removed any bonds with less than one year since issuance to avoid any unique liquidity considerations for new issue bonds (Schultz 2012). That reduced the number of CUSIPs to 39,553. I then removed all secondary market purchases from customers and inter-dealer trades, leaving only secondary market sales to customers. I also filtered out any obvious data entry errors in both the Refinitiv and MSRB data. After applying these filters, the final dataset includes 296,914 bond-quarter observations and 3,185,434 secondary market trades within those quarters.

3.2 Patterns of ETF Bond Holdings

Table 1 shows the trends over time in ETF and mutual fund holdings from 2006-2019. The second and third columns show the number of active muni ETFs and mutual funds each year. Columns three and four show the number of CUSIPs held across all funds in both categories. Columns five and six show the median size of a position in an individual bond for each type of fund. The last two columns show the median par value of holdings of individual bonds across fund types, and the median size of the maturity in which the bond was issued. All figures shown here are based on the fourth quarter filings for each respective year.

This table highlights some key stylized facts about past and current patterns of muni ETFs holdings. First and foremost, the number of muni ETFs increased from 21 in 2015 to 51 in 2019, a 143% increase, compared to a 14% increase for mutual funds. We also see that number of individual CUSIPs held in ETFs has grown exponentially since 2005. By 2019 that total was 22% of the total CUSIPs held by mutual funds. Contrast this with Figure 1, which shows that ETF's total assets under management are less than 6% of mutual funds' assets under management.

This trend is further reflected in the figures on median holdings and maturity size. The median size of an ETF holding in 2019 was $450,000. This is less than one-third the size of the $1,555,000 median holding in 2006. During this same time, the decrease in the median-sized mutual fund holding was not nearly as pronounced, from $1,770,000 in 2006 to $1,420,000 in 2019. We also see in the last two columns that ETFs have tended to hold positions in much larger bonds compared to mutual funds. In 2019 the median maturity of a bond held by ETF was nearly double that of mutual funds. At times since 2016 that ratio has been nearly three to one. Compared to mutual funds, ETFs have tended to take smaller positions in much larger bonds. At some level this is expected, given that the bonds included in the indices that ETFs track tend to be from larger, more visible issuers.

Given the large number of high-yield muni funds, it's important to consider how these holding patterns vary by credit quality. A muni bond's credit quality is closely tied to the revenues pledged as its repayment. Water/sewer revenue bonds, for example, are often called "essential revenue" bonds and enjoy solid credit quality. At the other end of the continuum, bonds for development-driven residential streets and sidewalks backed by special assessments are "non-essential" and are far less creditworthy. In between these two extremes are general or "full faith and credit" (i.e. general obligation (GO)) pledges, mortgage revenues, student loan revenues, and many others.

Figure 2 shows density plots of ETF holdings sorted by muni bond revenue pledges. It suggests an inverse relationship between the quality of a bond's revenue stream and the share of it held by ETFs. Bonds with more reliable revenues - Revenue (i.e. essential revenue), General Obligation, Loan Agreement (i.e. student loans), and Sales/Excise tax - generally see less than 10% of their total par value held by ETFs. By contrast, ETFs tend to hold much larger shares of outstanding par value of more speculative bonds like Special Tax, Special Assessment, and Limited General Obligation. In the multivariate analysis presented later I account for this variation across revenue pledges.

Table 2 shows fund holdings for ETFs and mutual funds aggregated to the issuer level. It shows that ETFs and mutual funds both tend to own bonds from high-profile jurisdictions with large amounts of outstanding debt. The most visible difference is in Panel C. It shows the median fund holdings across all of an issuer's active securities. Here we see that virtually all of the debt from many issuers lands in mutual fund portfolios. This is likely due to the large number of single-state mutual funds. This is not observed for ETFs.

It's also important to consider how ETF holdings vary across other bond characteristics. Table 3 breaks down those holdings by credit quality, call features, and security pledge. Numbers reported are medians across all years for each type of fund, with standard deviations in parentheses. Here we see that ETF ownership is broadly dispersed across bond characteristics, but, as shown in Figure 2, ETFs tend to hold slightly larger shares in higher credit risk sec- tors like special assessment bonds and tax allocation bonds. This is also consistent with the proliferation of high yield muni ETFs.

The first four rows of Table 4 show the summary statistics for ETF and mutual fund holdings across the sample. The mean ETF holding as a percent of a bond's outstanding par value was 5.198% and the median was 2.433%. For mutual fund the mean was 22.297% and was widely dispersed with a standard deviation of 63.17% and a median of 8.485%. In the regressions shown later I also include change in ETF and mutual fund holdings from quarter $t - 1$ to quarter t. Those summary statistics are in rows 3 and 4 of Table 4.

4. Measurement Framework

We cannot directly observe prospective muni buyers' willingness to buy and muni holders' willingness to sell. Or put differently, muni liquidity is like oxygen - only observable in its absence. Nonetheless, previous studies of both the corporate and muni bond contexts have developed reliable proxies for liquidity based on observed trades. The analysis presented here is in that same style.

Previous work has shown that fixed income liquidity is a multi-faceted concept. In turn, I employ four different measures to proxy the most commonly measured liquidity features and characteristics. Two of those measures are based on trade volume, and two are based on secondary market prices and yields. These measures were articulated by Dick-Nielsen, et. al (2012) as part of a broader framework for analysis of corporate bond liquidity. Several of the specific measures described here have been employed in papers on the ETF-liquidity relationship for corporate bonds (Rhodes and Mason 2019; Agapova and Volkov 2018; Dannhauser 2017) and in papers on municipal bond liquidity generally (Schwert 2017; Marlowe 2013).

4.1 Volume-Based Measures

I employ two liquidity proxies based on trading activity of individual bonds. *Turnover* is the total secondary market trading in a bond throughout the quarter as a percentage of its outstanding par value. *Zero Trade Days* is the percentage of days in the quarter where a bond did not trade.

Summary statistics for these and the liquidity proxies described below are also reported in Table 4. Turnover is widely dispersed, with a mean of 10.014% and a standard deviation of 34.769%. This suggests a typical bond will see total trade volume each quarter equivalent to roughly 10% of its outstanding par value. Zero Trade Days are much more tightly dispersed around a mean of 88.218%. This implies that the vast majority of munis do not trade in a given quarter.

4.2 Price-Based Measures

I also employ two liquidity proxies based on observed muni secondary market prices and yields. A question of keen interest to market regulators is whether trading activity brought on or suppressed by ETF ownership affects prices differently than trading and holdings from other institutional investors? These measures are designed to speak to those price impacts of trading.

The first is a measure of price dispersion based on a measure first employed in the muni market by Downing and Zhang (2004). It is computed as:

$$\left(\frac{\left(Price_{j,t,max} - Price_{j,t,min}\right)}{Price_{j,t,median}}\right) * 100 \qquad (1)$$

where $Price_{max}$ is the maximum price of bond j in week t, $Price_{j,t,min}$ is the minimum price of bond j in week t, and $Price_{j,t,median}$ is the median price of bond j in week t. I report quarterly medians of these weekly observations on dispersion. This measure follows from the idea that for less liquid bonds, prices on both sides of the market will diverge to reflect the liquidity premium. Specifically, prospective buyers will offer higher prices on the bid side, and bondholders will offer lower prices on the ask side. That dispersion is scaled to the median weekly price.

Row 7 of Table 4 shows the descriptive statistics for this measure. Dispersion is itself widely dispersed with a mean of 20 basis points and a standard deviation of 56 basis points. The median is zero, indicating that many trades within the same week happen at identical prices. This is not surprising given that multiple sales of the same bond at identical prices is common in the retail muni market (Green, et. al. 2007).

The second price-based liquidity indicator is a variation on Amihud's (2002) widely cited liquidity indicator. The intuition with this measure is that the greater liquidity associated with more contemporaneous trading volume and larger-sized trades should minimize mark-ups and limit the overall price impact of trading. This measure is particularly important, given that, as mentioned above, uninformed noise traders in index securities like ETFs can increase trading volume without improving liquidity (Hasbrouck 2003; Rhodes and Mason 2019).

Amihud's original measure was adapted for fixed income by Dick-Nielsen, et. al. (2012). It is computed as:

$$\frac{|r_j|}{volume} \quad (2)$$

Here $|r_j|$ is the absolute value of daily returns in a bond, where returns are calculated as $\frac{(Price_{j,t,mean} - Price_{j,t-1,mean})}{Price_{j,t-1,mean}}$ and *volume* is the total trade volume in bond *j* on day *t* in $ thousands. Recent applications of this measure for fixed income scale it to daily turnover. Consistent with Amihud's original measure, I instead scale it to volume. Sensitivity tests showed the results were essentially the same regardless of the denominator selected.

Row 8 of Table 4 shows the mean of the Amihud measure was 0.0185 with a standard deviation of 0.0559. Substantively, this means that for every thousand dollars of trading, daily returns are +/- 1.85 basis points, with a standard deviation of almost +/- six basis points. Note that this measure has considerably fewer observations because it requires trading on consecutive days.

Figure 3 shows the trends over time in these liquidity proxies. Each line plots the quarterly median of one of the liquidity proxies by buckets of bonds defined by the percent of ETF ownership of that bond. The blue line shows bonds where ETFs own less than one percent of that bond's total par value. The green line shows bonds where ETFs owned 1-10% of the bond's par - roughly equivalent to the 25th through 75th percentiles. The red line shows bonds where ETFs owned more than 10% of the bond.

These plots highlight three salient points about the relationship between ETF ownership and liquidity over time. First, the plots for price dispersion show that munis held by both ETFs and mutual funds trade have traded at considerably less dispersion over time. This could be part of a market-wide trend brought about by the MSRB's ongoing price transparency initiatives. At the same time, we also see the opposite for zero trading days. Here it seems both ETF and mutual fund ownership at all levels have increased the number of zero-trading days. This would support the claim that bonds that index-based funds tend to take particular index-included bonds largely out of the secondary market. We also see that ETF ownership tends to associate with higher turnover and stronger price impacts to trading than comparable levels of mutual fund ownership. This is expected to some degree because mutual funds tend to own higher proportions of munis, but it does suggest that ETF inclusion does lead to more trading and potentially more noise trading than comparable levels of mutual fund ownership.

4.3 Market Synchronicity

So far this analysis has focused on liquidity proxies. There is a corollary to the concern that ETFs induce trading without improving liquidity: ETFs can also induce systematic risk. This happens when uninformed investors who trade on technical market movements force price dynamics that crowd out bond-specific price-relevant information. Although this is not a concern about individual bonds' liquidity or lack thereof, it is another noteworthy aspect of market quality that concerns regulators and policymakers. Therefore, in addition to measuring and modeling how ETF ownership affects bond liquidity, I also consider how ETF ownership affects systematic risk.

To do this I adapt Rhodes and Mason's (2019) approach for measuring corporate bond market synchronicity. I first regress each bond's daily returns on the daily returns of the Barclay's Municipal Bond Index from January 2010 through December 2019. I do this for quarterly rolling windows. To be included in those regressions, a bond must have traded at least three times during the quarter. The mean

R^2 was 0.76 with a standard deviation of 0.13, which suggests good model fit. I then take those R^2 and transform them as follows:

$$logit\left(\frac{R_{j,t}^2}{1-R_{j,t}^2}\right) \qquad (3)$$

where $R_{j,t}^2$ is the R^2 from a regression of the daily returns of bond j on the daily returns of the Barclay's Municipal Bond Index, and *logit* is the logit function. The mean transformed value was -3.56 with a standard deviation of 0.23. This is consistent with Rhodes and Mason's (2019) reported mean of -2.817 for corporate bond market synchronicity, albeit with much narrower dispersion than their reported standard deviation of 2.491. Higher values on this measure indicate greater market synchronicity and, in turn, more systematic risk and less issuer-specific information incorporated into pricing.

4.4 Multivariate Model

My main quantity of interest is how ETF ownership affects muni liquidity. To that end, I run least squares regressions for four main specifications of a regression model with one of the liquidity measures as the dependent variable and a one or more measures of fund holdings as the key covariates. The first specification includes *ETF Holdings*$_t$. The second adds *Mutual Fund Holdings*$_t$. The third and fourth specifications are designed to capture the effect of fund holdings in the previous quarter. The third includes *ETF Holdings*$_{t-1}$ and the fourth adds to that *Mutual Fund Holdings*$_{t-1}$. I employ these four main specifications as the core of the analysis.

Previous work has identified several other bond-specific factors that also impact liquidity (see Marlowe 2013, among others). I incorporate those factors as additional covariates in every model specification.

Several characteristics of a muni have been shown to reduce liquidity. Summary statistics for those variables are shown in the bottom panel of Table 4. One is the bond's *coupon*. All else equal, higher coupons offer higher cash flows that appeal to the retail buy-and-hold investors who dominate the muni market. The median coupon for all bonds in the dataset was 5.00%, by far the most common coupon in the muni market throughout the past decade. More *years to maturity* also extend the bond's appeal to buy-and-hold investors and would dampen liquidity. The average years to maturity was 11.23 years. Many munis are also issued with a *call feature*, typically at 10 years, and those call features further reduce retail investors' incentives to trade. A total of 55% of the bonds in this dataset had a call feature.

Two characteristics are believed to increase liquidity. One is the bond's par value (i.e. *maturity size*) and the other is the par value of the issue in which the bond was sold (i.e. *issue size*). Larger bonds tend to attract more attention from institutional investors who are inherently more active muni buyers and sellers. Moreover, as shown earlier, the indices to which many ETFs and mutual funds are connected are often weighted toward bonds from active, visible issuers. Index inclusion draws attention to a bond from investors across the market, and active traders in particular. All that suggests maturity size and issue size would associate positively with liquidity. The mean maturity size was $51 million, and the mean issue size was $478 million. These average sizes from these data focused on institutional ownership are much larger than those for the municipal market as a whole. For instance, according to the Mergent data used in this analysis, the median maturity for all new muni issues from 2010 through 2019 was just over $1 million, while the median issue size was just over $20 million.

The multivariate model also includes the bond's credit quality. I define credit quality along two dimensions. One is the bond's rating, measured as the higher of Moody's or Standard & Poor's underlying long-term rating. I combine ratings into five buckets: AAA, AA, A, BBB, and < BBB. The ratings category also includes *Not Rated* bonds that have no reported rating from either Moody's or S&P. The other dimension of credit quality is bond insurance. *Insured* bonds carry default insurance from one of the major monoline insurers, and *Not Insured* bonds do not. Table 5 shows a cross-tab of the permutations of ratings and insurance found across the dataset. It shows that most of the bonds in the dataset had an underlying AA rating, 16.7% were "natural AAA", and less than three percent of the uninsured bonds were not rated. These proportions are considerably different than the market as a whole, where natural AAA ratings are far less common and unrated bonds are far more common (see, among many others, Cornaggia, et. al. 2018; Palumbo and Zaporowski 2012). Those differences are also a function of the institutional investor focus of this analysis.

All the model specifications employed here also include three separate fixed effects. To control for time-varying liquidity effects all specifications include fixed effects on quarter. They also include fixed effects on the issuer's state. This is to account for state-specific tax law considerations and the potential for "home bias" in muni yields and liquidity (Babina, et. al. 2020; Pirinsky and Wang 2011). And given the sharp differences illustrated in Figure 3, all specifications also include fixed effects on the bond's security pledge.

4.5 Other Modeling Considerations

The model specification described above reflects a few modeling choices that warrant some additional explanations.

My empirical approach is focused on bonds that are or were at some point held in ETFs, and is designed to identify liquidity variations conditioned on ETFs owning a small share of a muni's par compared to ETFs owning a larger share of that par. That raises a natural question: Is relative shares of ETF ownership different from any ETF ownership at all? In other words, isn't a better first step to model ETF ownership as "yes/no" rather than shares of a bond's par value?

To test this claim I run the same basic regression models as those described above, but with a dataset that includes all active CUSIPs, and a new measure of ETF ownership coded as a 1 if the bond was in an ETF portfolio in quarter t, and zero otherwise. I also constructed a new measure of mutual fund ownership the same way. This new dataset included 6.8 million bond-quarter observations based on 58 million secondary market trades, with ETF coded "1" in 197,643 of those bond-quarter observations. I then regressed each of the liquidity measures on these alternative measures of fund holdings and the other model covariates. The results of that exercise - not reported here - were that the coefficients on ETF and mutual fund ownership were largely the same as the coefficients reported hereafter. This suggests that a muni landing in an ETF portfolio does not affect liquidity in a qualitatively different way than ETFs owning a comparatively larger or smaller share of that same muni. Given that the results were largely the same, and given the identification challenges around a key covariate with so few observations relative to the larger dataset, I do not report those estimates here.

A related concern is endogeneity. It may be that ETFs prefer to buy munis that are inherently more liquid so that they can easily move in and out of positions as market conditions demand. In that case the hypothesized effect of ETFs on liquidity would work in reverse. I address this in three ways. One is to include the lagged values - $\textit{ETF Holdings}_{t-1}$ and $\textit{Mutual Fund Holdings}_{t-1}$ - in the main specifications. Another is to include time fixed effects in the base specifications, so as to incorporate into the model exogenous variation in liquidity over time that is unrelated to changes in ETF holdings. Third, I explicitly model the relationship between changes in ETF holdings and liquidity levels. Taken together, these modeling strategies should help to address any potential endogeneity concerns.

One final concern is the breadth of liquidity measures. Prior work on muni liquidity (Schwert 2017; Marlowe 2013) has employed measures not included here, including indicators of round- trip transaction costs (RTC); Roll's (1984) measure of covariance in daily returns; standard deviations of several different liquidity proxies to capture liquidity risk; and the first and second principal components from a factor analysis of several measures. I computed versions of both the round-trip transaction costs and the Roll measure. I also computed the first and second principal components from a factor analysis that included the four measures reported hereafter plus RTC and Roll. The factor loadings on those first two principal components were weak, explaining only 34% and 29% of the variance, respectively. As a result, the four measures reported here are those with the largest and most consistent number of observations.

5. Main Results

5.1 ETF Inclusion and Trade-Based Liquidity Measures

The estimates of the regression models for the trade-based liquidity measures are shown in Table 6. The first four columns are the main specifications with turnover as the dependent variable, and the second four are the specifications with zero-trading days as the dependent variable. Standard errors are in parentheses. Recall that all specifications include fixed effects on quarter, state, and bond security pledge. Also note that the coefficients on credit quality vary considerably across credit quality buckets.

Coefficients on all the ETF and mutual fund holdings are statistically significant at conventional levels. With the exception of maturity par value (less turnover and more zero trade days) and years to maturity (more turnover and fewer zero trade days), the coefficients on the control covariates are in their expected directions.

These results suggest that ETFs bolster muni turnover, but also increase the number of zero- trading days. In model (1) the coefficient on ETF ownership is 0.527. This indicates that a one percent increase in ETF ownership of a muni increases that bond's turnover within that same quarter by slightly more than one-half of one percent. By extension, increasing ETF ownership to 8.45% - a one standard deviation increase above the mean - increases turnover by roughly four percent. A more extreme but plausible scenario is that ETF ownership of roughly two- thirds of a bond's par would increase turnover to just under 45%, or a one-standard deviation increase. The effects for mutual funds, as shown in model (2) are at roughly the same scale. That is, a one standard deviation increase in mutual fund ownership (63%) increases turnover by 5.5%.

When we extend the analysis into the prior quarter ETFs' impact is reduced by more than two-thirds. In model (4), the coefficient on ETF ownership $t-1$ is 0.163. The reduction of the effect of mutual fund ownership from t to $t-1$ is not nearly as pronounced. This suggests that ETF ownership associates with more turnover generally, but especially with more contemporaneous turnover.

The effects for zero trading days suggest ETF ownership increases zero trading days, and by implication, reduces liquidity. However, although those results are statistically significant, they are not substantively meaningful. For instance, the coefficient on ETF Holdings ($t-1$) in model (7) suggests that a typical (i.e. one standard deviation) increase in ETF ownership adds less than one additional zero trading day per quarter. In the extreme scenario that an ETF owned 100% of a muni, that muni's zero trading days would increase from 79 per quarter to 82 per quarter. The estimates on mutual funds are roughly half that size.

5.2 ETF Inclusion and Price-Based Liquidity Measures

The estimates of the regression models for the price-based liquidity measures are shown in Table 7. Here the pattern of coefficients is different than the volume-based measures. Maturity par value, issue par value, and years to maturity all increase dispersion while a call feature, a higher coupon, and default insurance all decrease it. In other words, the factors that increase turnover also seem to increase price dispersion. We also see large variations across the credit quality buckets, with coefficients on the AA, A, and BBB categories not statistically significant.

These estimates show that ETF ownership's effect on price dispersion is statistically, but not substantively significant. For instance, the coefficient on ETF ownership in column (1) indicates that if an ETF holds 100% of a muni, that muni's quarterly price dispersion would decrease by roughly 2 basis points, or less than $\frac{1}{25}$ of price dispersion's standard deviation. The lagged effects for ETF ownership are even smaller. The estimates for mutual fund holdings are orders of magnitude larger, but still not economically meaningful.

However, the effects for the Amihud measure are both statistically and economically meaningful. The coefficient on ETF ownership in model (5) implies that a one percent increase in ETF ownership associates with a .02 basis point reduction in volume-adjusted absolute daily returns. This coefficient is small, but it does indicate that higher than average levels of ETF ownership can dampen the price impact of trading. If ETF ownership increases from 5% to 22% - a two standard deviation increase above the mean - the Amihud measure would decrease 34 basis points, or about a 20% reduction off the mean for Amihud. ETF ownership of 100% of a muni would decrease Amihud by 200 basis points, the equivalent of one half of one standard deviation. The effects for mutual funds are also negative, but half that amount.

5.3 ETF Flows and Liquidity

The results so far suggest that ETF ownership levels bolster liquidity. It's also clear that ownership levels in period t affect liquidity differently than ownership levels in period $t - 1$. That implies it would be instructive to consider the distinct relationship between liquidity and ETF flows from period t to period $t - 1$. The findings from that exercise are shown in Table 8.

The key takeaway here is that ETF holding flows associate with most of the liquidity indicators differently than they associate with ETF holding levels. The estimate for ETF flows in model (2) is essentially the same as the estimate for ETF levels in model (4) of Table 6. However, the other flow relationships are not comparable to the levels relationships.

Especially noteworthy is that ETF flows associate negatively with Zero Trade Days. This is intuitive, given that bonds moving in and out of ETF portfolios would increase the number of days a bond trades throughout the quarter. But it's noteworthy because its sign is opposite that of the coefficient on ETF holding levels. That suggests munis coming into ETF portfolios have higher ex ante zero trade days. In other words, ETFs are purchasing less liquid bonds and making them more liquid. This is a key finding given the previously mentioned concern that ETFs do not make less liquid bonds more liquid, but rather take liquid bonds and make them even more liquid. This finding lends evidence to the former. Note also that the coefficient on mutual fund flows is positive, suggesting that this liquidity-seeking behavior might characterize mutual funds' muni buying patterns more ETFs' buying patterns.

Meanwhile, none of the four coefficients on ETF flows for the price-based liquidity measures - columns (5)-(8) - are statistically significant. This suggests that when a bond moves in or out of an ETF, that movement does not correspond to any additional price dispersion or any appreciable price impact of trading.

6. Sub-Sample Results

The main results showed that in the aggregate, ETF ownership associates with improved muni liquidity. At the same time, those effects varied from period t to period $t - 1$, and the estimates for several of the control variables also varied across different liquidity measures and model specifications. All this suggests some additional analysis to further unpack this relationship. Here I present three separate follow-up analysis based on sub-samples designed to illuminate the specific conditions where ETF ownership does and does not improve liquidity.

6.1 ETF Inclusion, Liquidity, and Credit Quality

The previous estimates showed that liquidity varies considerably by credit quality. That trend is likely related to the proliferation of high-yield muni ETFs and mutual funds. If credit quality shapes liquidity generally, and if certain ETFs are focused on the high-yield/lower credit quality segment of the market, then the ETF ownership-liquidity relationship might be conditioned on credit quality.

To examine this possibility, I re-ran the base regression models on sub-samples sorted by credit quality and insured status. The results of that analysis are presented in Table 9. For brevity, I report only the coefficients on the lagged values of both ETF holdings and mutual fund holdings. Coefficients are statistically significant at $p < 0.01$ unless italicized. If italicized, the coefficient was not statistically significant at conventional levels.

Here we see sizable differences across credit quality. This is especially true for BBB rated bonds, where the estimate of 1.339 is 2.5 times larger than the estimate of this same model for the entire sample. To put this finding in context, consider that ETF ownership of just one quarter of a muni's par value increases turnover of BBB-rated bonds to approximately 35%. That's well within the top quartile of turnover for all bonds. For bonds rated < BBB we see a near similar result. Also note that for BBB and < BBB rated bonds the sign on the coefficient for zero-trade days is reversed and is orders of magnitude greater than the base model estimates. Further, these coefficients are 10-15 times the size of those same effects of mutual funds. At the same time, the coefficients for AAA, AA, and A rated bonds are much closer to the base model estimates for both turnover and zero-trade days. This pattern of results suggests the volume liquidity benefits of ETF ownership are especially strong in lower credit quality bonds.

By contrast, the relationship between ETF ownership and price-based liquidity is not nearly as contingent on credit quality. Here the coefficients for price dispersion and Amihud are either similar to the base model estimates, or not statistically significant. All that suggests ETF ownership of lower credit quality bonds tends to bolster liquidity of those bonds without any unique or appreciable impact on price.

6.2 ETF Inclusion, Liquidity, and Market Trends

The "COVID-19 Crisis" of March 2020 showed that flows out of muni ETFs can accelerate and exacerbate deviations between their price and their net asset value. This observation is consistent with Green, et. al.

(2010) who showed that muni prices rise faster than they fall because dealers are able to capitalize on the asymmetric speed of price adjustment on the bid and ask sides of the market. That would suggest that in falling markets, liquidity should be lower, as dealers need to respond with asymmetrically large price reductions on the sell side and bid increases on the buy side. But in rising markets, liquidity might not be as constrained, so prices might not need to respond in the same asymmetric way. To the extent that APs are market-makers, or that they interact with dealers intermediating these asymmetric price adjustments, we would expect liquidity to decrease in down markets. This is one manifestation of the liquidity mismatch concern surrounding ETFs generally, and muni ETFs in particular.

I test this claim two ways. For the first test I decompose the Amihud measure into two separate measures, one for positive returns and one for negative returns. The "Amihud Up" measure is as follows:

$$\frac{+r_j}{volume} \quad (4)$$

and the "Amihud Down" measure is as follows:

$$\frac{-r_j}{volume} \quad (5)$$

where r_j are the daily positive or negative returns in a bond, where returns are calculated $\frac{(Price_{j,t,mean}-Price_{j,t-1,mean})}{Price_{j,t-1,mean}}$ and *volume* is the total trade volume in bond j on day t in $ thousands.

I then re-ran the four main model specifications using these "Amihud Half" measures as dependent variables. All other covariates and fixed effects are the same as above. Those results are in Table 10. For brevity, I report only the estimates on the ETF and mutual fund holdings indicators.

The key finding here is that ETF's effect on liquidity is not contingent on the direction of returns. The sizes of the coefficients are identical to the full sample estimates. The change in the coefficient signs is expected given that the Amihud Up and Amihud Down measures have their own signs. These results offer further evidence that ETF ownership acts as a liquidity provider for many munis. Moreover, and perhaps more important, it suggests that claims about the liquidity mismatch during down markets may be overstated.

As a second test, I re-ran the regression models on a sub-sample limited to Q1 2020. This exercise is designed to isolate the ETF holding-liquidity dynamic during the COVID-19 crisis. Those results are reported in Table 11. Here I find the ETF ownership's effect on volume-based liquidity measures were reduced, albeit with no concomitant impact on the price-based liquidity measures. The coefficients on turnover are roughly half those of the full sample estimates, and the coefficients on zero trade days are quite similar to the full sample estimates. At the same time, the coefficients on the price-based measures are either not statistically significant or significant at only $p < 0.1$. This lends further support to the claim that ETF ownership can accelerate trading activity during certain market conditions, but with little or no impact on pricing.

6.3 ETF Inclusion and Market Synchronicity

Most of the evidence presented so far shows that ETF ownership increases trading activity in munis, but that additional trading activity has little if any impact on pricing. At the same time, another potential regulatory concern is whether that additional trading increases systematic risk and interferes with price discovery. That is, if a muni held in an ETF trades more frequently, but is priced less on its fundamentals and more on broader market movements, then ETFs obfuscate price discovery more than they facilitate it. This concern is well-founded given that ETFs are thought to attract noise traders and other uninformed investors.

To test this claim I model the relationship between ETF ownership and market synchronicity. Those results are reported in Table 12. The main finding here is simple: ETF ownership does not affect market synchronicity. The coefficients on the ETF measures are next to zero and are not statistically significant. Note, however, that mutual fund holdings do appear to increase synchronicity slightly.

In short, these results do not support the claim that the additional trading brought on by ETF ownership increases systematic muni risk.

7. Conclusion

In this paper I examine how exchange-traded funds (ETFs) affect the liquidity of municipal bonds. I find that bonds held by ETFs tend to trade more often than bonds held by mutual funds, but with little or no impact on price dispersion, returns, or systematic risk. However, these effects vary considerably by the type of bond. Lower credit quality bonds held by ETFs tend to trade much more frequently than those with higher credit quality. Market conditions also matter. During the COVID-19 market dislocation of March 2020, bonds held by ETFs traded far less often than under typical market conditions, but that diminished liquidity did not appear to affect pricing for bonds that did trade.

These findings have implications for concerns about the "liquidity mismatch" between ETFs and their underlying bonds. They imply that at best, ETFs increase muni liquidity overall, and at worst, bonds held by muni ETFs are no less liquid than bonds held by mutual funds. This is not to suggest that that the risk of the liquidity mismatch is overstated. But the evidence presented here does show that during the COVID-19 crisis, bonds held by muni ETFs traded with the same degree of liquidity as bonds held by other key institutional investors. At a minimum, that implies that ETFs do not reduce liquidity across the market. If anything, there is evidence here that ETFs act as market makers during otherwise difficult market conditions.

This paper's main limitation is timeliness of data. Data on ETF holdings - like with all institutional holdings - are available at the end of infrequent intervals. This means that many bonds could flow into an ETF on the first day of the reporting period and flow out on the next-to-last day, but never appear in the holdings data. Nonetheless, to the extent that ETFs tend to hold particular types of munis, these data do allow us to generalize about broad trends in liquidity across different municipal bond classes.

These results suggest at least three relevant follow-up studies. One is to more thoroughly explore the channels through which ETFs bolster liquidity. Do APs trade certain bonds more often as part of the arbitrage process? Do investors in the cash market replicate ETF trades they might not otherwise execute? Do noise traders pile in and out of ETFs in response to changes in technical factors? A second is examine ETFs' role in price discovery. My results suggest that ETFs do not increase market synchronicity. What these results do not reveal is whether ETFs help to incorporate more issuer-specific information into pricing. Future work can and should take up these questions. And third, muni ETFs offer a unique opportunity to examine important questions about the relationship between price transparency and liquidity. In particular, is liquidity different for ETFs that report holdings every day compared to those that report holdings less frequently?

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FIGURE 1: MUNICIPAL BOND HOLDINGS BY FUND TYPE, 2010-2019

This figure shows the total municipal bond assets under management (in $ billions) for exchange-traded funds (ETFs), closed-end mutual funds, and open-end mutual funds from 2010-2019. All figures are from the Federal Reserve's *Financial Accounts of the United States*, Series F212.

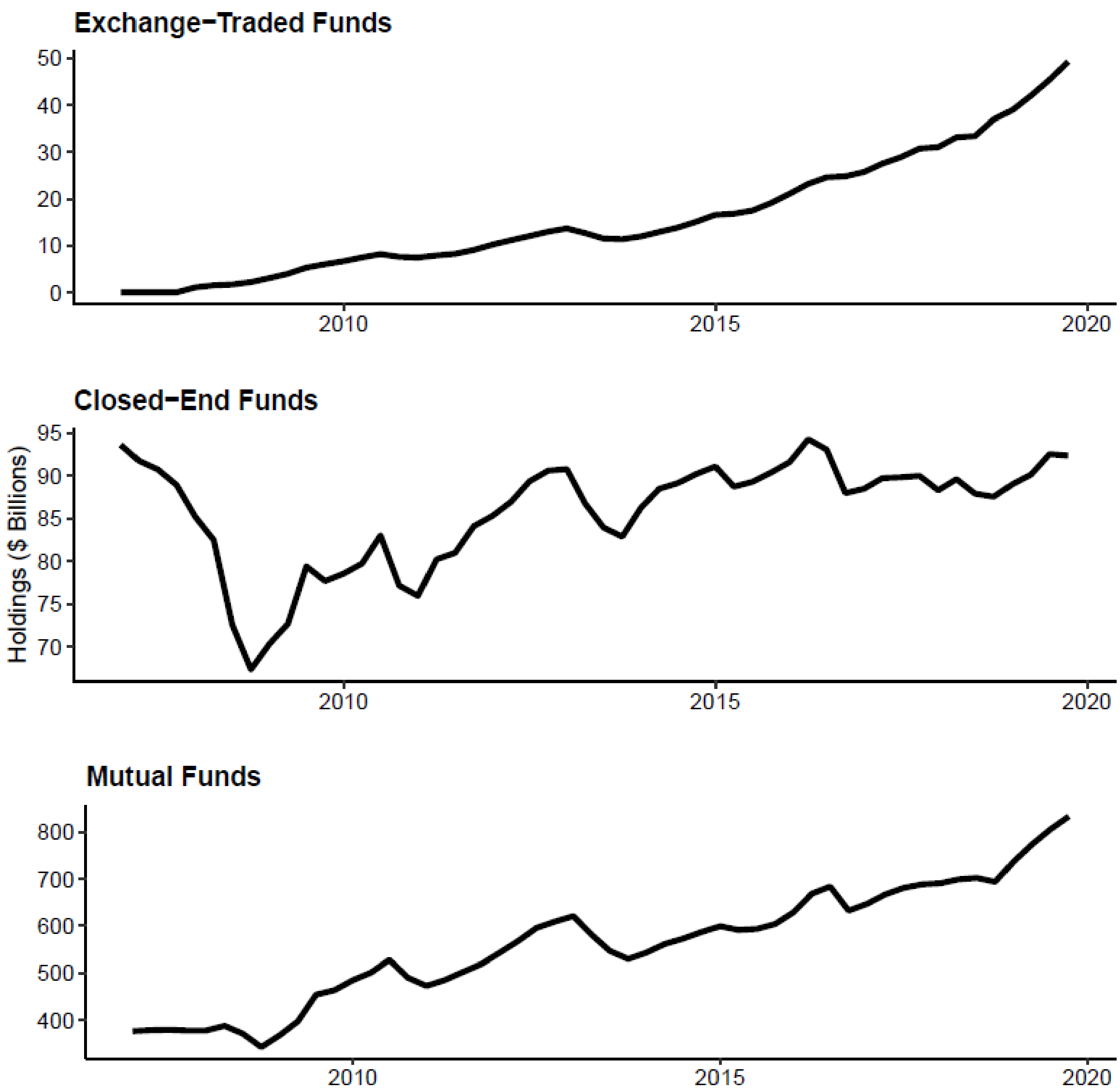


FIGURE 2: EXCHANGE-TRADED FUND HOLDINGS OF MUNICIPAL BONDS, BY SECURITY PLEDGE

This figure shows density plots of the percent of a municipal bond's total outstanding par value held by exchange-traded funds (ETFs). Each plot is for a sub-sample sorted by the nine largest categories of bond security pledges.

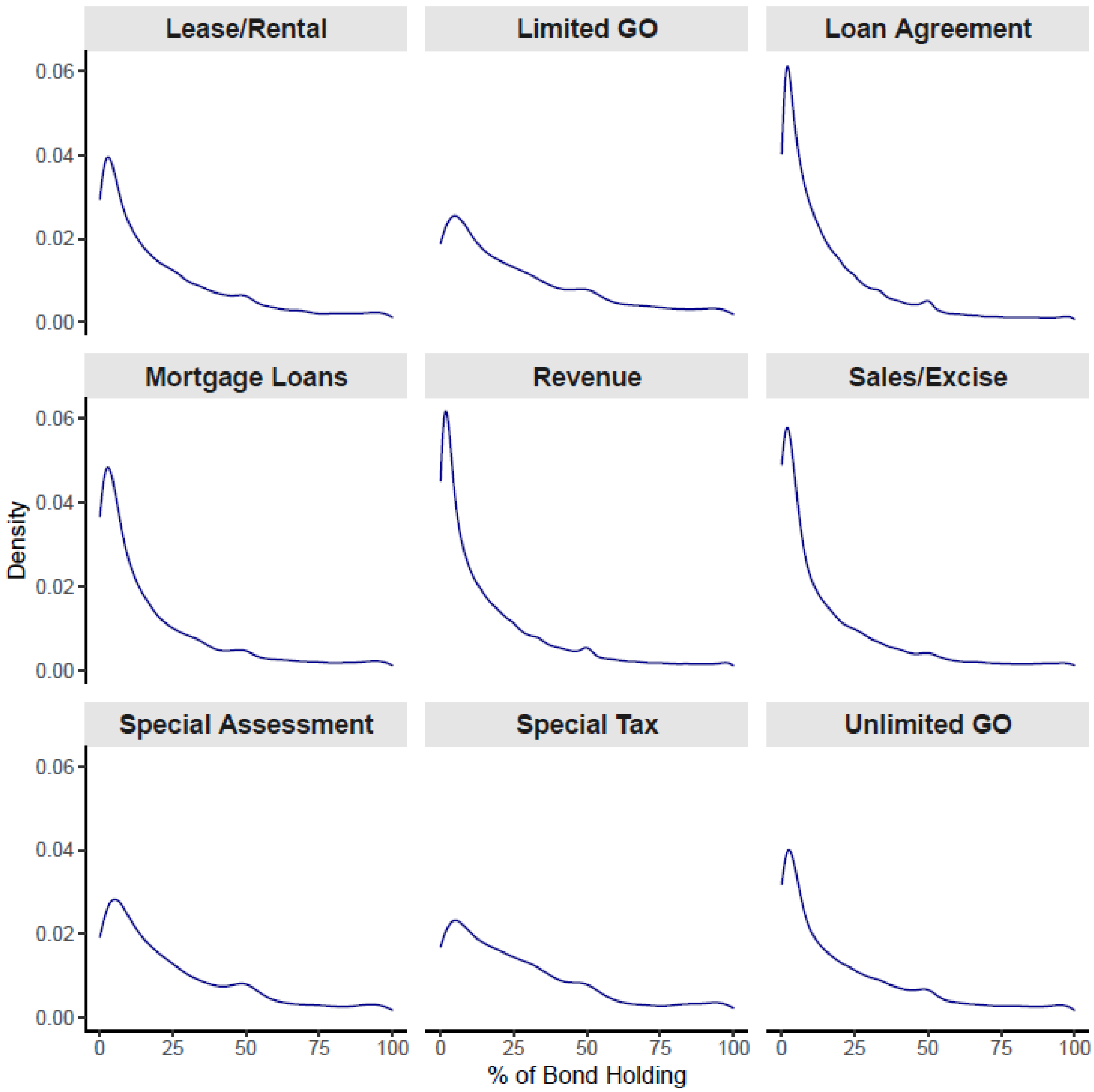
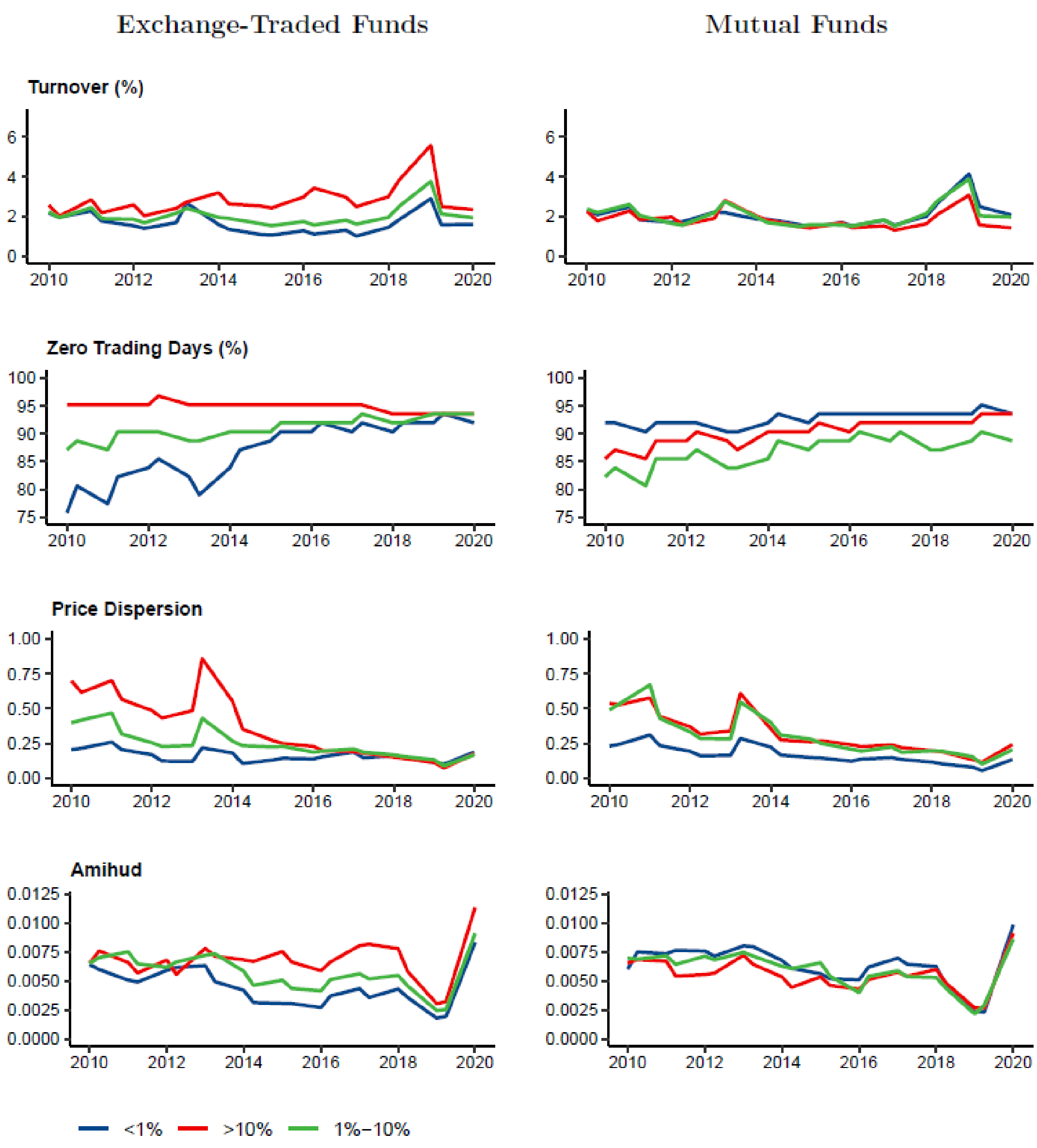


FIGURE 3: MEASURES OF MUNICIPAL BOND LIQUIDITY, 2010-2020



This figure shows the quarterly medians for municipal bond liquidity measures sorted by type of fund holding. The left panel shows medians for municipal bonds held by exchange-traded funds (ETFs) and the right panel shows medians for municipal bonds held by open-end and closed-end mutual funds. The blue, green, and red lines show medians of liquidity measures for bonds where funds hold less than 1%, 1-10%, and more than 10%, respectively, of the bonds' total outstanding par value. *Turnover* is the total secondary market trading in a bond throughout the quarter as a percentage of its outstanding par value. *Zero Trade Days* is the percentage of days in the quarter where a bond did not trade. *Price Dispersion* is $\frac{(Price_{j,t,max} - Price_{j,t,min})}{Price_{j,t.median}}$ where $Price_{max}$ is the maximum price of bond *j* in quarter t. $Price_{j,t,min}$ is the minimum price of bond *j* in quarter *t,* and $Price_{j,t.median}$ is the median price of bond *j* in quarter t. It is based on weekly minimum, maximum, and median prices. *Amihud* is computed as $\frac{|r_j|}{volume}$ and assumes $|r_j|$ is the absolute value of daily returns in a bond, where returns are calculated as $\frac{(Price_{j,t,mean} - Price_{j,t-1,mean})}{Price_{j,t-1,mean}}$ and *volume* is the total trade volume in bond *j* on day t. All measures are limited to secondary market sales to customers.

TABLE 1: MUNICIPAL BOND HOLDINGS IN ETFS AND MUTUAL FUNDS, 2010-2019

This table shows the size and scale of municipal bond holdings in exchange-traded funds (ETFs) and mutual funds from 2010 through 2019. *# of Funds* is the number of municipal bond-focused funds. *# of CUSIPs* is the total number of individual municipal bonds held across all funds. *Holding* is the median position in any individual bond across all funds, and *Maturity Size* is the median outstanding par value of individual bonds held across all funds. All observations are based on quarterly fund holdings from the final quarter of each year. Data for mutual funds include holdings in both open-end and closed-end funds.

	# of Funds		# of CUSIPs		Holding ($000)		Maturity Size ($000)	
	ETFs	Mutual Funds	ETFs	Mutual Funds	ETFs	Mutual Funds	ETFs	Mutual Funds
2006	1	333	63	41,734	1,555	1,770	14,005	12,000
2007	5	410	216	50,390	1,000	1,750	30,245	12,940
2008	13	457	1,129	55,522	1,000	1,750	44,867	14,050
2009	13	479	2,150	63,515	1,000	1,885	42,095	15,605
2010	13	493	2,749	66,299	1,000	1,920	43,345	16,295
2011	10	523	3,198	69,529	1,000	1,850	42,150	16,165
2012	14	512	4,397	75,166	1,000	1,750	41,650	15,765
2013	9	507	1,541	70,674	1,015	1,750	26,187	15,680
2014	13	548	2,340	74,978	1,000	1,655	22,890	15,855
2015	21	553	9,297	78,180	765	1,550	33,877	15,275
2016	25	577	13,139	87,568	500	1,500	32,377	14,600
2017	31	579	18,095	91,936	445	1,500	29,770	14,520
2018	41	606	20,954	92,106	420	1,465	27,875	14,905
2019	51	628	21,550	97,225	450	1,420	27,840	14,900

TABLE 2: MUNICIPAL BOND HOLDINGS IN EXCHANGE-TRADED FUNDS AND MUTUAL FUNDS, AGGREGATED BY ISSUER.

This table shows the ten largest issuer-level aggregated holdings for exchange-traded funds (ETFs) and mutual funds at the end of Q4 2019. *# of CUSIPS* is the total number of an issuer's CUSIPs held across all funds. *Holdings* is the total holdings of an issuer's bonds across all funds. *Median Holding as % of CUSIP* is the issuer-level median of the percentage of an individual bonds' outstanding par held by a fund.

Exchange-Traded Funds		**Mutual Funds**	
Panel A: # of CUSIPs			
CA State Department of Water Resources	8	NY State Dormitory Authority	3,165
State of IL	8	MA Development Finance Agency	2,782
NY State Urban Development Corporation	8	IL Finance Authority	2,365
NY State Dormitory Authority	8	State of IL	2,131
Puerto Rico Sales Tax Financing Corporation	8	CA Statewide Communities Development Corp.	1,951
State of CA	7	State of CA	1,740
FL Development Financing Corporation	7	NJ Economic Development Authority	1,612
NJ Economic Development Authority	7	CA Municipal Finance Authority	1,537
NJ State Transportation Trust Fund Authority	7	MI Finance Authority	1,499
NYC	7	NJ State Transportation Trust Fund Authority	1,479
Commonwealth of PA	7	Puerto Rico Sales Tax Financing Corporation	1,448
University System of CA	7	CO Health Facilities Authority	1,403
Panel B: Total Holdings ($ million)			
State of CA	2,015	NY State Dormitory Authority	11,933
NY State Dormitory Authority	1,357	State of CA	11,611
NYC Transitional Finance Authority	1,048	Metropolitan Transit Authority (NY)	9,622
NYC	826	State of IL	9,228
Commonwealth of MA	785	Puerto Rico Sales Tax Financing Corporation	8,107
NJ State Transportation Trust Fund Authority	659	NYC Transitional Finance Authority	7,999
NYC Municipal Water Finance Authority	653	NJ State Transportation Trust Fund Authority	7,474
Metropolitan Transit Authority (NY)	629	IL Finance Authority	6,887
State of IL	592	NYC	6,214
Commonwealth of PA	508	MA Development Finance Agency	5,533
Panel C: Median Holding as % of CUSIP Par			
Kelseyville, CA Unified School District	53%	Northstar Community Services District	99%
Southern CA Tobacco Securitization Authority	53%	Ogden City (UT) School District	97%
CA State Enterprise Development Authority	47%	City of Modesto (CA) Special Revenue	97%
Center Grove (IN)Community School Corp.	41%	Town of Shrewsbury (MA)	96%
MN State Housing Finance Agency	39%	Henry County (GA) Housing Authority	96%
NY Counties Tobacco Trust	39%	City of Liberty Hill (TX) Special Revenue	95%
Riverside County (CA) Transportation Comm.	38%	Town of Douglas (MA)	95%
City of Cicero (IL)	37%	Dawson-Boyd (MN) Independent School District	95%
Inland Valley (CA) Development Agency	36%	Chula Vista (CA) Redevelopment Agency	95%
North Park Isle (FL) Community Dev. Dist.	34%	Knoxville (TN) Utilities Board	94%

TABLE 3: SHARES OF MUNICIPAL BOND PAR VALUE HELD BY ETFS AND MUTUAL FUNDS, BY BOND CHARACTERISTICS.

This table shows the percentage of a bond's outstanding par value held by exchange-traded funds (ETFs) and mutual funds from 2010-2019. All figures are medians across categories of bonds sorted by a single underlying characteristic, and are limited to fixed coupon securities. Panel A shows the median holdings sorted by categories of credit ratings, where the rating is the higher of Moody's or Standard & Poor's underlying long-term rating. *Not Rated* bonds have no reported rating from either Moody's or S&P. *Insured* bonds carry default insurance from one of the major monoline insurers, and *Not Insured* bonds do not. Panel B shows median holdings by the presence or absence of a call feature. *Callable* bonds have an optional call feature, almost always at 10 years, where *Not Callable* bonds do not. Panel C shows holdings sorted by revenue source(s) pledged as the bond's security.

	% in ETF	% in MF
Panel A: Credit Quality		
AAA	5.7%	13.1%
	(8.9)	(33.8)
AA	5.6%	16.7%
	(9.0)	(38.2)
A	3.9%	35.7%
	(6.1)	(59.7)
BBB	4.3%	51.4%
	(7.2)	(94.0)
<BBB	4.4%	62.0%
	(7.4)	(43.6)
Not Rated	5.6%	23.0%
	(9.1)	(40.1)
Insured	4.9%	36.9%
	(8.7)	(48.2)
Not Insured	5.3%	20.5%
	(8.4)	(41.3)
Panel B: Call Feature		
Callable	4.6%	21.0%
	(6.9)	(83.3)
Not Callable	4.6%	23.4%
	(6.9)	(39.9)
Panel C: Security Pledge		
Unlimited General Obligation	6.0%	16.5%
	(9.7)	(47.0)
Limited General Obligation	5.7%	9.9%
	(9.2)	(17.0)
Revenue	4.7%	25.4%
	(7.4)	(80.6)
Special Assessment	8.2%	22.8%
	(10.8)	(24.9)
Tax Allocation	8.2%	22.0%
	(12.4)	(27.9)

TABLE 4: SUMMARY STATISTICS.

This table shows the bond-level summary statistics for all fixed coupon municipal bonds with at least 30 days since issuance that were held in exchange-traded funds (ETFs) at any point from 2010 Q1 through 2020 Q1. Measures based on secondary market trading are limited to sales to customers. *Exchange-Traded Fund Holdings* is the share of a bond's outstanding par value held by ETFs in quarter t or quarter $t-1$. *Mutual Fund Holdings* is the share of a bond's outstanding par value held by mutual funds in quarter t or quarter $t-1$. ETF Holdings $\Delta_{t,t-1}$ is the change in ETF holdings from quarter $t-1$ to quarter t as a percent of holdings in $t-1$, and Mutual Fund Holdings $\Delta_{t,t-1}$ is the change in mutual fund holdings from quarter t−1 to quarter t as a percent of holdings in t−1. *Price Dispersion* is $\frac{(Price_{j,t,max}-Price_{j,t,min})}{Price_{j,t.median}}$ where $Price_{max}$ is the maximum price of bond j in quarter t, $Price_{j,t,min}$ is the minimum price of bond j in quarter t, and $Price_{j,t.median}$ is the median price of bond j in quarter t. It is based on weekly minimum, maximum, and median prices. *Turnover* is the total secondary market trading in a bond throughout the quarter as a percentage of its outstanding par value. *Zero Trade Days* is the percentage of days in the quarter where a bond did not trade. *Amihud* is computed as $\frac{|r_j|}{volume}$ and assumes $|r_j|$ is the absolute value of daily returns in a bond, where returns are calculated as $\frac{(Price_{j,t,mean}-Price_{j,t-1,mean})}{Price_{j,t-1,mean}}$ and *volume* is the total trade volume in bond j on day t. *Return Synchronicity* is the logit transformation of $\frac{R^2_{j,t}}{1-R^2_{j,t}}$, where $R^2_{j,t}$ is the R^2 from a regression of the daily returns of bond j on the daily returns of the Barclay's Municipal Bond Index. Those regressions are limited to bonds that trade at least three times in a quarter. *Coupon* is the bond's coupon rate. *Maturity Par* is the bond's total outstanding par value. *Issue Par* is the total outstanding par value of the issue in which the bond was sold. *Callable* and *Insured* are dummy variables that identify if the bond has a call feature or carries default insurance, respectively.

	N	Mean	St. Dev.	Median	Min	Max
Exchange-Traded Fund (ETF) Holdings$_t$ (%)	296,914	5.198	8.450	2.433	0	100.000
Mutual Fund Holdings$_t$ (%)	296,914	22.297	63.170	8.485	0	100.000
Exchange-Traded Fund (ETF) Holdings $\Delta_{t,t-1}$ (%)	250,042	0.071	2.974	0.000	-100.000	87.772
Mutual Fund Holdings $\Delta_{t,t-1}$	250,042	-0.694	16.914	0.000	-100.000	2,188.513
Turnover (%)	296,914	10.014	34.769	1.981	0.000	955.621
Zero Trade Days (%)	296,914	88.218	12.072	91.935	3.226	98.387
Price Dispersion	296,913	0.200	0.526	0.000	0.000	44.743
Amihud	133,824	0.0185	0.0559	0.0052	0	0.8421
Return Synchronicity	55,290	-3.56	0.23	-3.03	-3.66	2.58
Coupon (%)	296,909	4.777	0.919	5.000	0.000	10.000
Years to Maturity	296,909	11.23	8.42	9.00	0	83.00
Maturity Par ($millions)	296,914	$51.70	$85.94	$30.09	$0.04	$8,000.00
Issue Par ($ millions)	296,914	$478.04	$583.12	$319.17	$0.97	$8,000.00
Callable	296,914	0.55	–	–	0	1
Insured	296,914	0.11	–	–	0	1

TABLE 5: CROSS-TAB OF CREDIT RATINGS AND INSURANCE

This table is a cross-tab of the credit quality indicators for fixed coupon mu- nicipal bonds with at least 30 days since is- suance that were held in exchange-traded funds at any point from 2010Q1 through 2020Q1. The columns indicate credit quality, measured as the higher of Moody's or Standard & Poor's long- term underlying rating. Insured status indicates whether the bond carried default insurance from one of the monoline insurers.

	Insured	Not Insured
AAA	1.8%	16.7%
AA	66.7%	56.7%
A	21.8%	17.0%
BBB	6.7%	4.8%
<BBB	1.5%	2.0%
Not Rated	1.5%	2.8%
N = 296,914		

TABLE 6: REGRESSION ESTIMATES OF TRADE-BASED MEASURES

	Turnover				Zero Trading Days			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ETF Holdings_t	0.527***	0.492***			0.036***	0.029***		
	(0.008)	(0.008)			(0.002)	(0.002)		
ETF Holdings_{t-1}			0.199***	0.163***			0.046***	0.041***
			(0.006)	(0.007)			(0.002)	(0.003)
Mutual Fund Holdings_t		0.087***				0.017***		
		(0.001)				(0.0003)		
Mutual Fund Holdings_{t-1}				0.079***				0.017***
				(0.001)				(0.0004)
Maturity Par Value	−2.785***	−2.784***	−1.167***	−1.256***	−4.981***	−4.981***	−5.338***	−5.610***
	(0.085)	(0.084)	(0.063)	(0.073)	(0.025)	(0.025)	(0.027)	(0.034)
Issue Par Value	1.275***	0.889***	0.944***	0.759***	−0.509***	−0.582***	−0.519***	−0.641***
	(0.089)	(0.088)	(0.066)	(0.075)	(0.026)	(0.026)	(0.028)	(0.035)
Years to Maturity	0.701***	0.597***	0.334***	0.218***	−0.180***	−0.200***	−0.149***	−0.195***
	(0.012)	(0.012)	(0.009)	(0.010)	(0.003)	(0.003)	(0.004)	(0.005)
Coupon	−2.754***	−1.102***	−2.519***	−0.998***	0.779***	1.091***	0.742***	1.135***
	(0.074)	(0.076)	(0.054)	(0.065)	(0.022)	(0.022)	(0.023)	(0.030)
Callable	−5.677***	−4.655***	−4.073***	−2.885***	1.138***	1.331***	1.340***	1.519***
	(0.175)	(0.174)	(0.129)	(0.146)	(0.051)	(0.051)	(0.055)	(0.068)
Insured	−2.595***	−3.286***	−0.835***	−0.962***	−1.950***	−2.081***	−1.905***	−1.959***
	(0.214)	(0.211)	(0.157)	(0.174)	(0.062)	(0.062)	(0.067)	(0.081)
Rating AAA	−5.527***	−2.605***	−4.578***	−1.747***	−3.093***	−2.541***	−3.136***	−1.779***
	(0.514)	(0.510)	(0.389)	(0.460)	(0.150)	(0.149)	(0.166)	(0.213)
Rating AA	−5.390***	−1.335***	−4.094***	−0.342	−2.098***	−1.331***	−2.186***	−0.541**
	(0.506)	(0.502)	(0.383)	(0.455)	(0.147)	(0.147)	(0.164)	(0.211)
Rating A	−4.184***	−0.015	−3.156***	0.544	−2.006***	−1.217***	−2.098***	−0.392*
	(0.529)	(0.525)	(0.399)	(0.473)	(0.154)	(0.154)	(0.170)	(0.220)
Rating BBB	−3.703***	−1.927***	−3.618***	−1.882***	−1.411***	−1.075***	−1.369***	−0.604***
	(0.545)	(0.539)	(0.412)	(0.484)	(0.159)	(0.158)	(0.176)	(0.225)
Rating $<$ BBB	−6.231***	−2.880***	−3.903***	−0.596	−1.711***	−1.077***	−1.827***	−0.255
	(0.623)	(0.617)	(0.471)	(0.548)	(0.182)	(0.181)	(0.201)	(0.255)
Observations	296,679	296,679	249,845	169,564	296,679	296,679	249,845	169,564
Adjusted R^2	0.055	0.076	0.040	0.076	0.334	0.340	0.348	0.361

This table shows the ordinary least squares regression estimates for the trade-based liquidity measures. The sample includes all fixed coupon municipal bonds with at least 30 days since issuance that were held in exchange-traded funds (ETFs) at any point from 2010 Q1 through 2020 Q1. All observations are at the bond-quarter level. Columns 1-4 show the estimates for *Turnover*, computed as the total secondary market trading in a bond throughout the quarter as a percentage of its outstanding par value. Columns 5-8 show the estimates for *Zero Trade Days*, defined as the percentage of days in the quarter when a bond did not trade. Both dependent variables are limited to secondary market sales to customers. All regression specifications include fixed effects on the quarter, the state where the issuer is located, and the bond's security pledge. *Exchange-Traded Fund Holdings* is the share of a bond's outstanding par value held by ETFs in quarter t or quarter $t - 1$. *Mutual Fund Holdings* is the share of a bond's outstanding par value held by mutual funds in quarter t or quarter $t - 1$. *Maturity Par* is the bond's total outstanding par value. *Issue Par* is the total outstanding par value of the issue in which the bond was sold. *Years to Maturity* is the number of years from trade date until the bond matures. *Coupon* is the bond's coupon rate. *Callable* and *Insured* are dummy variables that identify if the bond has a call feature or carries default insurance, respectively. Ratings categories are based on the higher of Moody's or Standard & Poor's long-term underlying rating. The excluded ratings category is No Rating. Note: $* = p < 0.1$; $** = p < 0.05$; $*** = p < 0.01$.

TABLE 7: REGRESSION ESTIMATES OF PRICE-BASED MEASURES

	Price Dispersion				Amihud			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ETF Holdings$_t$	−0.0002*	−0.0001			−0.0002***	−0.0002***		
	(0.0001)	(0.0001)			(0.00002)	(0.00002)		
ETF Holdings$_{t-1}$			−0.001***	−0.001***			−0.0002***	−0.0002***
			(0.0002)	(0.0002)			(0.00003)	(0.00003)
Mutual Fund Holdings$_t$		−0.0003***				−0.00000		
		(0.00002)				(0.00000)		
Mutual Fund Holdings$_{t-1}$				−0.0003***				−0.00001*
				(0.00002)				(0.00000)
Maturity Par Value	0.049***	0.049***	0.061***	0.061***	−0.005***	−0.005***	−0.005***	−0.005***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)
Issue Par Value	0.030***	0.031***	0.030***	0.032***	0.00003	0.00003	−0.00002	−0.00001
	(0.001)	(0.001)	(0.002)	(0.002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)
Years to Maturity	0.019***	0.019***	0.017***	0.018***	0.0002***	0.0002***	0.0002***	0.0002***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.00003)	(0.00003)	(0.00003)	(0.00003)
Callable	−0.026***	−0.030***	−0.036***	−0.039***	0.006***	0.006***	0.005***	0.005***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.0004)	(0.0004)	(0.001)	(0.001)
Coupon	−0.035***	−0.041***	−0.032***	−0.038***	−0.001***	−0.001***	−0.001***	−0.001***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Insured	−0.011***	−0.009***	−0.011***	−0.009**	0.002***	0.002***	0.002***	0.002***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.0005)	(0.0005)	(0.001)	(0.001)
Rating AAA	0.021***	0.010	−0.016	−0.025**	−0.011***	−0.011***	−0.011***	−0.012***
	(0.007)	(0.007)	(0.010)	(0.010)	(0.001)	(0.001)	(0.002)	(0.002)
Rating AA	−0.010	−0.026***	−0.051***	−0.065***	−0.013***	−0.013***	−0.013***	−0.013***
	(0.007)	(0.007)	(0.010)	(0.010)	(0.001)	(0.001)	(0.001)	(0.002)
Rating A	0.001	−0.015*	−0.037***	−0.051***	−0.014***	−0.014***	−0.014***	−0.014***
	(0.007)	(0.007)	(0.010)	(0.010)	(0.001)	(0.001)	(0.002)	(0.002)
Rating BBB	0.0002	−0.006	−0.038***	−0.044***	−0.011***	−0.011***	−0.011***	−0.011***
	(0.008)	(0.008)	(0.010)	(0.010)	(0.001)	(0.001)	(0.002)	(0.002)
Rating < BBB	−0.074***	−0.087***	−0.117***	−0.128***	−0.013***	−0.013***	−0.013***	−0.013***
	(0.009)	(0.009)	(0.012)	(0.012)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	296,678	296,678	169,564	169,564	132,172	132,172	79,648	79,648
Adjusted R^2	0.175	0.177	0.193	0.194	0.027	0.027	0.024	0.024

This table shows the ordinary least squares regression estimates for the price-based liquidity measures. The sample includes all fixed coupon municipal bonds with at least 30 days since issuance that were held in exchange-traded funds (ETFs) at any point from 2010 Q1 through 2020 Q1.

All observations are at the bond level and are based on quarterly medians. Columns 1-4 show the estimates for *Price Dispersion,* computed as $\frac{(Price_{j,t,max} - Price_{j,t,min})}{Price_{j,t.median}}$ where $Price_{max}$ is the weekly maximum price of bond j in week t, $Price_{j,t,min}$ is the weekly minimum price, and $Price_{j,t.median}$ is the weekly median price. Columns 5-8 show the estimates for *Amihud*, defined as $\frac{|r_j|}{volume}$ where $|r_j|$ is the absolute value of daily returns in a bond, and returns are calculated as $\frac{(Price_{j,t,mean} - Price_{j,t-1,mean})}{Price_{j,t-1,mean}}$ and *volume* is the total trade volume in bond j on day t. *Price Dispersion* and *Amihud* are limited to secondary market sales to customers. All regression specifications include fixed effects on the quarter, the state where the issuer is located, and the bond's security pledge. *Exchange-Traded Fund Holdings* is the share of a bond's outstanding par value held by ETFs in quarter t or quarter $t - 1$. Mutual Fund Holdings is the share of a bond's outstanding par value held by mutual funds in quarter t or quarter $t - 1$. *Maturity Par* is the bond's total outstanding par value. Issue Par is the total outstanding par value of the issue in which the bond was sold. *Years to Maturity* is the number of years from trade date until the bond matures. *Coupon* is the bond's coupon rate. *Callable* and *Insured* are dummy variables that identify if the bond has a call feature or carries default insurance, respectively. Ratings categories are based on the higher of Moody's or Standard & Poor's long-term underlying rating. The excluded ratings category is No Rating. Note: $* = p < 0.1$; $** = p < 0.05$; $*** = p < 0.01$

TABLE 8: REGRESSION ESTIMATES OF LIQUIDITY MEASURES, CHANGE IN ETF AND MUTUAL FUND HOLDINGS

	Turnover		Zero Trading Days		Price Dispersion		Amihud	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ ETF Holdings$_{t-1,1}$	0.225***	0.235***	−0.022**	−0.022**	0.001	0.0005	−0.0001	−0.0001
	(0.019)	(0.019)	(0.009)	(0.009)	(0.0004)	(0.0004)	(0.0001)	(0.0001)
Δ Mutual Fund Holdings$_{t-1,t}$		0.307***		0.010***		−0.001***		0.00002*
		(0.004)		(0.002)		(0.0001)		(0.00001)
Maturity Par Value	−1.492***	−1.433***	−5.668***	−5.666***	0.062***	0.062***	−0.005***	−0.005***
	(0.074)	(0.072)	(0.034)	(0.034)	(0.002)	(0.002)	(0.0003)	(0.0003)
Issue Par Value	1.088***	1.041***	−0.567***	−0.568***	0.030***	0.031***	−0.00003	−0.00004
	(0.077)	(0.075)	(0.035)	(0.035)	(0.002)	(0.002)	(0.0003)	(0.0003)
Years to Maturity	0.310***	0.296***	−0.174***	−0.175***	0.017***	0.017***	0.0002***	0.0002***
	(0.010)	(0.010)	(0.005)	(0.005)	(0.0002)	(0.0002)	(0.00003)	(0.00003)
Callable	−3.827***	−3.689***	1.298***	1.302***	−0.035***	−0.036***	0.006***	0.006***
	(0.149)	(0.146)	(0.068)	(0.068)	(0.003)	(0.003)	(0.001)	(0.001)
Coupon	−2.653***	−2.471***	0.767***	0.773***	−0.031***	−0.032***	−0.001***	−0.001***
	(0.063)	(0.062)	(0.029)	(0.029)	(0.001)	(0.001)	(0.0002)	(0.0002)
Insured	−0.599***	−0.799***	−1.888***	−1.894***	−0.010***	−0.010***	0.002***	0.002***
	(0.177)	(0.174)	(0.081)	(0.081)	(0.004)	(0.004)	(0.001)	(0.001)
Rating AAA	−4.449***	−3.918***	−2.382***	−2.364***	−0.015	−0.016	−0.011***	−0.011***
	(0.469)	(0.460)	(0.214)	(0.214)	(0.010)	(0.010)	(0.002)	(0.002)
Rating AA	−3.760***	−3.147***	−1.295***	−1.274***	−0.051***	−0.052***	−0.013***	−0.013***
	(0.463)	(0.454)	(0.211)	(0.211)	(0.010)	(0.010)	(0.002)	(0.002)
Rating A	−3.054***	−2.436***	−1.182***	−1.161***	−0.037***	−0.038***	−0.014***	−0.014***
	(0.482)	(0.473)	(0.220)	(0.220)	(0.010)	(0.010)	(0.002)	(0.002)
Rating BBB	−3.622***	−3.152***	−0.990***	−0.974***	−0.037***	−0.038***	−0.010***	−0.010***
	(0.495)	(0.485)	(0.226)	(0.226)	(0.010)	(0.010)	(0.002)	(0.002)
Rating $<$ BBB	−3.472***	−2.874***	−0.893***	−0.873***	−0.117***	−0.118***	−0.012***	−0.012***
	(0.560)	(0.549)	(0.255)	(0.255)	(0.012)	(0.012)	(0.002)	(0.002)
Observations	169,564	169,564	169,564	169,564	169,564	169,564	79,648	79,648
Adjusted R^2	0.033	0.071	0.354	0.354	0.193	0.193	0.023	0.023

This table shows the ordinary least squares regression estimates for all four liquidity measures from Q1 2010- Q1 2020. The sample includes all fixed coupon municipal bonds with at least 30 days since issuance that were held in exchange-traded funds (ETFs) at any point from 2010Q1 through 2020Q1. All observations are at the bond level and are based on quarterly medians. *Turnover* is the total secondary market trading in a bond throughout the quarter as a percentage of its outstanding par value. *Zero Trade Days* is the percentage of days in the quarter when a bond did not trade. *Price Dispersion* is computed as $\frac{(Price_{j,t,max} - Price_{j,t,min})}{Price_{j,t.median}}$ where $Price_{max}$ is the weekly maximum price of bond *j* in week *t*, $Price_{j,t,min}$ is the weekly minimum price, and $Price_{j,t.median}$ is the weekly median price. *Amihud* is defined as $\frac{|r_j|}{volume}$ where $|r_j|$ is the absolute value of daily returns in a bond, and returns are calculated as $\frac{(Price_{j,t,mean} - Price_{j,t-1,mean})}{Price_{j,t-1,mean}}$ and *volume* is the total trade volume in bond *j* on day *t*. All liquidity measures are limited to secondary market sales to customers. All regression specifications include fixed effects on the quarter, the state where the issuer is located, and the bond's security pledge. Δ *Exchange-Traded Fund Holdings*$_{t-1,t}$ is the change in the share of a bond's outstanding par value held by ETFs from quarter *t* – 1 to quarter *t* – 1. Δ *Mutual Fund Holdings*$_{t-1,t}$ is the change in the share of a bond's outstanding par value held by mutual funds from quarter *t* – 1 or quarter *t*. All other model covariates are as described earlier. Note: * = $p < 0.1$; ** = $p < 0.05$; *** = $p < 0.01$.

TABLE 9: ETF OWNERSHIP, CREDIT QUALITY, AND LIQUIDITY

This table summarizes the estimates from regressions on sub-samples defined by credit quality. The sample includes all fixed coupon municipal bonds with at least 30 days since issuance that were held in exchange-traded funds (ETFs) at any point from 2010 Q1 through 2020 Q1. All observations are at the bond level and are based on quarterly medians. *Turnover* is the total secondary market trading in a bond throughout the quarter as a percentage of its outstanding par value. *Zero Trade Days* is the percentage of days in the quarter when a bond did not trade. *Price Dispersion* is computed as $\frac{(Price_{j,t,max} - Price_{j,t,min})}{Price_{j,t.median}}$ where $Price_{max}$ is the weekly maximum price of bond j in week t, $Price_{j,t,min}$ is the weekly minimum price, and $Price_{j,t.median}$ is the weekly median price. *Amihud* is defined as $\frac{|r_j|}{volume}$ where $|r_j|$ is the absolute value of daily returns in a bond, and returns are calculated as $\frac{(Price_{j,t,mean} - Price_{j,t-1,mean})}{Price_{j,t-1,mean}}$ and *volume* is the total trade volume in bond j on day t. All liquidity measures are limited to secondary market sales to customers. All liquidity measures are limited to secondary market sales to customers. Figures reported here are the coefficients on each liquidity measure for sub-samples sorted on credit quality. Italicized coefficients have $p > 0.05$. All other coefficients have $p < 0.01$. All regression specifications include fixed effects on the quarter, the state where the issuer is located, and the bond's security pledge. *Exchange-Traded Fund Holdings* is the share of a bond's outstanding par value held by ETFs in quarter t or quarter $t-1$. *Mutual Fund Holdings* is the share of a bond's outstanding par value held by mutual funds in quarter t or quarter $t-1$. All specifications also include covariates whose estimates are not reported here, including: *Maturity Par*, *Issue Par*, *Years to Maturity*, *Coupon*, *Callable*, *Insured*, and the credit rating categories. Note: $* = p < 0.1$; $** = p < 0.05$; $*** = p < 0.01$.

Category	Turnover		Zero Trading Days		Dispersion		Amihud	
	ETF	MF	ETF	MF	ETF	MF	ETF	MF
AAA	0.482	0.043	0.023	0.021	0.0003	-0.0003	0.0002	0.00002
AA	0.407	0.109	0.038	0.029	-0.0003	-0.0001	-0.0003	0.00000
A	0.716	0.082	-0.029	0.009	0.0010	-0.0002	*-0.0003*	*0.00000*
BBB	1.339	0.071	-0.136	0.019	0.0040	-0.0002	*-0.0005*	*-0.00002*
<BBB	1.192	0.120	-0.201	0.021	0.0070	-0.0002	*-0.2010*	*0.02100*
Not Rated	0.288	0.060	0.027	0.025	-0.0004	0.00004	*0.0001*	*0.00001*
Insured	1.017	0.088	-0.033	0.005	0.0002	-0.00002	-0.0003	0.00000
Not Insured	0.421	0.080	0.032	0.037	-0.0002	-0.00100	0.0001	0.00001

TABLE 10: REGRESSION ESTIMATES OF AMIHUD "HALF" MEASURES

	Amihud Up				Amihud Down			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ETF Holdings$_t$	−0.0001***	−0.0002***			0.0002***	0.0002***		
	(0.00002)	(0.00002)			(0.00003)	(0.00003)		
Mutual Fund Holdings$_t$		0.00000***				−0.00000***		
		(0.00000)				(0.00000)		
ETF Holdings$_{t-1}$			−0.0001***	−0.0002***			0.0002***	0.0002***
			(0.00002)	(0.00002)			(0.00003)	(0.00003)
Mutual Fund Holdings$_{t-1}$				0.00000***				−0.00000*
				(0.00000)				(0.00000)
Observations	94,870	94,870	86,465	86,465	100,571	100,571	92,295	92,295
Adjusted R^2	0.038	0.038	0.041	0.041	0.025	0.025	0.026	0.026

This table shows the ordinary least squares regression estimates for the *Amihud* measures sorted by positive or negative returns. The sample includes all fixed coupon municipal bonds with at least 30 days since issuance that were held in exchange-traded funds (ETFs) at any point from 2010 Q1 through 2020 Q1. All observations are at the bond level and are based on quarterly medians. Columns 1-4 show the estimates for *Amihud Up*, defined as $\frac{+r_j}{volume}$ when $+r_j$ is a positive daily return, where returns are calculated as $\frac{(Price_{j,t,mean} - Price_{j,t-1,mean})}{Price_{j,t-1,mean}}$, and *volume* is the total trade volume in bond j on day t. Columns 5-8 show the estimates for *Amihud Down*, defined as $\frac{-r_j}{volume}$ where $-r_j$ is a negative daily return and the rest of the measure is identical to *Amihud Up*. Both measures are limited to secondary market sales to customers. All regression specifications include fixed effects on the quarter, the state where the issuer is located, and the bond's security pledge. *Exchange-Traded Fund Holdings* is the share of a bond's outstanding par value held by ETFs in quarter t or quarter $t - 1$. *Mutual Fund Holdings* is the share of a bond's outstanding par value held by mutual funds in quarter t or quarter $t - 1$. All specifications also include covariates whose estimates are not reported here, including: *Maturity Par, Issue Par, Years to Maturity, Coupon, Callable, Insured*, and the credit rating categories. Note: * = p < 0.1; ** = p < 0.05; *** = p < 0.01.

TABLE 11: REGRESSION ESTIMATES OF LIQUIDITY MEASURES, "COVID-19 CRISIS" OF Q1 2020

	Turnover		Zero Trading Days		Price Dispersion		Amihud	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ETF Holdings$_t$	0.228***		0.018***		−0.001*		−0.0002	
	(0.017)		(0.006)		(0.001)		(0.0002)	
Mutual Fund Holdings$_t$	0.031***		0.008***		−0.0001		−0.00002	
	(0.003)		(0.001)		(0.0001)		(0.0001)	
ETF Holdings$_{t-1}$		0.127***		0.034***		−0.0001		
		(0.020)		(0.008)		(0.001)		
Mutual Fund Holdings$_{t-1}$		0.068***		0.008***		−0.0001		
		(0.003)		(0.001)		(0.0001)		
Observations	16,406	11,950	16,406	11,950	16,406	11,950	6,578	5,550
Adjusted R^2	0.035	0.066	0.331	0.330	0.036	0.040	0.010	

This table shows the ordinary least squares regression estimates for all four liquidity measures during Q1 2020. The sample includes all fixed coupon municipal bonds with at least 30 days since issuance that were held in exchange-traded funds (ETFs) at any point from 2010 Q1 through 2020 Q1. All observations are at the bond level and are based on quarterly medians. *Turnover* is the total secondary market trading in a bond throughout the quarter as a percentage of its outstanding par value. *Zero Trade Days* is the percentage of days in the quarter when a bond did not trade. *Price Dispersion* is computed as $\frac{(Price_{j,t,max} - Price_{j,t,min})}{Price_{j,t.median}}$ where $Price_{max}$ is the weekly maximum price of bond j in week t, $Price_{j,t,min}$ is the weekly minimum price, and $Price_{j,t.median}$ is the weekly median price. *Amihud* is defined as $\frac{|r_j|}{volume}$ where $|r_j|$ is the absolute value of daily returns in a bond, and returns are calculated as $\frac{(Price_{j,t,mean} - Price_{j,t-1,mean})}{Price_{j,t-1,mean}}$ and *volume* is the total trade volume in bond j on day t. All liquidity measures are limited to secondary market sales to customers. All regression specifications include fixed effects on the quarter, the state where the issuer is located, and the bond's security pledge. *Exchange-Traded Fund Holdings* is the share of a bond's outstanding par value held by ETFs in quarter t or quarter $t - 1$. *Mutual Fund Holdings* is the share of a bond's outstanding par value held by mutual funds in quarter t or quarter $t - 1$. All specifications also include covariates whose estimates are not reported here, including: *Maturity Par*, *Issue Par*, *Years to Maturity*, *Years to Maturity*, *Coupon*, *Callable*, *Insured*, and the credit rating categories. Note: $* = p < 0.1$; $** = p < 0.05$; $*** = p < 0.01$.

TABLE 12: ESTIMATES OF RETURN SYNCHRONICITY

	Return Synchronicity			
	(1)	(2)	(3)	(4)
ETF Holdings$_t$	0.0001	−0.00000		
	(0.0002)	(0.0002)		
ETF Holdings$_{t-1}$			0.00000	−0.0001
			(0.0003)	(0.0003)
Mutual Fund Holdings$_t$		0.0002***		
		(0.00004)		
Mutual Fund Holdings$_{t-1}$				0.0002***
				(0.00005)
Maturity Par Value	−0.020***	−0.020***	−0.024***	−0.024***
	(0.002)	(0.002)	(0.002)	(0.002)
Issue Par Value	−0.001	−0.001	−0.003	−0.003
	(0.002)	(0.002)	(0.002)	(0.002)
Years to Maturity	−0.001***	−0.001***	−0.001***	−0.001***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Callable	−0.015***	−0.012***	−0.011**	−0.008*
	(0.004)	(0.005)	(0.005)	(0.005)
Coupon	0.008***	0.010***	0.006***	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)
Insured	−0.007*	−0.006	−0.010**	−0.008*
	(0.004)	(0.004)	(0.004)	(0.004)
Rating AAA	0.006*	0.007*	0.007*	0.008**
	(0.004)	(0.004)	(0.004)	(0.004)
Rating AA	0.003	0.005	0.002	0.004
	(0.006)	(0.006)	(0.007)	(0.007)
Rating A	−0.004	−0.006	−0.004	−0.005
	(0.016)	(0.016)	(0.016)	(0.016)
Rating BBB	0.016	0.010	0.010	0.004
	(0.015)	(0.016)	(0.017)	(0.017)
Rating < BBB	−0.005	−0.007	0.002	0.001
	(0.007)	(0.007)	(0.007)	(0.007)
Observations	30,305	30,305	27,304	27,304
Adjusted R^2	0.074	0.074	0.073	0.073

This table shows the estimates of *Return Synchronicity*, defined as the logit transformation of $\frac{R^2_{j,t}}{1-R^2_{j,t}}$ where $R^2_{j,t}$ is the R^2 from a regression of the daily returns of bond j on the daily returns of the Barclay's Municipal Bond Index. Those regressions are limited to bonds that trade at least three times in a quarter. The sample includes all fixed coupon municipal bonds with at least 30 days since issuance that were held in exchange-traded funds (ETFs) at any point from 2010 Q1 through 2020 Q1. Columns 1-4 show the estimates for *Price Dispersion*, computed as $\frac{(Price_{j,t,max}-Price_{j,t,min})}{Price_{j,t.median}}$ where $Price_{max}$ is the weekly maximum price of bond j in week t, $Price_{j,t,min}$ is the weekly minimum price, and $Price_{j,t.median}$ is the weekly median price. Columns 5-8 show the estimates for *Amihud,* defined as $\frac{|r_j|}{volume}$ where $|r_j|$ is the absolute value of daily returns in a bond, and returns are calculated as $\frac{(Price_{j,t,mean}-Price_{j,t-1,mean})}{Price_{j,t-1,mean}}$ and *volume* is the total trade volume in bond *j* on day *t*. *Price Dispersion* and *Amihud* are limited to secondary market sales to customers. All regression specifications include fixed effects on the quarter, the state where the issuer is located, and the bond's security pledge. *Exchange-Traded Fund Holdings* is the share of a bond's outstanding par value held by ETFs in quarter *t* or quarter *t* – 1. *Mutual Fund Holdings* is the share of a bond's outstanding par value held by mutual funds in quarter *t* or quarter *t* – 1. *Maturity Par* is the bond's total outstanding par value. *Issue Par* is the total outstanding par value of the issue in which the bond was sold. *Years to Maturity* is the number of years from trade date until the bond matures. *Coupon* is the bond's coupon rate. *Callable* and *Insured* are dummy variables that identify if the bond has a call feature or carries default insurance, respectively. Ratings categories are based on the higher of Moody's or Standard & Poor's long-term underlying rating. The excluded ratings category is No Rating. Note: $*$ = $p < 0.1$; $**$ = $p < 0.05$; $***$ = $p < 0.01$

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