Size-Adapted Bond Liquidity Measures and Their Asset Pricing Implications*

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Abstract

We develop a new class of transaction cost measures for the bond market. Standard liquidity measures suffer from the combination of two effects. First, transaction costs in OTC bond markets strongly depend on trade size. Second, many bonds are traded only scarcely with differing trading volumes over time and in the cross-section. As a result, a change in average transaction costs often indicates a change in the average trade size and not a change in liquidity. Combining full sample information for the size-cost relation with individual transaction data, our new approach does not suffer from such idiosyncratic measurement errors. Compared to standard measures, our size-adapted measures are able to explain a much larger part of yield spread variations. Furthermore, they uncover the joint pricing of liquidity level and corporate bond market liquidity risk in the cross-section of U.S. corporate bonds.

JEL classification: C10, C14, G11, G12, G14

Keywords: bond liquidity, transaction costs, bid-ask spread, trade size, asset pricing

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1 Introduction

Quantifying transaction costs of bonds is important for investors, issuers, and regulators. Investors, for example, have to trade off the higher yield they get from illiquid bonds with the higher cost of trading. Regulators and central banks closely monitor the liquidity of a market and issuers have to pay higher yields to compensate for their bonds' illiquidity. Despite their importance, measuring a bond's transaction costs is difficult mainly due to the over-the-counter (OTC) nature of bond trading. If, for example, an investor wants to compare the costs of trading for two different bonds, she can request quotations from dealers. But due to large search costs, she is typically restricted to only a few observations. Moreover, requesting individual quotations is not feasible when monitoring the liquidity of a large bond portfolio. As an alternative, the investor can use a standard liquidity measure based on past transaction data. These measures typically assess a bond's costs of trading as average across all individual trades. Considering the strong dependence of transaction costs on trade size (see, e.g., Edwards, Harris, and Piwowar (2007); Bessembinder, Jacobsen, Maxwell, and Venkataraman (2017)), they depend heavily on the idiosyncratic trade-size pattern observed for that bond. Thus, a fair comparison between the liquidity of different bonds or across time is in general not possible.

To illustrate this point, Panel A of Figure 1 depicts all buy and sell trade prices for a particular bond on one day. Using the average buy and sell price to calculate transaction costs, we get a relative bid-ask spread of roughly 2%. Now assume that, on the following day, the demand to trade large positions and the supply of liquidity stay identical but no investor has trading needs for volumes of less than \$500,000. On that day, the resulting bid-ask spread would be just 0.2% (see Panel B of Figure 1). So comparing those two days, an observer would mistakenly conclude that the liquidity of this bond improved strongly, although it did not change at all. Such a variation in the observed trade sizes and its impact on transaction cost measures is especially prevalent for the majority of bonds that only trade a few times during a month. Some researchers try to address this problem and delete all transactions below a threshold, which is in most cases \$100,000. This approach has two major shortcomings. First, about two thirds of the transactions in the U.S. corporate bond market are retail-sized trades below \$100,000. As a result, large amounts of information are ignored, for which we find that they are valuable to accurately assess a bond's liquidity. Second, Figure 1 shows that the negative dependence of transaction costs on volume persists beyond \$100,000.

Insert Figure 1 about here.

In this paper, we introduce a two-stage approach to eliminate the size dependence of transaction costs in the bond market. In the first step, we estimate a market-wide functional form for the dependence of transaction costs on trade size. In the second step, we calculate a scaling factor for each bond and each month that scales the market-wide average function so that it best explains the observed transaction costs for this bond. This factor can be interpreted as a measure of relative liquidity of the bond compared to a bond with average liquidity. Although the literature is aware of the relation of trade size and transaction costs in OTC markets, it is usually ignored when calculating common transaction cost measures. We are the first to incorporate this relation in a natural way, making liquidity measures immune to changes in the individually observed trade-size pattern. Importantly, our new approach offers investors an easy way to calculate transaction costs for arbitrary position sizes as the product of the individual scaling factor and the market-wide functional form evaluated at the trade size in question.[1]

The combination of the full-sample information for the market-wide functional form with the individual transaction data to extract a bonds relative liquidity exploits all available information in an efficient way. For that reason, our size-adapted measurement approach generally can be calculated with the same data requirements as standard measures when there is only one observation for transaction costs available. The new methodology is straightforward to implement and can be applied to adapt a large number of commonly used transaction cost measures. As different high-frequency liquidity measures are closely connected (see Schestag, Schuster, and Uhrig-Homburg (2016)), we exemplarily implement our approach for the Schultz (2001) and the average bid-ask spread measure (see, e.g., Hong and Warga (2000)), which are two very common transaction cost measures. We use U.S. corporate bond transaction data from Enhanced TRACE for the period from October 1, 2004 to December 31, 2014.

We demonstrate that ignoring the dependence of common liquidity measures on the idiosyncratic trade-size pattern has a strong impact on the results when studying liquidity effects on bond prices. Hence, our new, conceptually more precise measures make a difference and we can offer two additional contributions on the asset pricing effects of bond liquidity.

First, we show that the part of the yield spread variation attributable to liquidity changes is much larger than when measured with standard liquidity measures. In a panel setting, we regress yield spread changes on the changes of individual bond transaction costs and a set

[1] In the stock market, price impact measures like λ (see, e.g., Kyle (1985); Hasbrouck (2009)) are typically employed to calculate size-dependent trading costs (see, e.g., Goyenko, Holden, and Trzcinka (2009)). Schestag, Schuster, and Uhrig-Homburg (2016) find that these measures do not work well in the bond market.

of control variables. The part of the R^2 that can be attributed to transaction costs almost doubles when using our size-adapted measures compared to their standard counterparts. Additionally, we show in an out-of-sample analysis that the mean squared error decreases twice as much when employing our size-invariant approach. The improvements are even stronger when we compare our new measures with the approach of deleting all trades with volumes below $100,000. This result shows that the transaction costs of small trades are valuable for asset pricing.

Second, our size-adapted liquidity measures help to reconcile conflicting findings of previous studies regarding the question whether the level of liquidity or the risk of changing market-wide liquidity is priced. Building on the predictions of Amihud and Mendelson's (1986) model, there is a large literature confirming the influence of a bond's liquidity on its expected return (see, e.g., Amihud and Mendelson (1991); Chen, Lesmond, and Wei (2007); Bao, Pan, and Wang (2011)). In contrast to that, the results for liquidity risk are conflicting. Whereas studies like Lin, Wang, and Wu (2011) and Dick-Nielsen, Feldhütter, and Lando (2012) confirm that bonds with a stronger return sensitivity to market-wide liquidity shocks earn higher expected returns, Bongaerts, de Jong, and Driessen (2017) do not find a significant bond market liquidity risk premium. These authors develop an integrated asset-pricing model to simultaneously analyze the effects of liquidity level and risk on ex ante expected bond returns. We find that due to the strong correlation of transaction costs and liquidity beta, it is very difficult to disentangle the effects of liquidity level and risk. Indeed, when using standard measures of liquidity, the observed pricing pattern is strongly affected by the way test assets are constructed or betas are estimated, explaining the conflicting results so far. In contrast, when we use our more precise size-adapted liquidity measures, we consistently find that both liquidity level and bond market liquidity risk are priced in the cross-section of expected bond returns. Economically, the part of yield spreads related to liquidity level and risk is large and amounts to 0.8-0.9% for each of the two dimensions. More broadly, our work also contributes to the literature on the risk versus characteristics debate (see, e.g., Davis, Fama, and French (2000) or Daniel, Titman, and Wei (2001) for the stock market and Gebhardt, Hvidkjaer, and Swaminathan (2005) for the corporate bond market). Specifically, we show that an imprecise measurement of the characteristic can cause misleading conclusions on the question whether the characteristic or the associated risk are priced.

2 Size-Adapted Liquidity Measures

In this section, we show that the information in small and in large trades contains valuable information for a bond's liquidity. We then describe in Section 2.2 our size-adapted measurement approach that naturally captures and combines this information. We use a two-stage procedure to estimate the (relative) liquidity of a bond for each month. We implement this approach for the widely used Schultz (2001) and average bid-ask spread measure in Sections 2.3 and 2.4, using individual bond transaction data from Enhanced TRACE (see Appendix A for details on the data filters) from October 1, 2004 to December 31, 2014.

2.1 Information Content of Small and Large Trades

An econometrician who wants to measure the liquidity of a bond using past transactions has to decide on the data that provide the most accurate and comprehensive information. A large strand of the literature (see, e.g., Dick-Nielsen, Feldhütter, and Lando (2012) or Feldhütter, Hotchkiss, and Oğuzhan (2016)) exclude retail trades below $100,000 for the calculation of liquidity measures, essentially assuming that small trades provide no meaningful information. Because about two thirds of all transactions in the corporate bond market are below $100,000, it is often not possible to calculate a daily or even monthly liquidity measure just from large trades. Panel A of Table 1 shows that for the common Schultz (2001) measure, the number of months for which a bond's liquidity can be assessed drops by roughly 22% when ignoring small trades below $100,000. For the average bid-ask spread measure, this drop is with 42% even more pronounced as this measure has more stringent data requirements.[2] On a daily frequency, the problem is exacerbated and the observations for which a liquidity measure can be calculated are reduced by more than 50% for both measures when using only large trades.

Insert Table 1 about here.

We next challenge the literature's implicit assumption that small trades are uninformative for institutional trading costs when large trades are available. To this end, we run a panel regression explaining a bond's daily large-trade transaction costs with monthly bid-ask

[2]For the definitions of the standard Schultz (2001) and average-bid ask spread measure, we refer to Sections 2.3 and 2.4.

spread estimates based on large or small trades:

$$tc^{\text{large}}_{i,d,t} = \alpha + \beta^{\text{large}} \cdot tc^{\text{large}}_{i,t\setminus\{d\}} + \beta^{\text{small}} \cdot tc^{\text{small}}_{i,t\setminus\{d\}} + \epsilon_{i,d,t}, \tag{1}$$

where we calculate the monthly measures $tc_{i,t\setminus\{d\}}$ for bond i in month t excluding the day under consideration d. A significant estimate for β^{small} would show that small trades help to explain the transaction costs of large trades. The results of the panel regressions are presented in Panel B of Table 1. In specifications (1) and (4), we explain transaction costs of large trades using only the monthly estimates from large transactions, whereas in specifications (2) and (5), we only employ small trades. Finally, specifications (3) and (6) use both size categories. As expected, large trades from other days of the same month carry information for a bond's institutional transaction costs with an R^2 of 23% for the Schultz (2001) measure and 33.9% for the average bid-ask spread. When substituting the monthly bid-ask spread measure for large trades with the one calculated from small trades, the relation is still highly significant but with moderately decreased R^2 of 18.3% for the Schultz (2001) and 25.1% for the average bid-ask spread measure. Most interestingly, if we include bid-ask spreads from both small and large trades, the R^2 surpasses notably the R^2 of the specifications in which only the institutional bid-ask spreads are employed. These results show not only that small trades are valuable for assessing institutional transaction costs but rather that the combination of both size categories offers superior information.

Because retail transaction costs are relevant for a large group of corporate bond investors, we also plug in daily retail sized transaction costs $tc^{\text{small}}_{i,d,t}$ as the left-hand side of Equation (1). The results in Panel C of Table 1 show that again both size categories carry a significant information content. As in Panel B, the R^2 are higher when explaining bid-ask spreads using other similarly sized trades. Finally, we again observe the highest R^2 when employing monthly spreads of both size categories. Summarizing, incorporating past transactions of small and large trades provides the most accurate assessment of a bond's liquidity.

2.2 Basic Measurement Approach

Having shown that both small and large trades provide valuable information for a bond's liquidity, we now aim to aggregate this information into one single value. Edwards, Harris, and Piwowar (2007) find that transaction costs for large trades are only a small fraction of the costs for trading small volumes.[3] As illustrated in Figure 1, simply averaging across different transaction sizes ignores this dependence and a fair comparison between the liquidity of different bonds or even between a bond's liquidity for different periods is not possible. This problem is most severe for bonds that trade only very infrequently with varying trade sizes, which is the case for the vast majority of the U.S. corporate bond universe.

We develop a two-step liquidity measurement approach that does not suffer from this shortcoming. In the first step, we estimate a functional form $c(vol)$ capturing the dependence of transaction costs on the traded (notional) volume vol. This functional form serves as a market-wide benchmark for all bonds, representing an average state of liquidity. To ensure the highest possible generality for the functional form, we employ a nonparametric estimation based on all observations of all available bonds in the sample.[4] In the second step, the liquidity of a bond i in month t (or day t) is measured relative to this market-wide and time invariant functional form. We use the (estimated) transaction costs $tc_{k,i,t}$ of all observed transactions k of bond i in month t. We express the relative liquidity of bond i in month t then by an individual scaling factor $sf_{i,t}$, which is given as the best fit for the equation

$$tc_{k,i,t} = sf_{i,t} \cdot c(vol_{k,i,t}) + \epsilon_{k,i,t}, \tag{2}$$

with $vol_{k,i,t}$ as the transaction volume of the k-th transaction and $\epsilon_{k,i,t}$ as an error term. A liquid bond is characterized by a scaling factor below 1 (i.e., its transaction costs for all trade sizes are smaller than those of an average bond). Similarly, an illiquid bond has a scaling factor larger than 1. Thus, a comparison between different bonds or observation months is easily facilitated as all scaling factors are based on the same market-wide functional form. Given the assumption that the general dependence of transaction costs on trade size does not change much (which we verify later), changing trade size patterns for a particular bond do not affect the scaling factor. Most importantly, the full information regarding a bond's liquidity for all trade sizes can be expressed as one number that is easy to interpret.[5] Thus, we can use the scaling factor $sf_{i,t}$ as a measure for the liquidity of bond i in month t.[6]

[3]The negative relation is unchanged after the introduction of the Volcker rule (see, e.g., Adrian, Fleming, Shachar, and Vogt (2017); Bessembinder, Jacobsen, Maxwell, and Venkataraman (2017)) and it also holds for trades executed via electronic trading platforms (see Hendershott and Madhavan (2015)).

[4]It is also possible to estimate the functional form using parametric functions (see Edwards, Harris, and Piwowar (2007)). As these functions are in general easier to compute, we repeat our analyses employing liquidity measures based on a parametric functional form as a robustness check in Section 5.1.

[5]We have experimented with more sophisticated functional forms that allow, e.g., transaction costs for large trade sizes to vary (relatively) stronger than transaction costs for small trades. The higher complexity by introducing additional parameters to this function only increases the precision very moderately.

[6]Note that the interpretation as a liquidity measure would not be possible if the functional form were

The size-invariant measurement approach from Equation (2) can be applied to adapt a broad variety of common liquidity measures. To perform the asset pricing tests in Sections 3 and 4, we choose to adapt the transaction cost measure of Schultz (2001) and the average bid-ask spread measure (see, e.g., Hong and Warga (2000)).[7] As the adapted versions of the two measures no longer suffer from idiosyncratic changes in the observed trade sizes, we expect that they are better able to extract the liquidity-related component of asset prices.

2.3 Size-Adapted Schultz (2001) Measure

The first measure that we adapt to the new approach is the (relative) Schultz (2001) liquidity measure that is based on the model

$$\Delta_{k,i,t} = \alpha_{i,t} + c_{i,t} \cdot D_{k,i,t} + \epsilon_{k,i,t}. \tag{3}$$

Here, $c_{i,t}$ approximates the average (relative) half-spread of bond i in month t by regressing for each trade k the (relative) price deviation of the trade price to a consensus price $\Delta_{k,i,t}$ on a trade side indicator $D_{k,i,t}$. This trade side indicator equals 1 for customer buys, -1 for customer sells, and 0 if the trade is between two dealers. We obtain daily consensus prices from Bloomberg.

Following the intuition in (2), we replace in (3) the average half-spread with the average market-wide cost $c(vol_{k,i,t})$ of trading the transaction volume $vol_{k,i,t}$ multiplied by the bond-individual scaling factor $sf_{i,t}^{Schultz}$, leading to

$$\Delta_{k,i,t} = \alpha_{i,t} + sf_{i,t}^{Schultz} \cdot c(vol_{k,i,t}) \cdot D_{k,i,t} + \epsilon_{k,i,t}. \tag{4}$$

We can now interpret the scaling factor $sf_{i,t}^{Schultz}$ as a measure for the relative liquidity of bond i in month t.

To estimate the scaling factor $sf_{i,t}^{Schultz}$ from (4), we run an iterative two-stage weighted regression. In the first step, we estimate a nonparametric functional form $c(\cdot)$ from all observations in the sample using the scaling factor estimates from the previous iteration.[8] In

estimated for each bond and/or each month separately (see, e.g., Edwards, Harris, and Piwowar (2007)).

[7]Schestag, Schuster, and Uhrig-Homburg (2016) find that liquidity measures based on intraday transaction data are closely connected. Therefore, our results should be robust regarding the choice which measure to adapt.

[8]We employ locally weighted scatterplot smoothing (LOESS) as the nonparametric regression method. In the first iteration, we set all scaling factors to 1.

the second step, we use the transaction cost function from the first step and estimate (4) for each month t and each bond i separately to obtain individual scaling factors $sf_{i,t}^{Schultz}$. We exclude negative bid-ask spreads with the constraint $sf_{i,t}^{Schultz} \geq 0$. We weight observations in both steps to ensure that different volume segments contribute equally to the market-wide functional form and the scaling factors. In this spirit, we define eleven segments centered symmetrically around the individual trade sizes \$10,000, \$25,000, \$50,000, \$100,000, \$200,000, \$500,000, \$1 million, \$2 million, \$5 million, \$10 million, and \$20 million.[9] To put equal weight on each segment, we weight each trade with the inverse of the total number of observations in the respective volume segment. To ensure that the functional form represents a state of average liquidity, we scale after each iteration the functional form and the scaling factors such that the average of the factors equals 1. We iterate over steps one and two until convergence.[10] Note that the data requirements to estimate an individual scaling factor $sf_{i,t}^{Schultz}$ in (4), given a market-wide functional form $c(vol_{k,i,t})$, are identical to the standard Schultz (2001) measure in (3), i.e., the regression is identified whenever we have at least two trades with different trade sides $D_{k,i,t}$ and the corresponding consensus prices.

The resulting functional form is depicted in Figure 2. Consistent with previous studies, we confirm a negative relation between transaction costs and trade size. For example, a retail investor who wants to trade a position of \$10,000 pays on average round-trip costs between 1.5% and 2%. In contrast, an institutional position of \$5 million trades at bid-ask spreads of only about 20 basis points. The literature mainly attributes this difference to the stronger negotiation power of institutional investors that is due to their lower search costs (see Feldhütter (2012); Green, Hollifield, and Schürhoff (2007b)) or their more precise knowledge of a bond's fair value (see Green, Hollifield, and Schürhoff (2007a)). Fixed costs per trade might also play a role (see, e.g., Harris and Piwowar (2006)). For very large volumes though, we observe a slight increase in transaction costs. This increase probably comes from their higher inventory risk (Stoll (1978)) or difficulties in finding counterparties for these extremely large positions.

Insert Figure 2 about here.

[9] Our results do not depend on the exact specification of these segments.

[10] The iteration terminates when the average absolute difference between the factors of the current and the previous iteration is below 10^{-6}.

2.4 Size-Adapted Average Bid-Ask Spread Measure

The second measure that we adapt to our size-invariant measurement approach is the relative difference of average bid and ask prices

$$AvgBidAsk_{i,d} = \frac{\overline{P_{i,d}^{buy}} - \overline{P_{i,d}^{sell}}}{0.5 \cdot \left(\overline{P_{i,d}^{buy}} + \overline{P_{i,d}^{sell}}\right)}, \tag{5}$$

where $\overline{P_{i,d}^{buy}} = \frac{1}{n_{i,d}^{buy}} \sum_{k=1}^{n_{i,d}^{buy}} P_{k,i,d}^{buy}$ is the average customer buy price, $\overline{P_{i,d}^{sell}} = \frac{1}{n_{i,d}^{sell}} \sum_{k=1}^{n_{i,d}^{sell}} P_{k,i,d}^{sell}$ gives the average sell price, and $n_{i,d}^{buy/sell}$ is the number of buy/sell trade prices $P_{k,i,d}^{buy/sell}$ for bond i on day d, respectively. This measure was introduced by Hong and Warga (2000) and Chakravarty and Sarkar (2003). We can calculate it for each day with at least one buy and one sell trade. For a monthly measure, we calculate the mean of all daily bid-ask spreads.

Starting from our new approach (2), the adaption of this measure is slightly more involved than for the Schultz (2001) measure. Since the difference of average bid and ask prices is only available on a per day and not on a per trade basis, we have to evaluate the market-wide function for each trade that goes into the calculation of the daily average separately and then compute an average cost function:

$$AvgBidAsk_{i,d} = sf_{i,t}^{AvgBidAsk} \cdot \frac{1}{2} \left[\frac{1}{n_{i,d}^{buy}} \sum_{k=1}^{n_{i,d}^{buy}} c(vol_{k,i,d}^{buy}) + \frac{1}{n_{i,d}^{sell}} \sum_{k=1}^{n_{i,d}^{sell}} c(vol_{k,i,d}^{sell}) \right] + \epsilon_{i,d}, \tag{6}$$

where we plug in daily average bid-ask spreads $AvgBidAsk_{i,d}$ from (5) as the left hand side of (6). We again scale the costs now given by the average market-wide function with a bond-individual scaling factor $sf_{i,t}^{AvgBidAsk}$. Because, in general, the number of sell and buy trades on a given day is not identical, the underlying prices enter with differing weights into the calculation of $AvgBidAsk_{i,d}$. To match this imbalance, we calculate the average of the market-wide cost function $c(vol_{k,i,d}^{buy/sell})$ separately for both sides before computing the overall average. Again $n_{i,d}^{buy/sell}$ is the number of buy/sell trades and $vol_{k,i,d}^{buy/sell}$ gives the trade size of the k-th buy/sell trade.

We implement the size-adapted average bid-ask spread measure using the iterative two-stage weighted regression described in Section 2.3. As all trades of a day enter combined as only one observation (and not as separate observations for each trade), we have to adjust this procedure. The details on the adjustments are described in Appendix B. The data requirements to estimate an individual scaling factor remain the same as for the unadapted average bid-ask spread measure. Thus, a monthly size-adapted bid-ask spread measure can be calculated if we observe sell and buy prices for at least one day.

The resulting functional form is again depicted in Figure 2. Both size-adapted measures share the decreasing transaction cost and size relation and the slight increase at the right tail. But they are not fully identical, which is most likely caused by the different data requirements of the standard measures. Whereas the Schultz (2001) measure requires a daily consensus price, the average bid-ask spread measure can be calculated only when data on buy and sell trades on the same day are available.

Figure 3 shows average liquidity for all bonds calculated with the two size-adapted measures for the time period of October 2004 to December 2014. The interpretation of the measures as a scaling factor facilitates comparisons and shows that transaction costs were about 2.5 times higher during the crisis compared to the full observation period. Importantly, both measures are very consistent and move very closely together.

Insert Figures 3 and 4 about here.

As discussed earlier, we assume in Equation (2) that the general functional form of transaction costs does not change much over time. We verify this assumption in Figure 4 and plot a (normalized) function for each quarter during our observation period. For both liquidity measures, the pattern of a strongly decreasing function and a slight increase at the right tail is very stable over time. All quarterly functions are always located within a narrow range.

3 Corporate Bond Liquidity and Yield Spreads

In this section, we employ our new measurement approach to investigate the impact of liquidity on corporate bond yield spreads. To this end, we perform panel regressions explaining yield spread changes with changes in either standard or size-adapted liquidity measures. As many studies discard all trades below $100,000, whereas others keep all trades, we also compare these two approaches with our new methodology.

3.1 Methodology

Friewald, Jankowitsch, and Subrahmanyam (2012) test Amihud and Mendelson's (1986) hypothesis that an illiquid asset commands a higher (expected) return and thus trades at a larger spread between the bond's yield and the Treasury curve. We closely follow their approach and perform panel data regressions to measure the impact of transaction costs on corporate yield spreads using our new size-adapted transaction cost measures, while controlling for autocorrelation in the spreads and other effects:

$$\begin{aligned}\Delta(\text{Yield spread})_{i,t} = \alpha + \beta \cdot \Delta(\text{Yield spread})_{i,t-1} + \gamma \cdot \Delta(\text{Transaction costs})_{i,t} \\ + \delta \cdot \Delta(\text{Controls})_{i,t} + \epsilon_{i,t},\end{aligned} \tag{7}$$

where we use either the standard or the size-adapted versions of the Schultz (2001) or the average bid-ask spread measure as proxy for transaction costs.[11] We calculate yield spreads as the difference between the bond's yield and the yield of a (theoretical) risk-free Treasury bond having the same cash flow structure. To obtain a bond's daily yield spread, we calculate the volume-weighted average from all reported trades in TRACE in the bond on the specific day (for details, we refer to Appendix A). We then take averages of the daily observations to arrive at the monthly level. Following Friewald, Jankowitsch, and Subrahmanyam (2012), we control for other liquidity dimensions and for credit risk changes. We use monthly changes in the logarithm of the amount outstanding (our data from Bloomberg includes reopenings, repurchases, and other (early) redemptions). Moreover, we employ the logartihms of the average trading volume and the number of trades as proxies for trading activity. Finally, to control for credit risk, we include changes in 21 rating dummies based on the bond's average numerical rating across the three agencies Standard & Poor's, Moody's, and Fitch.[12] In a robustness check in Section 5, we use a bond's 1-year probability of default as an alternative proxy for credit risk. Yield spread changes and transaction cost changes are winsorized each month at the 1% and 99% level.

As discussed in the introduction and in Section 2.1, a common approach in the literature

[11] Note that we estimate the functional form of our size-adapted measures using the full sample period. Because yield spreads and transaction cost measures are from the same month, look-ahead bias should not be an issue. Thus, we decide on the full-sample approach to get the most stable size-cost relation and to estimate the economic relation between liquidity and yield-spread changes with the highest possible precision. Significance levels and R^2 remain qualitatively and quantitatively identical if we only use data from the last quarter of 2004 to estimate the functional form (results are available on request).

[12] To calculate the average numerical rating, we transform the ratings to integer numbers (for S&P and Fitch AAA=1, AA+=2, ... and for Moody's Aaa=1, Aa1=2, ...). For $k = 1, \ldots, 21$, we then set the k-th rating dummy to 1, if $k - 0.5 \leq$ average rating $< k + 0.5$.

to correct for the volume-dependence of transaction costs is to discard all trades below a threshold, which is in most cases \$100,000. We further analyze this approach and ask the question whether transaction costs from retail trades below \$100,000 contain valuable information for the liquidity premium embedded in transaction prices of large trades. To this end, we estimate Equation (7) for a sample in which we calculate yield spreads only from trades with volumes of at least \$100,000. We then use three different versions for the transaction cost proxy. First, the standard (unadjusted) measure based only on trades of at least \$100,000, second, the standard measure based on all trades, and third, our size-adapted measure that naturally is based on all trades.

3.2 Descriptive Statistics

We start with presenting cross-sectional summary statistics and the correlation structure for the variables used in the regression model (7).

Table 2 presents the mean, the standard deviation, and various quantiles for all variables in the sample using the standard and size-adapted Schultz (2001) measure in Panel A and the average bid-ask spread measure in Panel B. The mean yield spread in the two panels ranges between 2.2% and 2.4% and shows a broad distribution with about 0.5% in the 5th and 6% in the 95th percentile. Regarding credit risk, our sample spans bonds of all possible ratings with a mean rating of about 7 (corresponding to A-), a rating of about 2 (AA+) in the lowest, and a rating of about 13 (BB-) in the highest quantile. Regarding the liquidity across bonds, we observe average transaction costs of 1.19% (1.36%) for the standard Schultz (2001) (average bid-ask spread) measure, along with a high standard deviation of 0.87% (0.95%). In the same way, we find a strong variation for the size-adapted measures. Bonds in the 5th percentile trade to only a fifth of the mean costs, whereas in the 95th percentile, trading costs are twice the average costs. Lastly, bonds in both samples show strong variations in their outstanding amounts as well as in their number of trades and trading volumes.

Insert Table 2 about here.

Table 3 presents correlations of the yield spreads and the independent variables in Equation (7). Panel A reports results for the Schultz (2001) measure and Panel B for the average bid-ask spread measure. The correlations between the transaction cost measures and the control variables are all below 0.4. Interestingly, only our new measures confirm the well-documented positive relation between credit risk and liquidity consistently in both panels.

The table also provides first insights regarding the question which of the variables are related to yield-spread variations. As expected, we observe a strong correlation with the rating. Importantly, we can show that our new size-adapted liquidity measures are significantly stronger connected to corporate bond yield spreads than their unadapted counterparts.[13] This result can be interpreted as a first indication that our new measures are better able to capture the dimension of liquidity that is relevant for bond prices.

Insert Table 3 about here.

3.3 Results

As pointed out in Section 2.2, our size-adapted liquidity measures are, from a conceptual perspective, a more accurate measure of a bond's (relative) transaction costs and thus we expect them to explain a significantly larger part of a bond's liquidity premium. In this spirit, we expect that explanatory powers and significance levels when estimating panel regression (7) are larger for the size-adapted measures compared to their standard counterparts.

The results of the monthly panel regression for both the Schultz (2001) and the average bid-ask spread measure are presented in Table 4. For both measures, we use three different specifications. First, in specifications (1) and (4), we explain yield spread changes solely with their lagged changes and the control variables. This specification is the baseline from which we can analyze the increase in explanatory power after including either a standard or a size-adapted transaction cost measure. In specifications (2) and (5), we include the standard transaction cost measures, while in (3) and (6), we add the size-adapted versions.

Insert Table 4 about here.

In the specifications without a transaction cost measure, we find a significantly positive autocorrelation of yield spread changes. Consistent with the intuition that more liquid bonds trade in larger volumes, we find that a higher trading volume is associated with significantly lower spreads. In the same spirit, a larger outstanding amount indicates lower yield spreads but this only holds significantly in case of the average bid-ask spread measure. Contrary to the intuition, we find a significantly positive relation with the number of trades. We

[13] We test for differences in the correlations using Steiger's Z test. For both size-adapted liquidity measures, the correlations to yield spreads are significantly higher at the 1% level compared to their unadapted counterparts.

follow Friewald, Jankowitsch, and Subrahmanyam (2012), who attribute this finding to the fact that in illiquid markets, investors are forced to split up their trades. If we add the standard bond liquidity measures to the regression, we find a highly significant liquidity premium. Furthermore, the t-statistics of the transaction cost measures are the highest among the liquidity variables, emphasizing their importance. Regarding the explainable part of corporate bond yield spreads, adding a standard transaction cost measure leads to a relative improvement of the R^2 compared to the baseline regression of 4.3% in case of the Schultz (2001) measure and of 10.2% in case of the average bid-ask spread.[14] When adding our size-adapted measures instead of the standard versions, we also find a highly significant premium, with even more pronounced t-statistics. The relative improvement of the R^2 compared to the baseline regression increases to 7.7% in case of the size-adapted Schultz (2001) measure and to 19.3% in case of the size-adapted average bid-ask spread measure. Note that the different improvements when comparing the Schultz (2001) and the average bid-ask spread measure are partly due to the different data requirements of the two measures that lead to different sample sizes. In a robustness analysis in Section 5, we estimate the model in (7) for both measures on a combined data set.

We now validate that the explanatory power increases also out-of-sample when replacing the standard measures with the new size-adapted versions. To this end, we estimate the panel model (7) using a backward-looking rolling window of 24 months (requiring at least 12 months) and compare the implied with the actual yield spread changes for the following month. To test if changes in the mean squared error (MSE) are significant, we employ Diebold and Mariano (1995) tests in the spirit of Harvey, Leybourne, and Newbold (1997).[15] Consistent to our in-sample findings, we observe a monotonically decreasing MSE when adding a standard transaction cost measure to the baseline model and when replacing the standard measure with its size-adapted counterpart, respectively. The MSE drops significantly by 0.4% and 0.8% when adding the standard and size-adapted Schultz (2001) measure to the baseline model and by 0.8% and 1.6% in case of the average bid-ask spread. Moreover, the additional decreases of our size-adapted Schultz (2001) and average bid-ask spread measures are strongly significant. Thus, our in-sample and out-of-sample findings are consistent to our expectation that the new measures should explain a larger part of

[14] The improvements are comparable to the ones in Friewald, Jankowitsch, and Subrahmanyam (2012). These authors add four different liquidity measures at the same time and find a combined relative improvement of 11.7%.

[15] Since we use a rolling window to estimate parameters, the Diebold and Mariano (1995) test is identical to Giacomini and White's (2006) (unconditional) test that accounts for uncertainty in the parameter estimation (see, e.g., Giacomini and Rossi (2010)).

market-wide corporate bond yield spread changes. In fact, the improvements when adding a transaction cost proxy are almost twice as large for both size-adapted versions compared to their standard counterparts.

Finally, the new measures also increase the economic significance of the relation between liquidity and yield spreads. A one standard deviation change in the standard transaction cost proxy is associated with a yield spread change of 5.5 basis points for the Schultz (2001) and 10.2 basis points for average bid-ask spread measure. Our new measures increase this response to 7.3 and 13.9 basis points, respectively.[16] Thus, using unadapted measures leads to an underestimation of the liquidity premium.

As a next step, we consider the aforementioned approach of discarding all trades below \$100,000. As shown in Section 2.1, small trades contain valuable information for a bond's liquidity and we expect that they also help to explain liquidity induced yield-spread changes. To test this hypothesis, we repeat our analysis with the subset in which all trades below the threshold of \$100,000 are deleted. Yield spread changes, control variables as well as the standard bond liquidity measures are thus based on transactions with volumes $\geq \$100,000$. Table 5 presents the results for both measures. In specification (1) and (5), we perform the baseline regression by including only lagged yield spread changes and the control variables. In specifications (2) and (6), we include the standard transaction cost measures. To challenge the claim that retail trades are uninformative, we use the standard measures based on all trades in (3) and (7). Finally, in (4) and (8), we include the size-adapted measures, which, by construction, incorporate all trade sizes.

Insert Table 5 about here.

Consistent to the previous results, we find for all different transaction cost measures highly significant positive coefficients. The relative improvements of the R^2 using only trades of at least \$100,000 are 7.7% and 25.1% for the Schultz (2001) and average bid-ask spread measure, respectively. For the versions based on all trades, the relative improvements range between 13.5% and 33.2%. The larger improvement of the R^2 when including all trades in the calculation of the transaction cost measures is very interesting because it confirms the hypothesis that small trades contain valuable information for the liquidity premium that is embedded in trade prices of large trades. Including the size-adapted measures, which incorporate all trade sizes naturally, improves the explanatory power even further. The

[16] Note that the economic significance is based on the standard deviation of the first differences, which we omit for the sake of brevity.

relative improvements compared to the versions without a transaction cost measure are now 21.5% and 55.3% for the Schultz (2001) and average bid-ask spread measure, respectively.

In the out-of-sample analysis, we find the MSE of the baseline model of 0.682 to decrease significantly by 0.4% when adding the standard Schultz (2001) measure based on trades of at least $100,000. It decreases by 0.9% when employing the versions based on all trades. The best results are again obtained with the size-adapted version and an MSE decrease of 1.3%. This decrease is significantly larger compared to using the unadapted liquidity measure. The results for the average bid-ask spread are very similar. The baseline MSE of 1.403 decreases significantly by 1.6% or 2.2% for the standard versions using only large trades or all trades, respectively. Once again, the size-adapted version leads to the significantly largest reduction of the out-of-sample MSE by 3.8% compared to the baseline version.

Summarizing, we show that the more precise measurement of transaction costs provided by our new size-invariant approach consistently increases the explainable part of yield spread changes. Thus, a larger part of the yield spread variation in the corporate bond market can be attributed to changes in the bonds' liquidity. Moreover, we show that the information in small trades is valuable and can be best exploited with our new approach.[17]

4 The Pricing of Corporate Bond Liquidity

In this section, we analyze the effects of corporate bond liquidity and liquidity risk on expected bond returns using our new measurement approach. Previous studies find that investors are compensated for the individual level of a bond's transaction costs (see, e.g., Bao, Pan, and Wang (2011)). A second strand of the literature shows that investors require a premium for a bond's sensitivity to corporate bond market illiquidity shocks (see, e.g., Lin, Wang, and Wu (2011)). Bongaerts, de Jong, and Driessen (2017) analyze both effects jointly and find that only the level of liquidity but not corporate bond market liquidity risk bears a premium. We aim in this section to reexamine this question using our more precise size-invariant measurement approach. From an econometric perspective, a precise measurement of liquidity is important to disentangle the effects of liquidity level and risk because liquidity betas and transaction costs are typically highly correlated.

[17]Unreported results (available on request) show that our findings do not change if we exclude prearranged roundtrip transactions in the spirit of Choi and Huh (2017). The authors argue that these transactions take longer to arrange as other customers provide liquidity. Thus, transaction costs are biased and do not represent the costs of immediacy.

Because asset pricing results sometimes depend on the decisions how test assets are constructed (see, e.g., Lewellen, Nagel, and Shanken (2010) and Ang, Liu, and Schwarz (2018)) and betas are estimated, we introduce four different specifications: Three portfolio sorts using different criteria and one approach estimating the model on an individual bond basis. This exercise shows that the results using standard measures of liquidity are not robust to the chosen approach. In contrast, when we use our more precise size-adapted measures, we can consistently show that both individual bond liquidity and corporate bond market liquidity risk are priced.

4.1 Asset Pricing Model

Acharya and Pedersen (2005) argue that liquidity level and risk should be analyzed jointly due to the correlation of the two variables. In this spirit, Bongaerts, de Jong, and Driessen (2017) propose an asset pricing model, in which both the exposure to systematic bond market illiquidity shocks as well as the idiosyncratic illiquidity level can have an impact on expected bond returns. Additionally, they consider spill-over effects from the equity market. We follow these authors and estimate the following asset pricing model. In the first step, we regress for each portfolio j the monthly realized excess returns $r_{j,t}$ on the risk factors equity market return EQ_t, equity market illiquidity shocks $EQLIQ_t$, and corporate bond market illiquidity shocks $CBLIQ_t$,

$$r_{j,t} = \beta_j^0 + \beta_j^{\mathrm{EQ}} \cdot EQ_t + \beta_j^{\mathrm{EQLIQ}} \cdot EQLIQ_t + \beta_j^{\mathrm{CBLIQ}} \cdot CBLIQ_t + \epsilon_{j,t}. \tag{8}$$

In the second step, we regress monthly expected excess returns $E[r_{j,t+1}]$ on the cross-section of risk sensitivities which are estimated on a rolling basis in the first step and on the portfolios' transaction cost estimates $c_{j,t}$

$$E[r_{j,t+1}] = \lambda_0 + \lambda_{\mathrm{EQ}} \cdot \beta_{j,t}^{\mathrm{EQ}} + \lambda_{\mathrm{EQLIQ}} \cdot \beta_{j,t}^{\mathrm{EQLIQ}} + \lambda_{\mathrm{CBLIQ}} \cdot \beta_{j,t}^{\mathrm{CBLIQ}} + \lambda_{\mathrm{c}} \cdot c_{j,t} + \alpha_j. \tag{9}$$

We obtain market prices of the risk factors and the impact of liquidity level as the time series averages of the monthly cross-sectional estimates for which we calculate Fama-MacBeth standard errors.

We expect on average decreasing bond returns in times of equity market turmoils leading to positive estimates for β_j^{EQ} and a positive market risk premium λ_{EQ}. As increases in bond market illiquidity should lead to decreasing bond returns, we expect negative estimates for β_j^{CBLIQ} in Equation (8). Further, if investors require a compensation for systematic liquidity risk, more negative betas should lead to higher expected returns, implying negative estimates for λ_{CBLIQ}. Given several possible mechanisms for the influence of the equity market illiquidity on bond returns β_j^{EQLIQ}, we have no ex-ante expectation for its sign. In line with Amihud and Mendelson (1986), we expect a positive λ_{c} as illiquid bonds should compensate investors with higher returns.

4.2 Risk Factors, Returns, and Transaction Costs

For the time series regression (8), we calculate a bond's realized return between the last trading days in months t and $t-1$. To obtain excess returns, we deduct the return of a U.S. treasury bond having a maturity equal to the bond's duration.[18] For the equity risk factors, we employ excess returns of the S&P 500 as equity market returns. We characterize equity market liquidity using the Amihud (2002) illiquidity measure and calculate its equally weighted mean from all shares having a share code of 10 or 11 in CRSP.[19] As it is common practice, we exclude observations of extremely illiquid stocks, i.e., days without trading and months having less than three days with positive trading volume. Further, we exclude shares traded at NASDAQ[20] and winsorize the monthly cross-section of individual liquidity measures at the 5% and 95% level. Given the monthly aggregate Amihud (2002) illiquidity measure, we identify liquidity shocks as residuals of the autoregressive model proposed in Acharya and Pedersen (2005). Finally, we measure corporate bond market liquidity as the average across all portfolios using one of the measures introduced in Section 2. Bond market liquidity shocks are then defined as the residuals of an autoregressive process with two lags. For ease of comparability, we scale all risk factor innovations to have the same standard deviation as the equity market excess returns.

In the cross-sectional regression (9), we use forward-looking expected excess returns. Bongaerts, de Jong, and Driessen (2017) argue that the common approach, using realized returns as a proxy for expected returns, leads to extremely noisy estimates. We follow them

[18]We use updated data from Gürkaynak, Sack, and Wright (2007) available from the Federal Reserve to calculate Treasury prices and returns.

[19]In a recent study, Lou and Shu (2017) show that the pricing of the Amihud (2002) price impact measure in the stock market is not driven by price impact but rather by its trading volume component. Therefore, we repeat our analyses in Section 4.5 using the high-low measure of Corwin and Schultz (2012). We find that our results are robust to the choice of the stock market liquidity measure.

[20]Pástor and Stambaugh (2003) and Ben-Rephael, Kadan, and Wohl (2015) argue that an exclusion of NASDAQ is necessary due to the inflated volume on NASDAQ.

and calculate forward-looking expected excess returns based on the bond's yield corrected for the expected costs of default. This leads to

$$E[r_{i,t+1}] = (1 + y_{i,t}) \cdot (1 - L \cdot \pi_{i,t})^{1/T_{i,t}} - (1 + y_{i,t}^{\text{risk-free}}), \tag{10}$$

where we approximate bond i at time t with a zero coupon bond having a maturity equal to its duration $T_{i,t}$. Further, we assume default losses to incur only at maturity, leading to an expected return until maturity of $(1+y_{i,t})^{T_{i,t}} \cdot (1-L \cdot \pi_{i,t})$, where $y_{i,t}$ is the yield of the bond, L gives the loss given default, and $\pi_{i,t}$ is the cumulative probability of default (PD) over the bond's remaining life. Lastly, we annualize the expected return and deduct the yield of a risk-free U.S. Treasury bond having the same duration.

To calculate the cost of default, we assume a constant loss given default of 60%. We use company-specific PDs from the Risk Management Institute (RMI) of the University of Singapore (see Appendix A for details on the matching of corporate bond data and company-specific PDs). RMI publishes PDs for over 66,000 publicly traded companies based on the forward intensity model of Duan, Sun, and Wang (2012). For more than 33,000 companies, these probabilities are calculated on a daily basis for a large spectrum of maturities.[21] RMI provides cumulative PDs for the maturities 1 month, 3 months, 6 months, 1 year, 2 years, 3 years, and 5 years. We use them to calculate (annualized) conditional PDs for all possible periods (i.e., from 0 to 1 months, from 1 to 3 months, ...). Assuming a flat curve beyond 5 years, we can calculate the cumulative PD $\pi_{i,t}$ corresponding to the bond's duration $T_{i,t}$.

Finally, we calculate a bond's expected excess return $E[r_{i,t+1}]$ as the volume-weighted average from all trades in month t. Regarding bond i's transaction costs $c_{i,t}$, we use one of the standard or size-adapted liquidity measure from Section 2.[22] We aggregate returns and transaction costs to the portfolio level by calculating their equally weighted mean.[23]

[21]See NUS-RMI (2016) for more details on the methodology. For a comparison of RMI's PDs with Moody's expected default frequency (EDF) measure, see Berndt (2015).

[22]To ensure a tradable strategy and to address concerns of a look-ahead bias, we estimate the market-wide functional form for our size-adapted measures based solely on the last quarter of 2004. Further, for comparability between the Schultz (2001) and average bid-ask measure, we use only observations for which we can calculate both measures.

[23]We again winsorize realized and expected excess returns as well as transaction costs each month at the 1% and 99% level.

4.3 Four Different Specifications for the Construction of Test Assets and the Estimation of Betas

As asset pricing results sometimes depend on the decisions how to construct test assets (see, e.g., Lewellen, Nagel, and Shanken (2010) and Ang, Liu, and Schwarz (2018)) or how to estimate betas, we employ four different specifications. It turns out that when we use standard measures of liquidity, it is not possible to find a consistent pattern regarding the pricing of liquidity level and liquidity risk. The difficulty of getting stable results can potentially explain the contradictory findings in the previous literature. In contrast, when we use our more precise size-invariant liquidity measurement approach, the results for all four specifications are fully consistent.

Our first specification follows Daniel, Titman, and Wei (2001) and Bongaerts, de Jong, and Driessen (2017) in their argument on the necessity of sorting by characteristics and factor betas. This necessity arises to guarantee sufficient variation across liquidity and beta in the portfolios.[24] Thus, we form triple-sorted portfolios based on the previous quarters' credit quality, liquidity level, and liquidity beta (see Appendix C for details on the calculation of individual liquidity betas). For the first stage, we proxy a bond's credit quality with its average rating and assign the bonds to three distinct portfolios (terciles). In the second stage, we sort the bonds of each portfolio into liquidity terciles, which we approximate with their amount outstanding. For the last stage, we further divide the bonds of the preceding 9 portfolios into liquidity beta quintiles. In total this sorting leads to 45 portfolios for the Fama-MacBeth procedure. We estimate the betas of the time series regression (8) using a rolling window of 24 backward-looking monthly observations (requiring at least 12 observations).

Given the contradictory findings of the previous literature, our second specification is designed to be closely comparable to Bongaerts, de Jong, and Driessen (2017). Their approach differs from our first specification in two distinctive features. First, Bongaerts, de Jong, and Driessen (2017) increase the number of portfolios and allow that a bond is assigned simultaneously to up to six portfolios. Second, to increase precision, betas are estimated using a forward-looking kernel, which makes it impossible to collect the risk premia with a tradeable strategy. Regarding the first feature, the authors use multiple proxies for a bond's credit quality and liquidity for the first and second stage of the triple sorting. Thus, the sort on credit quality is either done using a bond's average rating (AAA-A, BBB, and BB-CCC) or its RMI 1-year cumulative PD (terciles). For the second sorting stage, a bond is classified

[24] See Daniel, Titman, and Wei (2001) for a general discussion regarding the triple sorting of portfolios to achieve a low correlation between characteristics (e.g., the level of liquidity) and factor loadings.

as liquid or illiquid using either its amount outstanding (median), age (median), or number of trades (70% percentile). Using the different proxies for credit risk and liquidity, a bond is simultaneously assigned to 6 portfolios. Given the 6 portfolios of the two sorting steps, the number of portfolios then increases to 36. These portfolios are finally split into a high-liquidity-beta and low-liquidity-beta category, leading to a total number of 72 portfolios. Regarding the second feature, they run the time series regression (8) using a two-sided (triangular) kernel for the rolling beta estimation. This tent-shaped kernel is both forward- and backward-looking, with linearly decreasing weights up to a maximum distance of 12 months relative to the current observation date. We require 12 backward-looking observations and use a truncated form of the kernel for dates with less than 12 future observations.

Further, we account for the suggestion in Lewellen, Nagel, and Shanken (2010) that asset pricing tests should include additional portfolio sorts on other characteristics. In this spirit, we introduce a third approach in which we sort bonds on their industry affiliation in the previous quarter. We use the 4-digits GICS code of the bond's issuer to ensure that each portfolio has a sufficient number of allocated bonds. Finally, we test our asset pricing model for individual bonds, given the argument in Ang, Liu, and Schwarz (2018) that portfolio sorts render the estimation of risk premia inefficient due to a loss in cross-sectional variation of the factor loadings. In both settings, we estimate the time series regression (8) using a backward-looking rolling window of 24 months. Because many bonds do not trade consecutively, we require for the individual bonds at least 12 observations.

4.4 Descriptive Statistics

Table 6 reports cross-sectional summary statistics for the panel of expected returns, betas, and transaction costs of the second step cross-sectional regression (9) for the non-overlapping triple sort (the first approach in Section 4.3, which is our main approach).[25] Panel A presents the statistics for the standard and size-adapted Schultz (2001) measure and Panel B for the average bid-ask spread measures. The choice of the corporate bond market liquidity measure has only a slight impact on the distribution of the expected excess returns across the triple-sorted portfolios. In the same way, portfolios show a similar distribution regarding the size of transaction costs for both Schultz (2001) and average bid-ask spread measures. For the equity market beta β^{EQ}, we find positive sensitivities with a mean beta of roughly 0.15 and a

[25]Descriptive statistics and correlations for the other two portfolio settings are qualitatively and quantitatively very similar to the ones in Tables 6 and 7. For the model estimated on individual bonds, beta standard deviations are, as expected, strongly inflated compared to the portfolio approaches.

standard deviation of 0.10, indicating that corporate bond returns decline in equity market downturns.

Insert Table 6 about here.

Regarding the liquidity risk sensitivities, we find for almost all beta quantiles strictly negative estimates, indicating that corporate bond returns drop when equity or bond market illiquidity rises. The patterns, however, differ for the standard and the size-adapted versions. In case of the standard measures, the mean equity market liquidity beta β^{EQLIQ} and the corporate bond market liquidity beta β^{CBLIQ} are roughly -0.09 and -0.14, respectively. In case of the size-adapted measures, the absolute mean β^{EQLIQ} drops by more than 20% and the absolute mean β^{CBLIQ} increases by more than 25%. This result is a first indication that our new measures might be better able to capture transaction cost variations which are relevant for corporate bond returns. Moreover, the (absolutely) larger equity market liquidity betas β^{EQLIQ} for the non-size adapted measures show that because of their correlation, an inaccurate measurement of bond market liquidity can increase the loadings of equity market liquidity.

Table 7 reports cross-sectional correlations of expected excess returns, betas, and transaction costs. In Panel A, we depict the results for the Schultz (2001) measures and in Panel B for the average bid-ask spread measures. Independent of the choice of the corporate bond liquidity measure, we find a comparably low negative correlation (-0.15 to -0.18) between the equity market and the equity market liquidity beta. Corporate bond market liquidity beta and liquidity level seem somewhat mildly more correlated (-0.35 to -0.53). Lastly, Table 7 gives a preview on the pricing patterns in the U.S. corporate bond market. Expected excess returns are correlated with equity market and equity market liquidity betas. Corporate bond liquidity effects also play an important role for expected excess returns. Most importantly, all correlations of expected excess returns with bond market liquidity risk β^{CBLIQ} and liquidity level c are (absolutely) stronger when using our more precise size-adapted liquidity measures.

Insert Table 7 about here.

4.5 Results

The results of the Fama-MacBeth regressions for all four specifications are reported in Table 8. We start with examining corporate bond liquidity effects that are identified by using the standard bond liquidity measures. The first and third column of Panel A display results based on the first setting – the non-overlapping triple sort. We find in both specifications a significantly negative λ_{CBLIQ}, which leads in combination with the negative average β^{CBLIQ} to a positive corporate bond liquidity risk premium. Moreover, we find a positive liquidity level premium λ_{c}. These results are contradictory to the significant level and insignificant corporate bond market liquidity risk premium in Bongaerts, de Jong, and Driessen (2017). Therefore, we run the Fama-MacBeth regressions again using their measure of transaction costs based on a repeat-sales method.[26] The results in specification (5) show a significant bond liquidity risk but insignificant level premium. Thus, common measures show in this setting either a pricing of both liquidity level and risk or solely a pricing of liquidity risk.

Insert Table 8 about here.

Given the contradictory findings of our first setting, we proceed to the results of our second setting in Panel B – the original approach of Bongaerts, de Jong, and Driessen (2017) using overlapping portfolios. For both standard measures in specifications (1) and (3), we now find a premium for corporate bond market liquidity risk but no premium for liquidity level. In contrast to the previous results but consistent with Bongaerts, de Jong, and Driessen (2017), we find for the repeat-sales measure in (5) a significant level and an insignificant corporate bond market liquidity risk premium. Again, common measures show no coinciding pricing pattern.

Finally, as none of the preceding settings provides a stable pricing pattern, we examine bond liquidity effects of the standard measures based on the third and fourth setting. In Panel C, we depict the results for the industry sort and in Panel D for the individual bonds.[27] Again, we find no consistent pricing pattern for the three measures. While the Schultz (2001) measure in both settings and the average bid-ask spread in the fourth setting indicate a pricing of both factors, the repeat-sales measure and the average bid-ask spread in the third setting exhibit only a liquidity risk premium. Summarizing, none of the standard measures is able to identify a stable pricing pattern of corporate bond liquidity level and risk across different approaches to form portfolios and to calculate betas. While five specifications lead to the conclusion of a pricing of both liquidity effects, five support only a significant liquidity risk premium and one specification provides evidence for just a liquidity level premium.

[26]For details, see Section 1.3 of Bongaerts, de Jong, and Driessen (2017).

[27]Note that the repeat-sales measure relies on portfolios to guarantee the estimation of hourly returns. Thus, it is not suited for the setting based on individual bonds.

In contrast, if we measure bond market and individual bond liquidity with the size-adapted measures of Section 2, we find a consistent pricing pattern. In all four panels of Table 8, specifications (2) and (4) show a significantly negative λ_{CBLIQ}. In combination with the negative β^{CBLIQ}, a significantly positive corporate bond market liquidity risk premium arises. Moreover, the significantly positive λ_{c} in all panels confirm a positive premium for the level of individual bond illiquidity. To support the finding that the size-adaptation dissolves the conflicting results, we further adapt the repeat-sales measure with our new measurement approach.[28] The size-adapted repeat-sales measures in specification (6) show always a significant premium for both effects. In summary, once we adapt a standard measure with our approach, we always find a significant premium for liquidity risk as well as for the individual liquidity level. It is interesting to note that the individual approach, in contrast to the portfolio settings, comes to the same conclusion, independent of the choice of the liquidity measure. On the one hand, our results thus support the recommendation of Ang, Liu, and Schwarz (2018) to test asset pricing models using individual assets. On the other hand, the scarce trading in the corporate bond market excludes many bonds when betas are estimated individually. While our portfolio sorts on average incorporate information of roughly 1,500 to 1,600 bonds per month, the individual approach on average covers only about 1,000 bonds.

Using the results for the size-adapted measures in Panel A of Table 8 and the cross-sectional average bond market liquidity beta β^{CBLIQ} and transaction cost level c in Table 6, we can quantify the liquidity risk and level premium as $\beta^{\text{CBLIQ}} \cdot \lambda_{\text{CBLIQ}}$ and $c \cdot \lambda_{\text{c}}$. The liquidity risk premium accounts for an expected excess return of about 0.90% (0.77%) p.a. and the level premium is responsible for an excess return of about 0.89% (0.88%) p.a. in case of the size-adapted Schultz (2001) (average bid-ask spread) measure. Thus, both effects show a high economic significance when taking into account that the mean expected excess return equals 2.26%.

Aside the corporate bond liquidity effects, we find, independent of the choice of the corporate bond liquidity measure, a significant premium for equity market risk and for equity market liquidity risk, confirming results of Bongaerts, de Jong, and Driessen (2017). However, it is noteworthy that the premia for equity market-specific effects (0.99% to 1.00%) become dominated by the corporate bond market liquidity risk and level premium when moving from standard to size-adapted liquidity measures (1.65% to 1.79%).[29]

[28]For details on the adaptation see Appendix D.

[29]These premia are based on the non-overlapping triple sort. In the other three settings, bond market liquidity effects also dominate equity effects when liquidity is measured with our new approach.

Therefore, our new approach shows that the corporate bond market-specific effects bear the highest premia in expected bond excess returns.

5 Robustness

In this section, we perform several robustness checks. We first show that our results are robust when using a parametric functional form instead of the nonparametric version employed in the main analyses. Second, we show the robustness of our results in Section 3 concerning the choice of the credit risk proxy. Lastly, we address the different sample sizes for the Schultz (2001) and average bid-ask spread measure in Section 3. We provide evidence that the better performance of the unadapted average bid-ask spread measure compared to the unadapted Schultz (2001) measure is mainly caused by the different samples for which the measures can be calculated.

5.1 Parametric Estimation of the Market-Wide Functional Form

A precise estimation of the market-wide functional form is crucial for our approach. Besides the presented nonparametric estimation of Section 2.2, it is also possible to estimate the functional form with a parametric function. A parametric approach has the advantage that it is easier to implement and faster to compute. Thus, we reexamine our findings on the corporate bond liquidity effects of Sections 3 and 4 with size-adapted liquidity measures based on a parametric functional form.

Following Edwards, Harris, and Piwowar (2007), we employ the following parametric function to calculate transaction costs $c(vol)$ for a trade with volume vol:

$$c(vol) = c_0 + \frac{c_1}{vol} + c_2 \cdot \ln(vol) + c_3 \cdot vol + c_4 \cdot vol^2 + c_5 \cdot vol^3, \tag{11}$$

where $c_i \in \mathbb{R}$ for $i = 0, \ldots, 5$. Using this parametric functional form, we run the iterative two-stage weighted regressions described in Sections 2.3 and 2.4. The resulting functional forms are depicted in Figure 5. Consistent to the nonparametric results of Figure 2, we find a monotonically decreasing relation for trade sizes up to about \$3 million and an increase for very large trades. However, the parametric forms suffer from a slightly oscillating pattern above \$1 million.

We employ the size-adapted measures based on the parametric functional form for our asset pricing tests of Sections 3 and 4. The results of the yield spread regressions are depicted in Table 9. For ease of comparability, we repeat the information from Table 4 for the baseline regressions and the unadapted measures in the specifications (1), (2), (4), and (5). Consistent to our previous findings, our size-adapted measures in (3) and (6) are strongly significant and the in-sample R^2 and out-of-sample MSE are nearly identical to their nonparametric counterparts in Table 4. Again, our size-adapted measures nearly double the in-sample and out-of-sample improvements. Lastly, we present the results of the Fama-MacBeth regressions using the parametric size-adapted measures in Table 10. Across all four different settings, we find for both measures a significantly positive corporate bond market liquidity risk and liquidity level premium. These results are confirmed when adapting the repeat-sales measure of Section 4.5 using the parametric functional form. Thus, the parametric size-adapted measures consistently show a pricing of both the liquidity risk and the liquidity level.

Insert Tables 9 and 10 about here.

5.2 Alternative Credit Risk Proxy

Controlling for credit risk with a bond's rating in the analyses of Section 3 assumes that the credit risk within a rating category is constant over time. To verify that our results do not depend on this assumption, we rerun the yield spread regression (7), but control for credit risk through changes in a bond's RMI 1-year probability of default. Table 11 shows the results. Note that we loose about 35% to 40% of the observations due to the match with the RMI dataset. Despite the higher in-sample R^2 and lower out-of-sample MSE of the baseline regressions (1) and (4), adding a standard liquidity measure still leads to significant improvements. Once again, the best results are obtained when adding the size-adapted liquidity measures. Compared to their standard versions, these measures increase the percentage in-sample and out-of-sample improvements by a factor of almost 2 to 3.

Insert Table 11 about here.

5.3 Combined Data Set

Common high-frequency transaction cost measures are highly correlated. Therefore, we would expect them to be equally suitable to explain corporate bond liquidity effects. However, in Section 3.3 we find diverging improvements in explaining corporate bond yield spread changes when measuring liquidity with the Schultz (2001) or the average bid-ask spread measure. As the two measures have different data requirements, we rerun the analysis on a combined data set to test if the divergence is caused by the different sample or if there are significant differences in their capability to explain the embedded liquidity premium.

The results of the combined analysis are reported in Table 12. When adding a standard liquidity measure, the in-sample R^2 increases by about 8% for both measures. The out-of-sample MSE drops significantly for both measures by 0.8%, with an insignificant difference (t-stat 0.61). Thus, both standard measures indeed perform equally well in explaining yield spread changes. Consistent to our previous findings, the size-adapted measures are even more suited to explain these changes. When adding the size-adapted Schultz (2001) measure, the R^2 increases by 13.8% and the MSE drops significantly by 1.4%. We find a similar pattern for the size-adapted average bid-ask spread measure. The R^2 rises by 20.2% and the MSE decreases significantly by 2.2%. The additional improvements of our size-adapted measures are on the same order of magnitude as before. Interestingly, the size-adapted average bid-ask spread measure outperforms the size-adapted Schultz (2001) measure in terms of explanatory power. Their difference in the out-of-sample MSE is statistically significant with a t-statistic of 4.08.

Insert Table 12 about here.

6 Conclusion

In this study, we address the problem that common transaction cost measures for the bond market do not account for the fact that trading costs of small trades are typically much larger compared to large trades. We first show that the information in small trades is valuable to accurately assess a bond's liquidity. We then develop a simple two-stage liquidity measurement approach that accounts for the size dependence and aggregates trading costs from all trade sizes into one single value. Our approach is easily implementable, applicable to a broad variety of liquidity measures, and has no influence on a measure's data requirements. In this spirit, we adapt two standard measures of transaction costs, the Schultz (2001) and the average bid-ask spread measure, to our new approach.

We use the new measures to reevaluate the impact of liquidity on corporate bond yields. We find that our size-adapted measures strongly increase the explainable part of yield spread changes compared to their unadapted counterparts. This effect is even stronger when we compare the new methodology with the popular approach to exclude retail-sized trades with volumes below $100,000 from the calculation of liquidity measures. As the new measures naturally incorporate all available information from retail and institutional trades, this finding shows that small trades, which account for about two-thirds of all trades in the U.S. corporate bond market, also contain valuable information regarding the liquidity premium of a bond.

Finally, we examine the impact of our new liquidity measures on the asset pricing implications of corporate bond market liquidity risk and individual liquidity level for expected corporate bond excess returns. Using established standard measures of the literature, we show that they lead to non-consistent pricing patterns and that results depend critically on the portfolio selection and beta estimation approach. In contrast, we find for the size-adapted liquidity measures that bonds with higher transaction costs or with a stronger sensitivity to corporate bond market liquidity earn higher expected excess returns. This finding does not depend on the construction of test assets and the beta estimation procedure. Thus, our new measurement approach consistently uncovers that U.S. corporate bonds pay a liquidity premium for both their individual liquidity and their exposure to market-wide bond liquidity risk. Given the economically large size of these premia, investors should consider both effects for their optimal portfolio choice.

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A Data Filters, Bond Yields, and Matching Procedure

We use U.S. corporate bond transaction data from the Enhanced TRACE database from October 1, 2004 to December 31, 2014. Starting with only investment-grade bonds in 2002, TRACE was gradually expanded to finally cover essentially all corporate bonds in October 2004. We apply several data filters to remove bonds with special features and erroneous trade entries. Our filters are similar to the ones used in Schestag, Schuster, and Uhrig-Homburg (2016) and Bongaerts, de Jong, and Driessen (2017). In a first step, we apply the procedures of Dick-Nielsen (2009, 2014) to remove duplicates, withdrawn and corrected entries. Further, we eliminate erroneous entries and extreme outliers by applying the median and reversal filters of Edwards, Harris, and Piwowar (2007). We demand bonds to be actively traded for at least twelve months during our observation period or for at least 50% of the months they are active. Additionally, we exclude observations of defaulted bonds after the default date. We discard perpetuals, convertible and puttable bonds as well as bonds with floating coupon payments. We also demand bonds to be USD denominated, senior unsecured, and we exclude guaranteed bonds. After applying all filters, our final sample consists of 21,233 bonds and 42,190,265 trades, corresponding to roughly 53% of the about 79 million trades in the U.S. corporate bond market during our observation period.

For the analyses in Sections 3 and 4, we require yields and durations. If the yield-to-maturity is larger than the yield-to-call, the reported yield in TRACE often (but not always) corresponds to the yield-to-call. We calculate both yields and select the one that is closest to the reported yield. We drop observations for which both differences are larger than 1 basis point (about 0.7% of all observations). For the yield-spreads in Section 3, we discount the bond's cash flows with the risk-free Treasury curve to calculate the price of an artificial Treasury bond with the same cash flow structure (using updated data from Gürkaynak, Sack, and Wright (2007) published by the Federal Reserve on http://www.federalreserve.gov). Finally, the yield spread is defined as the continuously compounded yield computed from the reported price minus the corresponding yield calculated from the price of the artificial Treasury bond (see Gehde-Trapp, Schuster, and Uhrig-Homburg (2018)).

For the asset pricing tests in Section 4, we calculate expected excess returns using probabilities of default (PD) from the Risk Management Institute (RMI) of the University of Singapore for all publicly traded companies (identified by the stock's ISIN and its Bloomberg Ticker). Since there is no consensus on a procedure to match debt and equity data in the presence of M&A activities,[30] we develop our own approach that makes use of the specific

[30]For example, some researchers match bonds and companies via the issuer-specific first 6 digits of the

information we get from RMI and Bloomberg. Particularly, RMI provided us with a full list of M&A activities. Moreover, we download from Bloomberg for each bond the 'Issuer Equity' ticker that contains the original issuer of the bond and thus is unchanged after an acquisition. Moreover, we download the 'Bond to Equity' ticker that always references the company currently backing the bond. Using this data, we implement a three-step matching procedure without any manual input. First, we check if the 'Issuer Equity' ticker and the 'Bond to Equity' ticker are identical. If they are, the bond is assigned to this company. Second, if the two tickers differ but we have only PD data either for the original issuer or for the current ticker, we assign the bond to its original or current ticker but only for the time period before the first or back to the last M&A event. In the third step, if the two tickers differ and we have PD data for both underlying companies, we check if we can track the acquisition path in RMI's M&A list and assign this path if possible. If we find only an incomplete path, we try to complete it with corporate action data from Bloomberg by checking if the last available company on the unfinished path is a target/parent of the 'Bond to Equity' ticker.[31] Finally, if the 'Issuer Equity' ticker is not listed in RMI's M&A list, we use Bloomberg's corporate action functionality and check if the 'Bond to Equity' ticker is the acquirer/spin-off of the 'Issuer Equity' ticker and assign this direct path if possible. In total, our matching procedure is able to assign company-specific PDs to 16,742 bonds in the sample.

B Adjustments for the Average Bid-Ask Spread

The iterative two-stage weighted regression introduced in Section 2.3 relies on observations entering on a per trade basis into both stages. This means that when estimating the market-wide functional form, one transaction-cost observation is uniquely assigned to one volume. And for the second step, when estimating the individual scaling factor, each trade is weighted with its volume category weight. In case of the average bid-ask spread measure, such an assignment is not possible as all trades in a bond i on a day d are combined to a single observation of $AvgBidAsk_{i,d}$. Therefore, we have to make two adjustments to the iterative estimation procedure.

CUSIP and additionally hand-match CUSIPs in case of M&A activities (see, e.g., Feldhütter and Schaefer (2018)). Others use 6-digit CUSIPS and historical CUSIPS in CRSP (see, e.g., Chordia, Goyal, Nozawa, Subrahmanyam, and Tong (2017) or Ederington, Guan, and Yang (2015)).

[31] If we are not able to complete the acquisition path, we partly assign the bond to the tickers for which we know the mapping and drop it for the remaining period.

First, when estimating the market-wide functional form, we face the problem that the nonparametric regression model only allows to estimate functions of the general form $y = \hat{m}(x)$. In other words, each bid-ask spread (on the left-hand side) has to be uniquely assigned to a trading volume vol. Since the functional form $c(vol)$ is not linear in vol, we cannot assign the average trade size of day d to $AvgBidAsk_{i,d}$. Therefore, we calculate $AvgBidAsk_{i,d}$ in Equation (5) for each traded volume on the day separately and assign to this observation the corresponding trade size. As this adjustment can lead to several observations representing the same day, we correct the weights of these observations such that each day contributes equally to the estimation of the market-wide functional form. To do so, the weight of each observation is obtained by the product of its volume category weight (see Section 2.3) and the ratio of how often this volume v is traded compared to all traded volumes on the respective day for which we can calculate the size-dependent bid-ask spread. Again, to match the imbalance between sell and buy trades on a trading day, we calculate this ratio seperately for both sides. The final ratio is then given by $\frac{1}{2}\left(\frac{(\#\ trades\ with\ volume\ v)_{i,d}^{buy}}{(\#\ trades)_{i,d}^{buy}} + \frac{(\#\ trades\ with\ volume\ v)_{i,d}^{sell}}{(\#\ trades)_{i,d}^{sell}}\right)$. Note that calculating the daily average bid-ask spread for each volume separately requires at least one sell and one buy trade with the same volume. Thus, the sample for the estimation of the market-wide functional form in the first step of the iteration is only a subset of the sample used for the estimation of the individual scaling factors in the second step. However, since the estimation of the market-wide functional form combines data from all bonds, the subset remains large enough to ensure a reliable estimation.

Second, since the bid-ask spread $AvgBidAsk_{i,d}$ on one day represents several volume categories, we have to adjust the weighting in the second step of the iteration. Given the weights of the volume categories $w(\cdot)$, we calculate the observation-day weight as the average of these weights, i.e., $\frac{1}{2}\left(\frac{1}{n_{i,d}^{buy}}\sum_{k=1}^{n_{i,d}^{buy}} w(vol_{k,i,d}^{buy}) + \frac{1}{n_{i,d}^{sell}}\sum_{k=1}^{n_{i,d}^{sell}} w(vol_{k,i,d}^{sell})\right)$.

For the estimation of a parametric functional form in Section 5.1, the first step is not necessary as Equation (11) is linear in the coefficients c_i. Instead, in the spirit of Edwards, Harris, and Piwowar (2007), we multiply for both measures the volume category weight with the inverse of this category's average squared residual and use this new weight in the first step of each iteration. This correction is necessary as the estimation noise is much larger for retail-sized trades. Without the correction, retail-sized trades would thus have a much larger influence on the OLS estimation of the market-wide function, leading to a relatively bad fit for large trades. For the nonparametric approach, such a correction is not necessary as the nonparametric estimation procedure automatically decreases the weights for volumes farther away from the point that is estimated.

C Individual Beta Estimation

In Section 4.3, we perform triple sorts, sorting on credit risk, liquidity, and liquidity betas. To estimate a bond's sensitivity to the corporate bond market liquidity risk, we use a Vasicek (1973)-like Bayesian approach.[32] In this approach, a bond's liquidity beta is estimated as the variance-weighted average of the individual beta and the prior, i.e., the beta of a double-sorted portfolio the bond is assigned to. The individual beta is estimated (if possible) by regressing the bond's returns on innovations in corporate bond market liquidity.

To ensure that not all bonds from the same double-sorted portfolio have the same prior beta, we need a finer grid for this (auxiliary) double sort. Thus, we sort bonds in the first stage into credit rating quintiles and in the second stage into liquidity quintiles based on a bond's amount outstanding. For the overlapping triple sort of the second approach, we follow Bongaerts, de Jong, and Driessen (2017) and use seven categories for the ratings (AAA, AA, A, BBB, BB, B, CCC) and PD quintiles. The classification of liquid and illiquid bonds is identical to the second step in the triple-sorting procedure.[33] A bond is again assigned to several portfolios simultaneously. Thus, we finally calculate the prior beta as the average of the betas from all portfolios the bond is assigned to.

Given the returns of the auxiliary portfolios and (if possible) the individual bond returns, we estimate the portfolio and individual betas using a rolling window of 24 months for which we require at least 12 observations.

D Adapting the Repeat-Sales Measure

Adapting the repeat-sales measure of Bongaerts, de Jong, and Driessen (2017) requires minor changes to the iterative two-stage procedure of Sections 2.3 and 2.4. However, employing the basic measurement approach follows the same intuition.

Starting with the unadapted measure, estimating a trade's transaction costs is based on the idea that trade prices consist of a bond's fundamental value adjusted for transaction costs (see Section 1.3 of Bongaerts, de Jong, and Driessen (2017)). As a result, the log-difference between two consecutive prices $P_{k-1,i}$ and $P_{k,i}$ for bond i in portfolio j is the change in the

[32]For details, see Appendix B of Bongaerts, de Jong, and Driessen (2017).

[33]Note that we do not sort bonds with AAA and CCC rating by their liquidity, as in both portfolios the number of bonds is not sufficient for a further classification.

fundamental value and the transaction costs , i.e.,

$$\ln(P_{k,i}) - \ln(P_{k-1,i}) = \sum_{s=t_{k-1}+1}^{t_k} R_{j,s} + c_j \cdot (Q_{k,i} - Q_{k-1,i}) + e_{k,i}. \tag{12}$$

The fundamental return in this equation is expressed by hourly latent portfolio returns $R_{j,s}$ between the two trade times t_{k-1} and t_k and an idiosyncratic term $e_{k,i}$. Transaction costs c_j in month t are assumed to be constant within a portfolio and are multiplied with each trade's direction $Q_{k,i}$, which equals 1 in case of a buyer-initiated trade and -1 for a seller-initiated trade.

Applying our basic approach in (2) to Equation (12), we replace the constant portfolio transaction costs with the market-wide cost function evaluated at the transaction's volume $c(vol_{k,i})$ multiplied by portfolio j's individual scaling factor $sf_j^{Bongaerts}$, leading to

$$\ln(P_{k,i}) - \ln(P_{k-1,i}) = \sum_{s=t_{k-1}+1}^{t_k} R_{j,s} + sf_j^{Bongaerts} \cdot (c(vol_{k,i}) \cdot Q_{k,i} - c(vol_{k-1,i}) \cdot Q_{k-1,i}) + e_{k,i}. \tag{13}$$

We estimate the scaling factor $sf_j^{Bongaerts}$ in (13) using the iterative two-stage procedure of Sections 2.3 and 2.4.[34] To prevent concerns of a look-ahead bias in Section 4, we estimate in the first step the functional form $c(\cdot)$ using only the observations of the first quarter (see also footnote 22). In the second step, we follow Bongaerts, de Jong, and Driessen (2017) and estimate portfolio j's hourly returns and monthly scaling factors for an entire quarter in a pooled regression. Consistent to the two other size-adapted measures, the adapted repeat-sales measure can be estimated whenever the data requirements of the standard measure are satisfied.

We use the size-adapted repeat-sales measure in Sections 4 and 5.1. While we estimate the standard nonparametric functional form in Section 4, we employ the parametric approach in the robustness section. Similar to the average bid-ask-spread measure (see Appendix B), the nonparametric estimation leads to the problem that trades do not enter separately into Equation (13) but as two consecutive trades. Hence, to estimate the market-wide functional form in the first step of the iteration, we can only employ log-differences between two consecutive trades if they share the same volume. Despite the resulting sample reduction, using data of all bonds still ensures a reliable estimation of the market-wide functional form.

[34] In the first iteration, we perform an additional step. In this step, we estimate a prior for the hourly portfolio returns using the standard measure. Thus, we can estimate the functional form by using the return priors and by setting all scaling factors to 1.

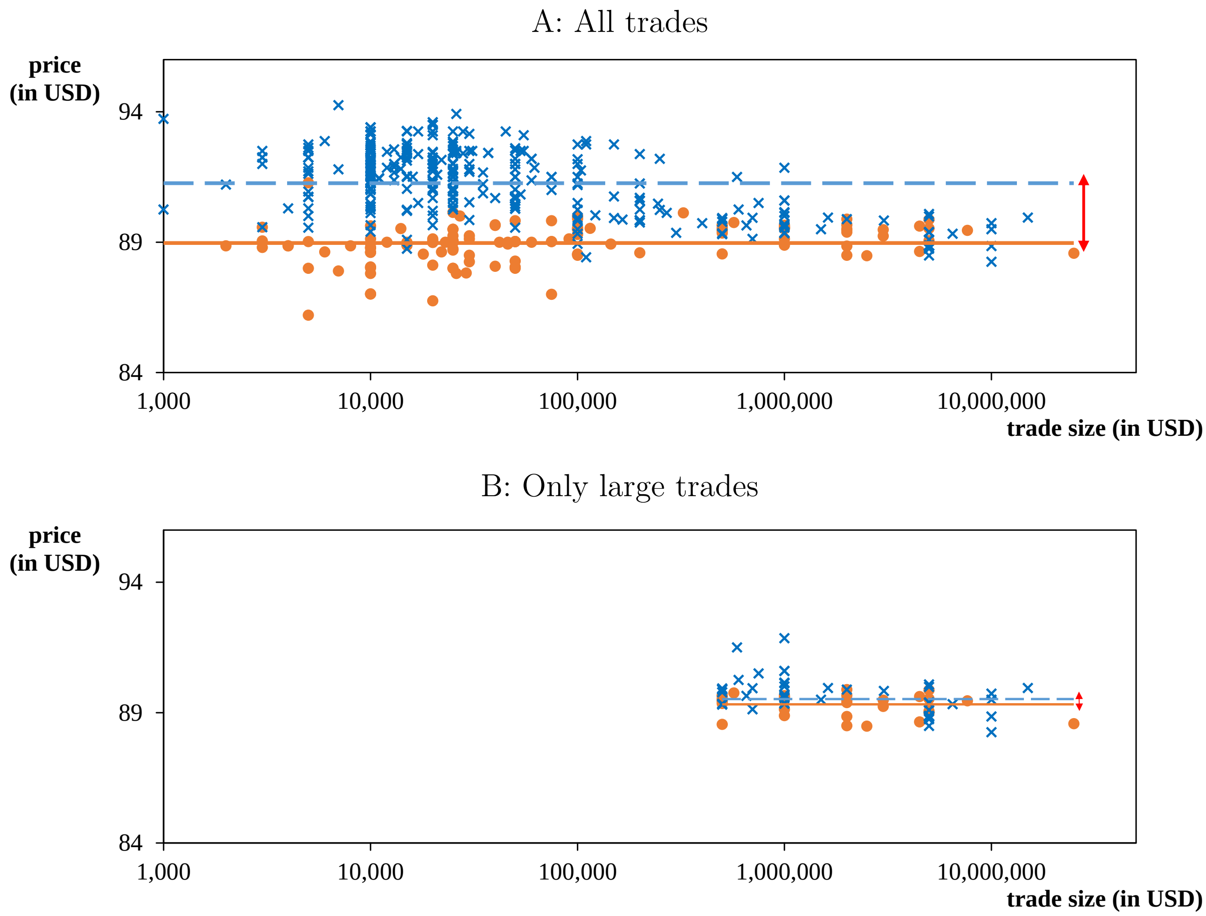


Figure 1: **Daily trades in a heavily traded bond**
This figure depicts an exemplary trading day in a U.S. corporate bond. The trading day is selected as the one with the largest number of observations for both buy and sell trades. The bond is issued by General Motors, has a fixed coupon of 8.375%, and matures in July 2033. The trading day is March 17, 2005. Blue crosses represent trades in which the dealer sells (ask) and orange dots depict trades in which the dealer buys (bid). The blue dashed line indicates the average sell price, the orange solid line the average buy price, and the red arrow the bid-ask spread. Panel A includes all available trades, while Panel B shows only trades with a trading volume larger than $500,000.

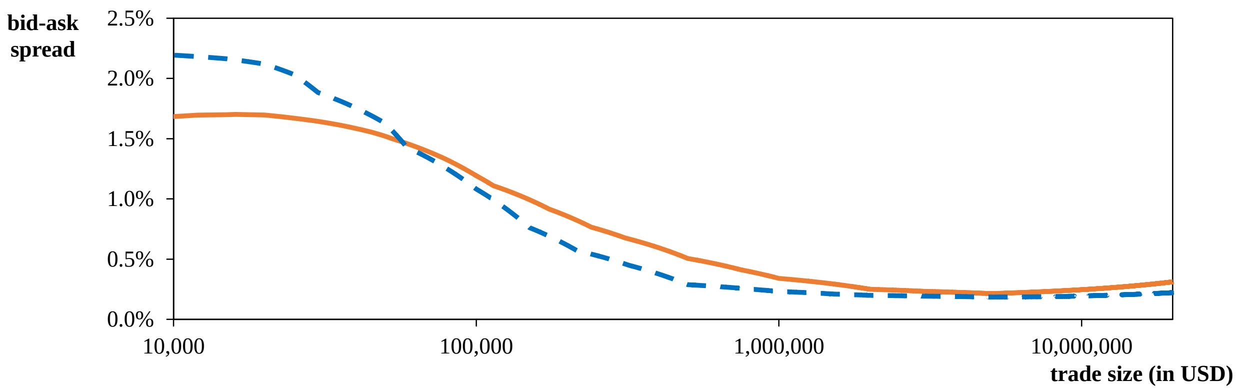


Figure 2: **Market-wide functional form of U.S. corporate bond transaction costs**
The figure depicts transaction costs dependent on trade size for the size-adapted Schultz (2001) measure (orange solid line) and the size-adapted average bid-ask spread measure (blue dashed line). The functional forms are based on a nonparametric regression. They are estimated with the two-step measurement approach described in Sections 2.3 and 2.4.

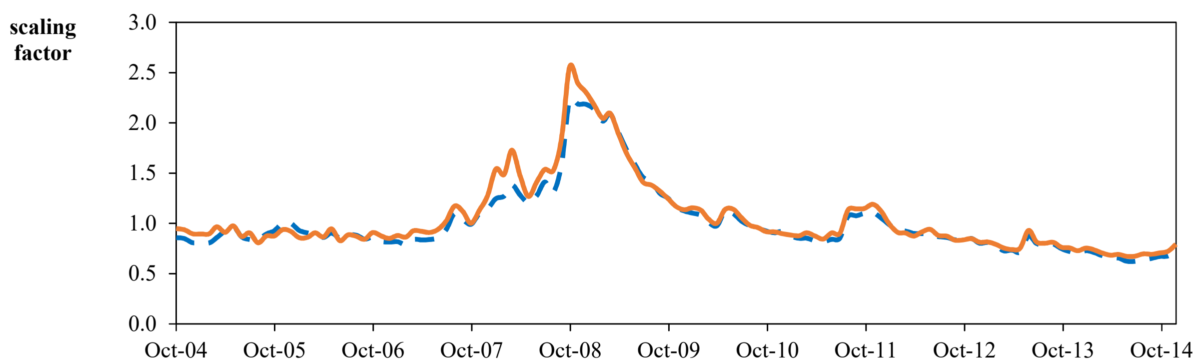
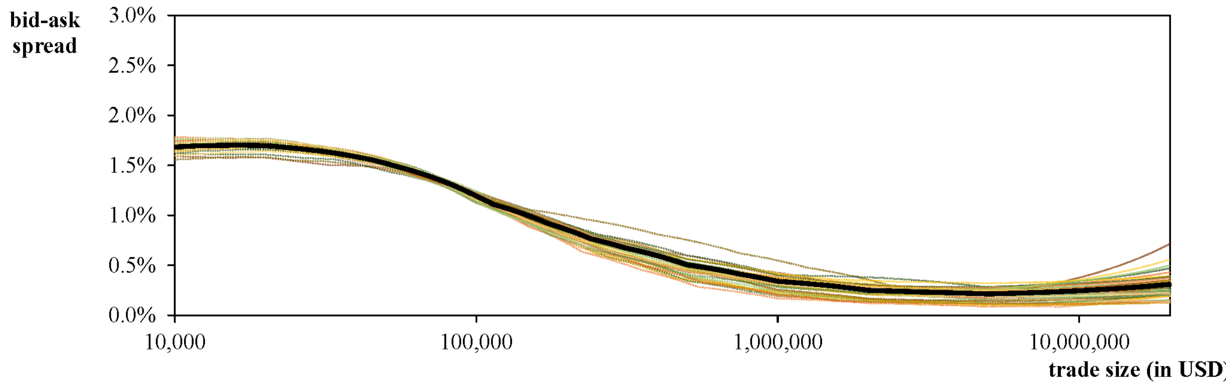


Figure 3: **Time series of U.S. corporate bond transaction costs**
The figure depicts the time series of average liquidity across all bonds for the size-adapted Schultz (2001) measure (orange solid line) and the size-adapted average bid-ask spread measure (blue dashed line). The time period spans from October 2004 to December 2014. Both measures can be interpreted as a scaling factor that, together with the functional forms in Figure 2, can be used to calculate transaction costs for arbitrary trade sizes. Both measures are estimated with the two-step measurement approach described in Sections 2.3 and 2.4.

A: Schultz (2001) measure



B: Average bid-ask spread measure

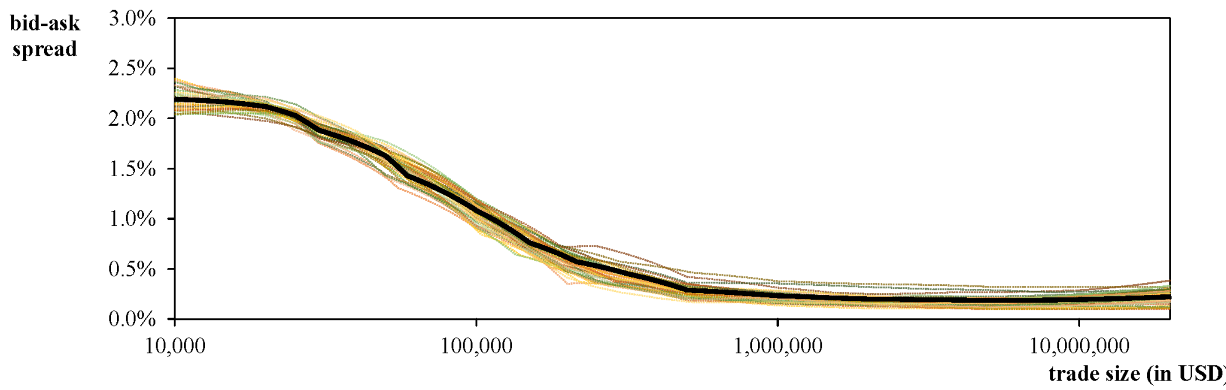


Figure 4: **Time variation of functional forms**
Panels A and B depict functional forms for the Schultz (2001) and average bid-ask spread measure. The functional forms are estimated with the two-step measurement approach described in Sections 2.3 and 2.4. We use either all observations (black solid line) or all observations in a quarter (dashed lines) for the estimation. Quarterly functional forms are estimated for the time period from October 2004 to December 2014. To ensure comparability, we scale the quarterly functional forms to the average level of the functional form that is based on all observations.

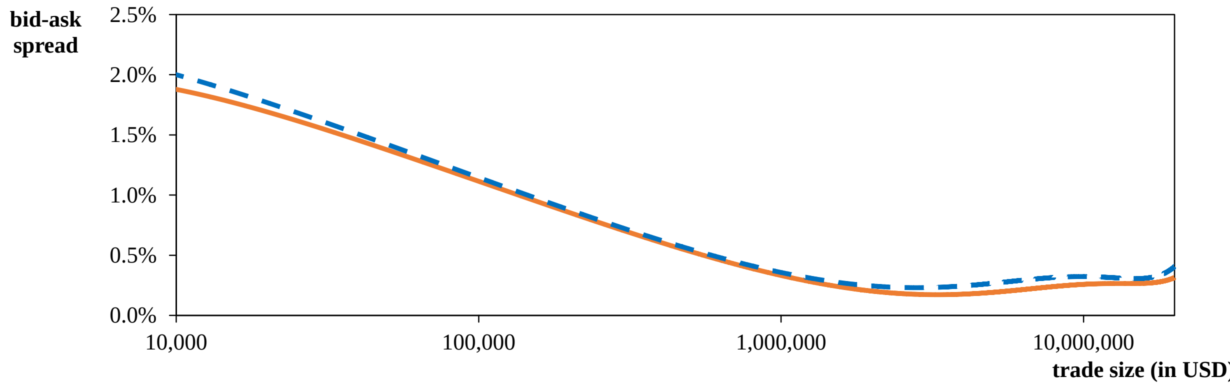


Figure 5: **Parametric functional form of U.S. corporate bond transaction costs**
The figure depicts parametric functional forms for the size-adapted Schultz (2001) measure (orange solid line) and the size-adapted average bid-ask spread measure (blue dashed line). The functional forms are based on the parametric function

$$c(vol) = c_0 + \frac{c_1}{vol} + c_2 \cdot \ln(vol) + c_3 \cdot vol + c_4 \cdot vol^2 + c_5 \cdot vol^3$$

and are estimated with the two-step measurement approach described in Section 5.1.

Table 1: **Information content of small and large trades**

Trades with a notional < \$100,000 are classified as small trades, volumes ≥ \$100,000 are large trades. We measure transaction costs with either the Schultz (2001) measure or the average bid-ask spread measure. In Panel A, we report for a daily and monthly frequency the number of observations for which a transaction cost measure can be calculated using either all trades or only large trades. Panels B and C report results for a panel regression explaining daily transaction costs of large or small trades with monthly transaction costs based on either large or small trades:

$$tc_{i,d,t}^{\text{large/small}} = \alpha + \beta^{\text{large}} \cdot tc_{i,t\setminus\{d\}}^{\text{large}} + \beta^{\text{small}} \cdot tc_{i,t\setminus\{d\}}^{\text{small}} + \epsilon_{i,d,t}.$$

For the monthly measures, we use information from all days in the month excluding the day under consideration. In Panel B (C), we estimate the regression models with daily transaction costs of large (small) trades on the left-hand side. In specifications (1) and (4) ((2) and (5)), we include only monthly transaction costs of large (small) trades on the right-hand side. Specifications (3) and (6) combine both categories. Standard errors are clustered by bond. The t-statistics are given in parentheses. ** and * represent statistical significance at the 1% and 5% level.

Panel A:Observations with available liquidity measure

	daily		monthly	
	Schultz (2001)	Avg. bid-ask spread	Schultz (2001)	Avg. bid-ask spread
All trades	2,967,320	2,726,414	388,029	523,096
Large trades only	1,435,389	1,210,404	302,904	303,319

Panel B: Explaining transaction costs of large trades

	Schultz (2001)			Average bid-ask spread		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.0025**	0.0012**	0.0008**	0.0012**	0.0005**	0.0002**
	(43.59)	(15.79)	(18.05)	(33.75)	(7.24)	(6.40)
$tc_{i,t\setminus\{d\}}^{\text{large}}$	0.6257**		0.4548**	0.7895**		0.6062**
	(70.57)		(49.86)	(123.15)		(65.07)
$tc_{i,t\setminus\{d\}}^{\text{small}}$		0.3434**	0.1792**		0.3607**	0.1452**
		(47.55)	(42.13)		(45.60)	(30.81)
R^2	0.2300	0.1829	0.2626	0.3391	0.2514	0.3616
Observations		742,159			358,740	

Panel C: Explaining transaction costs of small trades

	Schultz (2001)			Average bid-ask spread		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.0092**	0.0026**	0.0025**	0.0070**	0.0013**	0.0012**
	(60.24)	(27.58)	(26.72)	(46.04)	(28.49)	(27.45)
$tc_{i,t\setminus\{d\}}^{\text{large}}$	0.8623**		0.1763**	1.2458**		0.1881**
	(57.27)		(20.76)	(68.22)		(25.27)
$tc_{i,t\setminus\{d\}}^{\text{small}}$		0.7832**	0.7196**		0.9047**	0.8379**
		(119.35)	(89.08)		(261.07)	(157.74)
R^2	0.1987	0.4329	0.4383	0.3185	0.5965	0.6005
Observations		742,159			358,740	

Table 2: **Yield spread analysis: Descriptives**

This table reports cross-sectional descriptive statistics of the panel data for the yield spread regression (7). For all variables, we first calculate the average across time, the statistics are then computed from the cross-section of individual bonds. The credit rating is measured as the average across numerical ratings from S&P, Moody's, and Fitch (AAA=1, AA+=2, ...). Average traded volumes and the number of trades from TRACE are calculated on a daily basis and then averaged across all days of the month. The history of the outstanding amount is from Bloomberg. Transaction cost measures are calculated as described in Section 2. We winsorize yield spreads and transaction costs at the 1% and 99% level. Using the Schultz (2001) measure in Panel A, the sample consists of 15,312 bonds. In Panel B, the sample for the average bid-ask-spread measure contains 19,513 bonds.

Panel A: Schultz (2001) measure							
	Mean	Std. dev.	$Q_{5\%}$	$Q_{25\%}$	$Q_{50\%}$	$Q_{75\%}$	$Q_{95\%}$
Yield spread (%)	2.20	2.14	0.47	0.97	1.53	2.59	6.27
Rating	7.49	3.39	2.00	5.25	7.28	9.46	13.50
Volume (mn)	0.56	0.79	0.01	0.02	0.27	0.88	1.85
Trades	3.77	4.37	1.63	2.08	2.58	3.63	9.74
Amount outstanding (bn)	0.33	0.50	0.00	0.01	0.16	0.48	1.25
Standard liquidity measure (%)	1.19	0.87	0.18	0.53	0.98	1.63	2.98
Size-adapted measure (sf^{Schultz})	0.91	0.59	0.18	0.47	0.79	1.24	2.07
Panel B: Average bid-ask spread measure							
	Mean	Std. dev.	$Q_{5\%}$	$Q_{25\%}$	$Q_{50\%}$	$Q_{75\%}$	$Q_{95\%}$
Yield spread (%)	2.40	2.10	0.51	1.16	1.84	2.82	6.43
Rating	7.29	3.25	2.17	5.02	7.00	9.20	13.15
Volume (mn)	0.52	0.82	0.01	0.02	0.10	0.80	1.86
Trades	3.91	4.26	1.82	2.29	2.81	3.77	9.63
Amount outstanding (bn)	0.30	0.50	0.00	0.01	0.08	0.40	1.25
Standard liquidity measure (%)	1.36	0.95	0.18	0.58	1.16	2.00	3.15
Size-adapted measure ($sf^{\text{AvgBidAsk}}$)	0.94	0.54	0.21	0.54	0.86	1.24	1.95

Table 3: **Yield spread analysis: Panel correlations**

This table reports correlations of the panel data for the yield spread regression (7). The credit rating is measured as the average across numerical ratings from S&P, Moody's, and Fitch (AAA=1, AA+=2, ...). Average traded volumes and the number of trades from TRACE are calculated on a daily basis and then averaged across all days of the month. The history of the outstanding amount is from Bloomberg. Transaction cost measures are calculated as described in Section 2. We winsorize yield spreads and transaction costs at the 1% and 99% level. Using the Schultz (2001) measure in Panel A, the sample consists of 15,312 bonds. In Panel B, the sample for the average bid-ask-spread measure contains 19,513 bonds.

Panel A: Schultz (2001) measure

	Yield spread	Rating	Volume	Trades	Amount outstanding	Std. liquidity measure	Size-adapted measure
Yield spread	1	0.53	-0.04	0.08	-0.13	0.35	0.39
Rating		1	0.05	0.00	-0.19	0.12	0.17
Volume			1	-0.05	0.12	-0.19	-0.04
Trades				1	0.36	0.12	0.09
Amount outstanding					1	-0.19	-0.11
Std. liquidity measure						1	0.86
Size-adapted measure							1

Panel B: Average bid-ask spread measure

	Yield spread	Rating	Volume	Trades	Amount outstanding	Std. liquidity measure	Size-adapted measure
Yield spread	1	0.45	-0.02	0.08	-0.11	0.31	0.39
Rating		1	0.12	0.03	-0.06	-0.02	0.15
Volume			1	-0.04	0.16	-0.26	0.01
Trades				1	0.39	0.06	0.04
Amount outstanding					1	-0.27	-0.14
Std. liquidity measure						1	0.72
Size-adapted measure							1

Table 4: **Yield spread regressions**

This table reports results for the panel regressions explaining monthly yield spread changes with monthly changes in standard or size-adapted transaction cost measures. The regression model is given by

$$\Delta(\text{Yield spread})_{i,t} = \alpha + \beta \cdot \Delta(\text{Yield spread})_{i,t-1} + \gamma \cdot \Delta(\text{Transaction costs})_{i,t} + \delta \cdot \Delta(\text{Controls})_{i,t} + \epsilon_{i,t}.$$

The control variables are traded volume, number of trades, and amount outstanding. We further employ rating dummies as a proxy for credit risk. Specifications (1) and (4) are the baseline regressions that include only lagged yield spread changes and the control variables. In (2) and (5), we add standard transaction cost measures, while in (3) and (6), we add the size-adapted versions. We winsorize yield spread and transaction cost changes at the 1% and 99% level. Standard errors are clustered by bond. We test for differences between out-of-sample mean squared errors (MSE) using the test statistic proposed by Harvey, Leybourne, and Newbold (1997). Comparing R^2 or MSE, we first compare a specification to the baseline and second to its preceding specification. The t-statistics are given in parentheses. ** and * represent statistical significance at the 1% and 5% level.

	Schultz (2001)			Average bid-ask spread		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.0229**	0.0234**	0.0236**	0.0422**	0.0441**	0.0442**
	(17.34)	(17.80)	(17.93)	(27.11)	(28.06)	(28.25)
$\Delta(\text{Yield spread})_{i,t-1}$	0.0960**	0.0955**	0.0956**	0.0906**	0.0896**	0.0893**
	(9.17)	(9.13)	(9.16)	(8.14)	(8.04)	(8.04)
$\Delta(\text{Standard measure})_{i,t}$		5.5337**			9.6839**	
		(12.67)			(21.32)	
$\Delta(\text{Adapted measure})_{i,t}$			0.0831**			0.1679**
			(16.23)			(26.54)
$\Delta(\text{Volume})_{i,t}$	-0.0132**	-0.0065**	-0.0149**	-0.0259**	-0.0124**	-0.0353**
	(-8.56)	(-4.06)	(-9.70)	(-14.26)	(-6.54)	(-19.34)
$\Delta(\text{Trades})_{i,t}$	0.0055**	0.0052**	0.0052**	0.0076**	0.0071**	0.0071**
	(10.25)	(9.98)	(9.95)	(10.73)	(10.28)	(10.33)
$\Delta(\text{Amount outstanding})_{i,t}$	-0.0576	-0.0499	-0.0519	-0.1527*	-0.1412*	-0.1382*
	(-1.12)	(-0.97)	(-1.00)	(-2.32)	(-2.14)	(-2.12)
$\Delta(\text{Rating dummies})_{i,t}$	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.0777	0.0810	0.0837	0.0637	0.0702	0.0760
$\Delta(R^2)$		4.3%	7.7%/3.3%		10.2%	19.3%/8.3%
MSE	0.909	0.905	0.902	1.683	1.670	1.656
Δ(MSE)		-0.4%**	-0.8%**/-0.3%**		-0.8%**	-1.6%**/-0.8%**
		(6.24)	(7.35)/(4.96)		(9.39)	(13.27)/(9.37)
Observations		327,251			454,461	

Table 5: **Yield spread regressions: Trades with volumes $\geq \$100,000$**

This table reports results for the panel regressions explaining monthly yield spread changes based on trades with volumes $\geq \$100,000$ with monthly changes in standard or size-adapted transaction cost measures. The regression model is given by

$$\Delta(\text{Yield spread})_{i,t} = \alpha + \beta \cdot \Delta(\text{Yield spread})_{i,t-1} + \gamma \cdot \Delta(\text{Transaction costs})_{i,t} + \delta \cdot \Delta(\text{Controls})_{i,t} + \epsilon_{i,t}.$$

The control variables are traded volume, number of trades, and amount outstanding. We further employ rating dummies as a proxy for credit risk. Specifications (1) and (5) are the baseline regressions that include only lagged yield spread changes and the control variables. In (2) and (6), we add standard transaction cost measures based on trades with volumes $\geq \$100,000$, while in (3) and (7) we add the measures based on all trade sizes. Finally, (4) and (8) incorporate the size-adapted measures, which, by construction, employ all trade sizes. We winsorize yield spread and transaction cost changes at the 1% and 99% level. Standard errors are clustered by bond. We test for differences between out-of-sample mean squared errors (MSE) using the test statistic proposed by Harvey, Leybourne, and Newbold (1997). Comparing R^2 or MSE, we first compare a specification to the baseline and second to its preceding specification. The t-statistics are given in parentheses. ** and * represent statistical significance at the 1% and 5% level.

	Schultz (2001)				Average bid-ask spread			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.0083**	0.0084**	0.0088**	0.0090**	0.0192**	0.0198**	0.0208**	0.0211**
	(7.43)	(7.51)	(7.94)	(8.10)	(11.13)	(11.54)	(12.09)	(12.29)
$\Delta(\text{Yield spread})_{i,t-1}$	0.1156**	0.1152**	0.1156**	0.1158**	0.1562**	0.1562**	0.1543**	0.1553**
	(10.88)	(10.88)	(10.87)	(10.94)	(10.49)	(10.57)	(10.37)	(10.49)
$\Delta(\text{Standard measure})_{i,t}$		6.3869**	8.3854**			22.1686**	23.1594**	
		(11.74)	(15.25)			(19.08)	(22.76)	
$\Delta(\text{Adapted measure})_{i,t}$				0.1037**				0.2175**
				(17.29)				(22.71)
$\Delta(\text{Volume})_{i,t}$	-0.0110**	-0.0056**	-0.0036	-0.0133**	-0.0186**	0.0014	-0.0011	-0.0238**
	(-6.07)	(-3.05)	(-1.94)	(-7.34)	(-6.32)	(0.45)	(-0.36)	(-8.11)
$\Delta(\text{Trades})_{i,t}$	0.0227**	0.0206**	0.0236**	0.0217**	0.0350**	0.0300**	0.0348**	0.0318**
	(11.57)	(11.00)	(11.78)	(11.31)	(9.56)	(8.90)	(9.67)	(9.19)
$\Delta(\text{Amount outstanding})_{i,t}$	-0.0366	-0.0342	-0.0213	-0.0224	-0.2642*	-0.2549*	-0.2588*	-0.2464*
	(-0.67)	(-0.63)	(-0.39)	(-0.41)	(-2.38)	(-2.31)	(-2.36)	(-2.27)
$\Delta(\text{Rating dummies})_{i,t}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.0571	0.0615	0.0648	0.0694	0.0537	0.0672	0.0715	0.0834
$\Delta(R^2)$		7.7%	13.5%/5.4%	21.5%/7.1%		25.1%	33.2%/6.4%	55.3%/16.6%
MSE	0.682	0.679	0.676	0.673	1.403	1.380	1.372	1.350
Δ(MSE)		-0.4%**	-0.9%**/-0.4%**	-1.3%**/-0.4%**		-1.6%**	-2.2%**/-0.6%**	-3.8%**/-1.6%**
		(5.51)	(7.42)/(3.58)	(7.98)/(4.20)		(9.92)	(11.56)/(3.11)	(12.73)/(6.70)
Observations			271,235				255,294	

Table 6: **Fama-MacBeth analysis: Descriptives**

This table reports cross-sectional descriptive statistics of the panel data for the cross-sectional regression (9). For all variables, we first calculate the average across time, the statistics are then computed from the cross-section of portfolios. Sensitivities are estimated for the risk factors equity market return (EQ), shocks in equity market liquidity (EQLIQ), and shocks in corporate bond market liquidity (CBLIQ). Cross-sectional statistics are calculated based on the non-overlapping portfolio sort on credit quality, amount outstanding, and liquidity beta (described in detail in Section 4.3). In Panels A and B, we use the standard and size-adapted Schultz (2001) or average bid-ask-spread measure to calculate bond transaction costs and liquidity betas.

Panel A: Cross-sectional descriptives – Schultz (2001)

	Standard measure					Size-adapted measure				
	Mean	Std. dev.	$Q_{5\%}$	$Q_{50\%}$	$Q_{95\%}$	Mean	Std. dev.	$Q_{5\%}$	$Q_{50\%}$	$Q_{95\%}$
$E[r_{i,t}]$ (%)	2.26	1.28	0.81	1.87	5.04	2.26	1.27	0.88	1.90	5.03
β^{EQ}	0.1549	0.1017	0.0341	0.1511	0.3846	0.1550	0.0968	0.0399	0.1465	0.3885
β^{EQLIQ}	-0.0922	0.0544	-0.1702	-0.0854	-0.0143	-0.0730	0.0449	-0.1508	-0.0761	0.0090
β^{CBLIQ}	-0.1429	0.0532	-0.2516	-0.1376	-0.0650	-0.1841	0.0656	-0.2935	-0.1946	-0.0921
c (%)	1.34	0.37	0.70	1.29	1.98	1.11	0.27	0.62	1.12	1.55

Panel B: Cross-sectional descriptives – Average bid-ask spread

	Standard measure					Size-adapted measure				
	Mean	Std. dev.	$Q_{5\%}$	$Q_{50\%}$	$Q_{95\%}$	Mean	Std. dev.	$Q_{5\%}$	$Q_{50\%}$	$Q_{95\%}$
$E[r_{i,t}]$ (%)	2.26	1.28	0.87	1.89	5.15	2.26	1.29	0.84	1.87	5.12
β^{EQ}	0.1494	0.0972	0.0451	0.1308	0.3880	0.1546	0.1015	0.0458	0.1234	0.4090
β^{EQLIQ}	-0.0895	0.0474	-0.1491	-0.0995	-0.0131	-0.0692	0.0382	-0.1339	-0.0720	-0.0010
β^{CBLIQ}	-0.1352	0.0575	-0.2558	-0.1224	-0.0593	-0.1708	0.0646	-0.2772	-0.1590	-0.0806
c (%)	1.32	0.37	0.80	1.27	2.06	1.10	0.26	0.65	1.15	1.51

Table 7: **Fama-MacBeth analysis: Average cross-sectional correlations**

This table reports average cross-sectional correlations of the variables in the cross-sectional regression (9). We compute pairwise cross-sectional correlations across portfolios for each month and report their average across time. The set of risk factors consists of the equity return (EQ), shocks in equity market liquidity (EQLIQ), and shocks in corporate bond market liquidity (CBLIQ). Cross-sectional correlations are calculated based on the non-overlapping portfolio triple sort on credit quality, amount outstanding, and liquidity beta (described in detail in Section 4.3). In Panels A and B, we use the standard and size-adapted Schultz (2001) or average bid-ask-spread measure to calculate bond transaction costs and liquidity betas.

Panel A: Cross-sectional correlation – Schultz (2001)

	Standard measure					Size-adapted measure				
	$E[r_{i,t+1}]$	β^{EQ}	β^{EQLIQ}	β^{CBLIQ}	c	$E[r_{i,t+1}]$	β^{EQ}	β^{EQLIQ}	β^{CBLIQ}	c
$E[r_{i,t+1}]$	1	0.71	-0.30	-0.46	0.54	1	0.70	-0.23	-0.54	0.67
β^{EQ}		1	-0.18	-0.34	0.42		1	-0.18	-0.42	0.57
β^{EQLIQ}			1	0.16	-0.28			1	0.02	-0.28
β^{CBLIQ}				1	-0.35				1	-0.40
c					1					1

Panel B: Cross-sectional correlation – Average bid-ask spread

	Standard measure					Size-adapted measure				
	$E[r_{i,t+1}]$	β^{EQ}	β^{EQLIQ}	β^{CBLIQ}	c	$E[r_{i,t+1}]$	β^{EQ}	β^{EQLIQ}	β^{CBLIQ}	c
$E[r_{i,t+1}]$	1	0.71	-0.28	-0.54	0.47	1	0.73	-0.23	-0.62	0.65
β^{EQ}		1	-0.17	-0.36	0.34		1	-0.15	-0.57	0.59
β^{EQLIQ}			1	0.21	-0.24			1	0.10	-0.20
β^{CBLIQ}				1	-0.40				1	-0.53
c					1					1

Table 8: **Fama-MacBeth regression**

This table reports time series averages of the monthly results from the cross-sectional Fama-MacBeth regression (9). We estimate premia for equity market risk (λ_{EQ}), equity market liquidity risk (λ_{EQLIQ}), corporate bond market liquidity risk (λ_{CBLIQ}), and individual bond liquidity (λ_c). Specifications (1) and (3) use the standard measures, whereas (2) and (4) employ their size-adapted counterparts. In specifications (5) and (6), transaction costs are calculated with a standard and size-adapted repeat-sales method. Results in Panels A and B are based on the non-overlapping and overlapping triple sorts. Panels C and D present the results for the industry sort and the individual bonds (all settings are described in Section 4.3). The Fama-MacBeth t-statistics are calculated based on Newey and West (1987) standard errors with six lags and are given in parentheses. ** and * represent statistical significance at the 1% and 5% level.

Panel A: Non-overlapping triple sort

	Schultz (2001)		Average bid-ask spread		Repeat-sales	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.004	-0.001	0.004	0.000	0.006	0.001
	(1.60)	(-0.76)	(1.36)	(0.08)	(1.57)	(0.51)
λ_{EQ}	0.058**	0.054**	0.059**	0.053**	0.057**	0.059**
	(4.75)	(5.39)	(4.89)	(5.23)	(4.84)	(5.10)
λ_{EQLIQ}	-0.032**	-0.021**	-0.030**	-0.026**	-0.029**	-0.025**
	(-3.54)	(-3.14)	(-3.34)	(-4.26)	(-3.69)	(-3.33)
$\lambda_{\text{CBLIQ}}^{\text{Standard}}$	-0.039**		-0.045**		-0.041**	
	(-5.71)		(-8.07)		(-5.85)	
$\lambda_{\text{CBLIQ}}^{\text{Size-adapted}}$		-0.049**		-0.045**		-0.047**
		(-3.69)		(-4.24)		(-4.08)
$\lambda_{\text{c}}^{\text{Standard}}$	0.431**		0.360*		0.573	
	(3.13)		(2.54)		(1.77)	
$\lambda_{\text{c}}^{\text{Size-adapted}}$		0.008**		0.008**		0.008**
		(4.48)		(4.92)		(4.00)
R^2	72.5%	73.1%	73.5%	73.2%	74.5%	74.1%

Panel B: Overlapping triple sort

	Schultz (2001)		Average bid-ask spread		Repeat-sales	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.005	-0.002	0.006	0.000	0.004	-0.004
	(1.40)	(-0.72)	(1.57)	(0.04)	(1.37)	(-1.02)
λ_{EQ}	0.063**	0.055**	0.065**	0.067**	0.067**	0.056**
	(3.60)	(3.22)	(3.94)	(5.09)	(4.69)	(3.74)
λ_{EQLIQ}	-0.037**	-0.044**	-0.029**	-0.034**	-0.031**	-0.031**
	(-3.06)	(-2.66)	(-2.69)	(-2.70)	(-3.25)	(-3.06)
$\lambda_{\text{CBLIQ}}^{\text{Standard}}$	-0.033**		-0.043**		-0.016	
	(-3.01)		(-3.25)		(-1.21)	
$\lambda_{\text{CBLIQ}}^{\text{Size-adapted}}$		-0.053**		-0.047*		-0.048**
		(-2.95)		(-2.55)		(-4.04)
$\lambda_{\text{c}}^{\text{Standard}}$	0.474		0.435		1.060*	
	(1.50)		(1.51)		(2.46)	
$\lambda_{\text{c}}^{\text{Size-adapted}}$		0.012**		0.008*		0.016**
		(3.11)		(2.42)		(3.99)
R^2	83.1%	83.5%	82.5%	81.7%	84.1%	85.3%

Table 8 continued

Panel C: Industry sort

	Schultz (2001)		Average bid-ask spread		Repeat-sales	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.005*	-0.001	0.009*	0.000	0.007*	0.005
	(2.13)	(-0.36)	(2.01)	(0.01)	(2.39)	(1.47)
λ_{EQ}	0.048**	0.041**	0.050**	0.045**	0.047**	0.041**
	(6.09)	(5.51)	(6.19)	(6.01)	(6.39)	(5.20)
λ_{EQLIQ}	-0.018**	-0.015**	-0.021**	-0.015**	-0.018**	-0.017**
	(-3.31)	(-4.23)	(-3.45)	(-3.68)	(-4.48)	(-4.36)
$\lambda_{\mathrm{CBLIQ}}^{\mathrm{Standard}}$	-0.040**		-0.041**		-0.034**	
	(-4.11)		(-4.38)		(-3.17)	
$\lambda_{\mathrm{CBLIQ}}^{\mathrm{Size\text{-}adapted}}$		-0.035**		-0.041**		-0.043**
		(-2.79)		(-3.03)		(-3.05)
$\lambda_{\mathrm{c}}^{\mathrm{Standard}}$	0.413*		0.217		0.643	
	(2.27)		(0.95)		(1.80)	
$\lambda_{\mathrm{c}}^{\mathrm{Size\text{-}adapted}}$		0.011**		0.010**		0.006*
		(5.09)		(4.72)		(1.99)
R^2	76.0%	77.5%	75.7%	74.7%	76.6%	77.4%

Panel D: Individual bonds

	Schultz (2001)		Average bid-ask spread	
	(1)	(2)	(3)	(4)
Intercept	0.008**	0.008**	0.009**	0.008**
	(5.85)	(6.11)	(6.10)	(6.92)
λ_{EQ}	0.031**	0.030**	0.031**	0.031**
	(4.03)	(3.70)	(4.19)	(4.27)
λ_{EQLIQ}	-0.015**	-0.015**	-0.015**	-0.015**
	(-2.98)	(-2.97)	(-3.15)	(-3.34)
$\lambda_{\mathrm{CBLIQ}}^{\mathrm{Standard}}$	-0.026**		-0.027**	
	(-3.21)		(-3.53)	
$\lambda_{\mathrm{CBLIQ}}^{\mathrm{Size\text{-}adapted}}$		-0.022**		-0.026**
		(-2.70)		(-3.02)
$\lambda_{\mathrm{c}}^{\mathrm{Standard}}$	0.409**		0.355**	
	(5.07)		(4.48)	
$\lambda_{\mathrm{c}}^{\mathrm{Size\text{-}adapted}}$		0.006**		0.005**
		(6.61)		(8.38)
R^2	41.5%	40.1%	39.2%	36.8%

Table 9: **Yield spread regressions: Parametric functional form**

This table reports results for the panel regressions explaining monthly yield spread changes with monthly changes in standard or size-adapted transaction cost measures. The regression model is given by

$$\Delta(\text{Yield spread})_{i,t} = \alpha + \beta \cdot \Delta(\text{Yield spread})_{i,t-1} + \gamma \cdot \Delta(\text{Transaction costs})_{i,t} + \delta \cdot \Delta(\text{Controls})_{i,t} + \epsilon_{i,t}.$$

The control variables are traded volume, number of trades, and amount outstanding. We further employ rating dummies as a proxy for credit risk. For ease of comparability, specifications (1), (2), (4), and (5) are identical to Table 4, while in (3) and (6), we add the size-adapted versions based on the parametric functional form of Section 5.1. We winsorize yield spread and transaction cost changes at the 1% and 99% level. Standard errors are clustered by bond. We test for differences between out-of-sample mean squared errors (MSE) using the test statistic proposed by Harvey, Leybourne, and Newbold (1997). Comparing R^2 or MSE, we first compare a specification to the baseline and second to its preceding specification. The t-statistics are given in parentheses. ** and * represent statistical significance at the 1% and 5% level.

	Schultz (2001)			Average bid-ask spread		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.0229**	0.0234**	0.0236**	0.0422**	0.0441**	0.0445**
	(17.34)	(17.80)	(17.94)	(27.11)	(28.06)	(28.38)
$\Delta(\text{Yield spread})_{i,t-1}$	0.0960**	0.0955**	0.0956**	0.0906**	0.0896**	0.0890**
	(9.17)	(9.13)	(9.16)	(8.14)	(8.04)	(8.01)
$\Delta(\text{Standard measure})_{i,t}$		5.5337**			9.6839**	
		(12.67)			(21.32)	
$\Delta(\text{Adapted measure})_{i,t}$			0.0949**			0.1784**
			(16.10)			(27.03)
$\Delta(\text{Volume})_{i,t}$	-0.0132**	-0.0065**	-0.0154**	-0.0259**	-0.0124**	-0.0296**
	(-8.56)	(-4.06)	(-10.05)	(-14.26)	(-6.54)	(-16.29)
$\Delta(\text{Trades})_{i,t}$	0.0055**	0.0052**	0.0053**	0.0076**	0.0071**	0.0069**
	(10.25)	(9.98)	(9.99)	(10.73)	(10.28)	(10.10)
$\Delta(\text{Amount outstanding})_{i,t}$	-0.0576	-0.0499	-0.0521	-0.1527*	-0.1412*	-0.1374*
	(-1.12)	(-0.97)	(-1.01)	(-2.32)	(-2.14)	(-2.10)
$\Delta(\text{Rating dummies})_{i,t}$	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.0777	0.0810	0.0838	0.0637	0.0702	0.0757
$\Delta(R^2)$		4.3%	7.9%/3.5%		10.2%	18.8%/7.8%
MSE	0.909	0.905	0.902	1.683	1.670	1.657
$\Delta(\text{MSE})$		-0.4%**	-0.8%**/-0.3%**		-0.8%**	-1.5%**/-0.8%**
		(6.24)	(7.26)/(4.79)		(9.39)	(13.16)/(10.84)
Observations		327,251			454,461	

Table 10: **Fama-MacBeth regression: Parametric functional form**
This table reports time series averages of the monthly results from the cross-sectional Fama-MacBeth regression (9). We use the size-adapted Schultz (2001) and average bid-ask measures based on the parametric functional form of Section 5.1 to calculate transaction costs. Additionally, we employ in the same way a size-adapted repeat-sales method. We present results for the overlapping and non-overlapping triple sort, the industry sort, and individual bonds (all settings are described in Section 4.3). The Fama-MacBeth t-statistics are calculated based on Newey and West (1987) standard errors with six lags and are given in parentheses. ** and * represent statistical significance at the 1% and 5% level.

	Non-overlapping triple sort			Overlapping triple sort		
	Schultz (2001)	Avg. bid-ask spread	Repeat-sales	Schultz (2001)	Avg. bid-ask spread	Repeat-sales
Intercept	-0.001	0.001	0.001	-0.002	0.001	-0.002
	(-0.48)	(0.26)	(0.33)	(-0.57)	(0.20)	(-0.50)
λ_{EQ}	0.055**	0.054**	0.054**	0.056**	0.065**	0.055**
	(5.30)	(4.61)	(5.85)	(3.28)	(4.60)	(3.29)
λ_{EQLIQ}	-0.023**	-0.028**	-0.021**	-0.045**	-0.028*	-0.024**
	(-3.16)	(-4.41)	(-3.65)	(-2.71)	(-2.53)	(-2.79)
$\lambda_{\mathrm{CBLIQ}}^{\text{Size-adapted}}$	-0.053**	-0.043**	-0.050**	-0.053**	-0.046*	-0.043**
	(-3.84)	(-4.45)	(-3.29)	(-2.99)	(-2.36)	(-3.79)
$\lambda_{\mathrm{c}}^{\text{Size-adapted}}$	0.008**	0.008**	0.009**	0.012**	0.009*	0.015**
	(3.91)	(4.92)	(4.03)	(2.88)	(2.45)	(3.92)
R^2	73.2%	73.5%	75.0%	83.1%	82.7%	85.1%

	Industry sort			Individual bonds	
	Schultz (2001)	Avg. bid-ask spread	Repeat-sales	Schultz (2001)	Avg. bid-ask spread
Intercept	0.000	0.000	0.006	0.008**	0.008**
	(-0.19)	(-0.07)	(1.58)	(5.89)	(6.18)
λ_{EQ}	0.041**	0.044**	0.044**	0.030**	0.030**
	(5.58)	(5.85)	(5.27)	(3.80)	(4.16)
λ_{EQLIQ}	-0.015**	-0.013**	-0.018**	-0.015**	-0.015**
	(-3.72)	(-3.04)	(-5.06)	(-3.02)	(-3.27)
$\lambda_{\mathrm{CBLIQ}}^{\text{Size-adapted}}$	-0.036**	-0.042**	-0.042**	-0.023**	-0.028**
	(-2.91)	(-3.23)	(-3.20)	(-2.79)	(-2.96)
$\lambda_{\mathrm{c}}^{\text{Size-adapted}}$	0.011**	0.010**	0.007*	0.006**	0.006**
	(4.80)	(4.33)	(2.53)	(6.58)	(7.56)
R^2	77.4%	75.4%	78.1%	40.1%	38.1%

Table 11: **Yield spread regressions: Alternative credit risk proxy**

This table reports results for the panel regressions explaining monthly yield spread changes with monthly changes in standard or size-adapted transaction cost measures. The regression model is given by

$$\Delta(\text{Yield spread})_{i,t} = \alpha + \beta \cdot \Delta(\text{Yield spread})_{i,t-1} + \gamma \cdot \Delta(\text{Transaction costs})_{i,t} + \delta \cdot \Delta(\text{Controls})_{i,t} + \epsilon_{i,t}.$$

The control variables are traded volume, number of trades, and amount outstanding. We further employ RMI 1-year PDs as a proxy for credit risk. Specifications (1) and (4) are the baseline regressions that include only lagged yield spread changes and the control variables. In (2) and (5), we add standard transaction cost measures, while in (3) and (6), we add the size-adapted versions. We winsorize yield spread and transaction cost changes at the 1% and 99% level. Standard errors are clustered by bond. We test for differences between out-of-sample mean squared errors (MSE) using the test statistic proposed by Harvey, Leybourne, and Newbold (1997). Comparing R^2 or MSE, we first compare a specification to the baseline and second to its preceding specification. The t-statistics are given in parentheses. ** and * represent statistical significance at the 1% and 5% level.

	Schultz (2001)			Average bid-ask spread		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.0121**	0.0124**	0.0125**	0.0317**	0.0325**	0.0328**
	(11.91)	(12.25)	(12.40)	(21.30)	(21.77)	(21.99)
$\Delta(\text{Yield spread})_{i,t-1}$	0.1582**	0.1575**	0.1575**	0.1025**	0.1013**	0.1009**
	(16.05)	(16.03)	(16.06)	(8.27)	(8.15)	(8.16)
$\Delta(\text{Standard measure})_{i,t}$		4.8628**			6.2495**	
		(10.22)			(11.19)	
$\Delta(\text{Adapted measure})_{i,t}$			0.0695**			0.1202**
			(13.06)			(18.35)
$\Delta(\text{Volume})_{i,t}$	-0.0130**	-0.0071**	-0.0144**	-0.0187**	-0.0094**	-0.0249**
	(-7.81)	(-4.02)	(-8.72)	(-8.94)	(-4.21)	(-12.05)
$\Delta(\text{Trades})_{i,t}$	0.0041**	0.0039**	0.0039**	0.0062**	0.0060**	0.0060**
	(6.55)	(6.33)	(6.32)	(6.99)	(6.82)	(6.84)
$\Delta(\text{Amount outstanding})_{i,t}$	-0.0254	-0.0209	-0.0215	-0.0637	-0.0603	-0.0563
	(-0.59)	(-0.48)	(-0.49)	(-0.96)	(-0.91)	(-0.85)
$\Delta(\text{PD})_{i,t}$	18.4463**	18.4557**	18.3961**	19.3402**	19.3446**	19.2659**
	(19.54)	(19.56)	(19.47)	(17.34)	(17.33)	(17.28)
R^2	0.2070	0.2103	0.2129	0.1711	0.1742	0.1795
$\Delta(R^2)$		1.6%	2.9%/1.2%		1.8%	4.9%/3.0%
MSE	0.523	0.521	0.519	1.139	1.135	1.126
$\Delta(\text{MSE})$		-0.4%**	-0.8%**/-0.4%**		-0.4%**	-1.1%**/-0.8%**
		(4.47)	(5.56)/(4.10)		(3.46)	(7.56)/(7.59)
Observations	213,435			278,446		

Table 12: **Yield spread regressions: Combined data set**

This table reports results for the panel regressions explaining monthly yield spread changes with monthly changes in standard or size-adapted transaction cost measures based on a combined data set. The regression model is given by

$$\Delta(\text{Yield spread})_{i,t} = \alpha + \beta \cdot \Delta(\text{Yield spread})_{i,t-1} + \gamma \cdot \Delta(\text{Transaction costs})_{i,t} + \delta \cdot \Delta(\text{Controls})_{i,t} + \epsilon_{i,t}.$$

The control variables are traded volume, number of trades, and amount outstanding. We further employ rating dummies as a proxy for credit risk. Specification (1) is the baseline regression that includes only lagged yield spread changes and the control variables. In (2) and (4), we add standard transaction cost measures, while in (3) and (5), we add the size-adapted versions. We winsorize yield spread and transaction cost changes at the 1% and 99% level. Standard errors are clustered by bond. We test for differences between out-of-sample mean squared errors (MSE) using the test statistic proposed by Harvey, Leybourne, and Newbold (1997). Comparing R^2 or MSE, we first compare a specification to the baseline and second, for the size-adapted measures, to its preceding specification. The t-statistics are given in parentheses. ** and * represent statistical significance at the 1% and 5% level.

		Schultz		Average bid-ask spread	
	(1)	(2)	(3)	(4)	(5)
Intercept	0.0186**	0.0196**	0.0198**	0.0196**	0.0200**
	(13.16)	(13.89)	(14.10)	(13.86)	(14.20)
$\Delta(\text{Yield spread})_{i,t-1}$	0.0903**	0.0903**	0.0902**	0.0890**	0.0886**
	(8.29)	(8.29)	(8.31)	(8.17)	(8.19)
$\Delta(\text{Standard measure})_{i,t}$		8.8867**		8.1575**	
		(16.22)		(17.85)	
$\Delta(\text{Adapted measure})_{i,t}$			0.1282**		0.1499**
			(19.01)		(23.05)
$\Delta(\text{Volume})_{i,t}$	-0.0116**	-0.0009	-0.0131**	0.0007	-0.0164**
	(-6.30)	(-0.47)	(-7.22)	(0.35)	(-9.05)
$\Delta(\text{Trades})_{i,t}$	0.0057**	0.0053**	0.0053**	0.0054**	0.0054**
	(10.59)	(10.21)	(10.17)	(10.46)	(10.46)
$\Delta(\text{Amount outstanding})_{i,t}$	-0.0255	-0.0092	-0.0139	-0.0109	-0.0106
	(-0.36)	(-0.13)	(-0.20)	(-0.16)	(-0.15)
$\Delta(\text{Rating dummies})_{i,t}$	Yes	Yes	Yes	Yes	Yes
R^2	0.0853	0.0922	0.0971	0.0920	0.1025
$\Delta(R^2)$		8.1%	13.8%/5.3%	7.9%	20.2%/11.4%
MSE	0.873	0.866	0.861	0.866	0.854
Δ(MSE)		-0.8%**	-1.4%**/-0.6%**	-0.8%**	-2.2%**/-1.4%**
		(6.40)	(7.48)/(4.72)	(7.59)	(12.86)/(10.85)
Observations	271,877				