# Transaction costs and capacity of systematic corporate bond strategies

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**Abstract**

Recent scientific advances in return predictability and competitive pressures have led to a growing interest in systematic strategies and factor investing in corporate bonds in academia and industry. In this paper, we employ a recently developed methodology to estimate transaction costs and capacity constraints in systematic corporate bond strategies. We apply principles of market microstructure invariance to evaluate corporate bond transaction costs. Unlike prevailing transaction-based estimates of bond trading costs, pricing functions implied by microstructure invariance have a positive market impact. As the size of the bond fund increases, the market impact part of transaction costs drives net return down to zero. We find that high-turnover strategies that exploit reversal and illiquidity signals reach capacity fast. Low-turnover strategies targeting credit risk premia have capacities up to twenty times higher than high-turnover strategies. The capacity can be increased considerably by placing restrictions on portfolio rebalancing. We also find that the corporate bond market risk premia are not absorbed by transaction costs even in the largest possible market portfolios.

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# Introduction

Interest in systematic strategies and factor investing in corporate bonds has grown at an accelerated pace in academia and industry. This is partly attributable to recent scientific advances in the understanding of corporate bond return predictability, the increased ease of trading corporate bonds due to the use of automation or electronification, as well as competitive pressures due to the commoditization of systematic factor strategies in equity markets.

Recent papers have not only identified factor structures in corporate bond returns (Bai et al. 2019, Chordia et al. 2017) but also incorporated ESG considerations into systematic corporate bond strategies (Diep et al. 2022) and applied machine learning to the forecasting of bond returns based on stock and bond characteristics (Bali et al. 2022).

In industry, index providers such as MSCI offer multi-factor and ESG corporate bond indices,[1] several large asset managers such as Blackrock, Robeco, and Amundi sell corporate bond ETFs, and asset management companies[2] promote the concept of systematic corporate bond strategies. The electronification of corporate bond trading has reached levels of around 40 percent, according to a recent Financial Times article,[3] thus making the trading in corporate bonds and the implementation of systematic strategies more accessible than before.

The adoption of systematic or factor-based investing in corporate bond markets lags behind that of equity markets in terms of assets under management (AUM) in mutual funds and ETFs. According to Morningstar, at the end of 2020, $1.35 trillion ($14.36 billion) in equity (corporate bond) fund AUM was categorized as strategic beta. At the same time, the potential for catchup is

[1] See details at the MSCI website.

[2] According to the websites of AQR, Cantab Capital, Dimensional Fund Advisors, GAM and Man Numeric and, for instance, this story by Financial Times.

[3] See here.

significant for systematic corporate bond strategies since the size of the US equity market is similar to that of the global corporate bond market in terms of USD equivalent notional outstanding.[4]

There are at least two important unanswered questions in the corporate bond pricing literature. First, do systematic corporate bond strategies survive realistic transaction cost adjustments? Second, what are the capacity constraints of systematic corporate bond strategies? In this paper, we set out to answer these questions. As we explain below, given the nature of corporate bond markets, it is not trivial to answer these questions. To overcome some of the hurdles, we leverage on the recent work of Kyle and Obizhaeva (2016) on market microstructure invariance (MMI) and trading cost functions to provide novel estimates of net systematic bond returns.

Bond trading costs are hard to estimate because trades are infrequent, large, and often non-anonymously pre-negotiated by dealers and investors. Nevertheless, several studies have successfully applied different approaches to the estimation of bond trading costs, including effective spreads, regression-based approaches, and size-adapted measures (Edwards et al. 2007, Harris 2015, and Reichenbacher and Schuster 2022). However, the above techniques do not lend themselves to an estimation of capacity constraints since their resulting price impact coefficients estimated on transactional corporate bond data (TRACE) are negative. This poses a problem because, with negative price impacts, the capacity of any systematic bond strategy (with positive gross returns) is virtually infinite. Logically, the larger the fund, the larger the rebalancing trades, and the lower would be the costs of each transaction. This is clearly counterfactual.

The reason for the negative price impact estimates is that relationship motives often result in large corporate bond trades in the TRACE data being priced more favorably. Since bonds trade over-the-counter, we have no information on trades that did not go through. Using more recent

[4] According to an August 2022 ICMA estimate, the overall size of the global corporate bond market is approximately \$40.9tn. This compares to a 2022 SIFMA estimate of \$44tn for the size of the US equity market.

TRACE data, we confirm the classic negative price impact result and illustrate it in Figure 1 using the EHP transaction cost function.

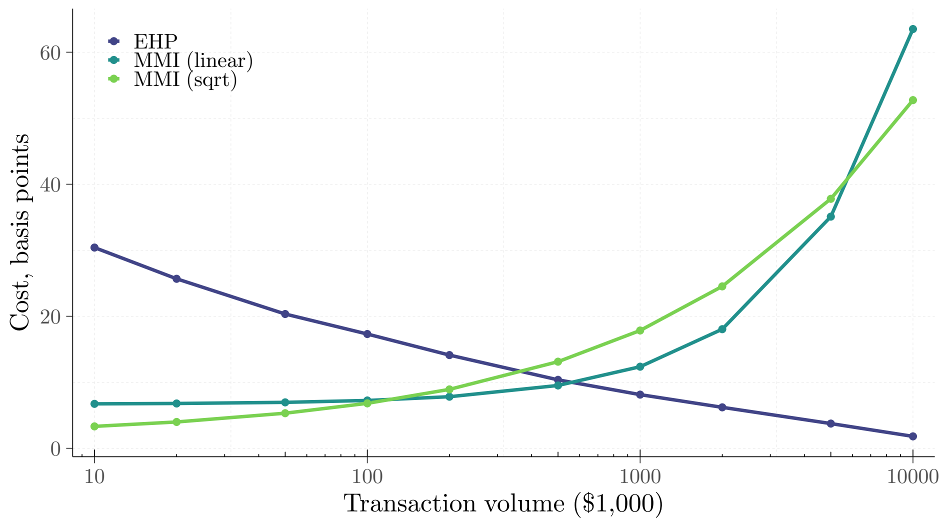


Figure 1: **Average MMI-implied and transaction-based corporate bond trading costs.** MMI-implied functions are linear and square-root transaction costs of Kyle and Obizhaeva (2016) adapted to individual corporate bonds. The average is trading-volume-weighted across bonds. The EHP is a transaction cost function of Edwards et al. (2007) estimated on TRACE data for individual bonds, then weighted across bonds with the precision of individual estimates. Both types of functions are estimated on the data from Jan 2010 to Jun 2019. The cross-section of bonds is described in Table 1. Transaction volume is on the log scale. The limits of the x-axis ($10K and $10M) are close to the 5$^{\text{th}}$ and 99$^{\text{th}}$ percentile of trades observed in TRACE.

To overcome the challenge posed by negative price impact estimates, we adapt trading cost functions from market microstructure invariance (MMI) of Kyle and Obizhaeva (2016) to corporate bonds to provide novel estimates of net systematic bond returns and capacity constraints. These cost functions are increasing in trade size by construction. We calibrate MMI costs that differ strikingly from TRACE-estimated costs for large transactions (see Figure 1 again). The MMI estimates represent the costs for large systematic trades better because an asset manager who follows a rule-based rebalancing strategy hardly has much discretion on which trades to execute and which not to execute based on the cost suggested by a bond dealer. Building on the positive MMI price impacts, we estimate the capacity of systematic bond strategies.

To make our results comparable to the existing literature, we closely follow the Bai et al. (2019) and Chordia et al. (2017) portfolio construction approaches to represent systematic bond portfolio strategies. Bai et al. (2019) portfolios are double-sorted, in different combinations, on historical VaR (Value-at-Risk), credit rating, past return, and liquidity. We also use two of the Chordia et al. (2017) reversal strategy portfolios. These two portfolios are constructed with univariate sorts on past bond and equity returns. Using the terminology of the mutual fund industry, a bond investor may view such rule-based portfolios as 'style' or 'smart-beta' corporate bond portfolios. Additionally, we also include two broad market portfolios and one multi-factor portfolio in our set of systematic strategies. For each strategy, we report summary statistics, including their performance, risk, turnover, and number of holdings.

We have three main findings on 'smart beta' corporate bond strategies. First, similar to recent results for equities (Novy-Marx and Velikov 2015), low-turnover strategies fare much better. Second, portfolios with more holdings seem to perform better net of costs for a given size of the fund. Third, turnover constraints are helpful in improving the net of cost performance across the board, especially for reversal strategies. Overall, the leaderboard of actively-managed bond strategies (beyond market portfolios) looks like this: credit ($\approx$ high-yield portfolios), default (the name is due to Bai et al. 2019, essentially it's a high historical VaR portfolio), then (il)liquidity (long illiquid bonds), then all sorts of reversal signals. A multi-factor portfolio, which combines credit, default, and liquidity signals, behaves as the weighted average of the components because pure-factor constituent portfolios do not overlap much in holdings.

We also derive capacity estimates of systematic broad bond market strategies. We make our 'theoretical' market portfolios more realistic by imposing several selection and rebalancing criteria. Additionally, we vary the size of the fund invested in each systematic portfolio to find the level at which the strategy no longer makes money after transaction costs. Our capacity estimates for market portfolios range from \$8 tn to \$17 tn under square-root MMI-implied transaction costs. The lower end is for investment-grade-only portfolios, and the upper end is for a broad market portfolio. The total outstanding amount of all bonds in our sample is, on average, around \$4.2 tn. Hence, we find that the corporate bond market risk premia are not absorbed by transaction costs even in the largest possible market portfolios. Compared to the aforementioned Morningstar estimates for the AUM of systematic bond funds, our results suggest that there is still room for growth in terms of the size of the systematic corporate bond fund market.

Our paper is related to three streams of literature. First, our paper is related to the literature on factor structures and return predictability in bond markets. Houweling and van Zundert (2017) and Israel et al. (2018) discuss a practical design of systematic bond strategies and the factor structure in bond returns. Chordia et al. (2017) study whether preceding equity return characteristics also impact bond returns. Bai et al. (2019) derive bond-implied risk factors. Bali et al. (2022) apply machine learning to show that superior performance can be achieved compared to univariate bond-implied risk factors. Our contribution to this literature is that we provide net-of-transaction-cost performance and capacity estimates for systematic bond portfolios documented in the literature.

Second, our work is related to the market microstructure and bond transaction costs literature.[5] Kyle and Obizhaeva (2016) pioneer the market microstructure invariance approach and Kyle and Obizhaeva (2020) use an invariance-based illiquidity measure calibrated from stock market data to extrapolate transaction costs in representative Treasury and corporate fixed income securities. Our empirical findings contribute to this literature by extending the MMI approach to the entire universe of US corporate bonds and estimating MMI-based transaction costs for systematic corporate bond strategies.

[5] An incomplete list of papers on bond market trading costs includes: Edwards et al. (2007), Bao et al. (2011), Feldhütter (2012), Harris (2015), Reichenbacher and Schuster (2022), and Kargar et al. (2021)

Third, our work is related to the literature on estimating net-of-transaction-cost performance and capacity constraints in equity and other markets (Frazzini et al. 2015, Novy-Marx and Velikov 2015, Joenväärä et al. 2019, Bonelli et al. 2019, Patton and Weller 2020, and Ardia et al. 2022). Frazzini et al. (2015) use live equity trading data to estimate real-world price impact functions and discuss strategies designed to reduce transaction costs and increase capacity. We extend this literature by studying implementation constraints in systematic corporate bond strategies and innovations to increase capacity constraints in corporate bond markets.

The rest of the paper is structured as follows. Section 1 describes the data and the sample. Section 2 reports our trading costs and net bond portfolio return estimates. In Sections 3 and 4, we incorporate various implementation constraints and discuss our capacity estimates for each strategy. Section 5 concludes.

# 1 Data and sample

We largely follow Bai et al. (2019) (BBW hereafter) in sample selection and only include 'plain-vanilla' (non-convertible, non-asset-backed, fixed-coupon, USD-denominated bonds with more than one year to maturity, etc.) corporate bonds in our monthly sample that extends to June 2019. Bond transactions are from TRACE, bond characteristics – from Mergent FISD, and issuer characteristics (if it is a traded company) – from CRSP and Compustat. We deviate from the BBW in two aspects. Firstly, we only sample bonds with an outstanding amount of at least \$100 mln. Bonds of smaller issue size are excluded from major broad bond market indices, are rarely traded, and hence do not have comprehensive transaction price statistics.[6] Secondly, we recognize returns of infrequently traded bonds differently.

[6]Adding all outstanding bonds with less than \$100 mln issue size would roughly add 1.3 mln bond-month observations (i.e., double the sample size), but only about 10% of those bond-month observations would have transaction prices.

The BBW only recognizes month-$t$ returns if the bond is traded either in the last five business days of months $t$ and $t-1$ or in the first five and the last five business days of month $t$. These are strict criteria for securities that trade as infrequently as US corporate bonds. Our sample of all outstanding plain-vanilla US corporate bonds with more than one year to maturity and at least \$100 mln outstanding amount contains about 1.3 million bond-month observations. For about 21% of these bond-months, there is not a single trade recorded in TRACE. Another 13% of bond-months do not have trades in the last/first five business days of the month. The BBW return recognition criteria reduce the sample to 0.9 million bond-month observations, roughly two-thirds of an original sample of all eligible outstanding bonds. While this approach is reasonable for the extraction of cross-sectional pricing signals, it would not be appropriate for the analysis of returns and transaction costs in systematic strategies for at least two reasons. Firstly, the bond investment universe, in principle, consists of all outstanding bonds, and a portfolio manager can not perfectly predict which bonds will have sufficient trading activity in the future. Secondly, if a portfolio contains a coupon bond that is not traded in month $t$, this bond still earns a 'carry' in month $t$ in the form of accrued interest; hence its unconditional total expected return is above zero. For these reasons, we complement BBW returns with 'imputed' total expected returns calculated as the bond coupon rate divided by twelve for bond-months with few or no trades.[7]

[7] For portfolio performance without imputed returns, see Table 10b in Appendix.

| | N.obs. | Mean | Median | S.D. | 1st | 5th | 25th | 75th | 95th | 99th |
|---|---|---|---|---|---|---|---|---|---|---|
| Bond return, imputed (%) | 1258586 | 0.56 | 0.52 | 3.41 | -8.33 | -3.04 | -0.19 | 1.15 | 4.34 | 10.37 |
| Bond return, BBW (%) | 865516 | 0.55 | 0.38 | 3.77 | -9.46 | -3.46 | -0.41 | 1.46 | 4.79 | 11.65 |
| Rating | 1240405 | 8.82 | 8.00 | 3.70 | 1.00 | 4.00 | 6.00 | 10.00 | 16.00 | 19.00 |
| Time to maturity (years) | 1258586 | 9.98 | 6.38 | 10.35 | 1.10 | 1.52 | 3.51 | 12.30 | 28.34 | 32.57 |
| Size ($ mn) | 1258586 | 573.7 | 400.0 | 582.8 | 100.0 | 125.0 | 250.0 | 700.0 | 1714.3 | 3000.0 |
| Coupon rate (%) | 1258586 | 5.95 | 5.96 | 2.10 | 1.30 | 2.45 | 4.60 | 7.25 | 9.50 | 11.25 |
| Bond yield spread (%) | 1065865 | 2.55 | 1.44 | 5.29 | -0.36 | 0.32 | 0.82 | 2.68 | 7.04 | 19.26 |
| Downside risk (5% VaR) | 595583 | 3.80 | 2.67 | 5.05 | -4.11 | -0.20 | 1.39 | 4.72 | 11.86 | 27.12 |
| BPW illiquidity | 852351 | 0.73 | 0.10 | 2.59 | -0.65 | -0.06 | 0.02 | 0.42 | 3.06 | 14.39 |
| MMI illiquidity (b.p.) | 1117419 | 61.1 | 56.7 | 33.1 | 11.0 | 18.3 | 37.3 | 78.7 | 117.7 | 173.9 |
| Bond market beta | 592133 | 1.01 | 0.80 | 1.50 | -2.10 | -0.24 | 0.39 | 1.48 | 2.90 | 5.12 |

(a) Pooled bond-month sample: descriptive statistics (Oct 2004 – Jun 2019)

| | Rating | Maturity | Size | VaR | BPW illiq | MMI illiq | Bond beta |
|---|---|---|---|---|---|---|---|
| Rating | 1 | -0.116 | -0.195 | 0.461 | 0.137 | 0.059 | 0.202 |
| Maturity | | 1 | 0.012 | 0.290 | 0.185 | 0.352 | 0.418 |
| Size | | | 1 | -0.026 | -0.142 | -0.459 | 0.091 |
| VaR | | | | 1 | 0.270 | 0.235 | 0.574 |
| BPW illiq | | | | | 1 | 0.249 | 0.111 |
| MMI illiq | | | | | | 1 | 0.166 |
| Bond beta | | | | | | | 1 |

(b) Time-series averages of cross-sectional correlations

Table 1: **Descriptive statistics.** We follow Bai et al. (2019) in bond-month sample construction. The sample consists of USD-denominated non-convertible, non-asset-backed, publicly-issued fixed-coupon bonds with at least one year to maturity and a $100 mln outstanding amount. Bond transactions are from TRACE and bond characteristics are from Mergent FISD. Trades less than $10,000 are removed. Panel A presents full-sample descriptive statistics. The BBW bond return is the return that is recognized if the bond is either traded in the last fast business days of months $t$ and $t-1$ or the last five and the first five business days of month $t$. The BBW returns are total returns, are based on volume-weighted average dirty prices, and are winsorized at 0.1% and 99.9% in a pooled sample. We complement BBW return observations by adding carry for bond-months when BBW returns are not available to construct 'imputed' bond returns (top line in the table). Credit rating is on a numerical scale (1 corresponds to AAA, 2 to AA+, ... , 21 to C). Defaulted bonds are excluded. Size is an outstanding notional amount. The bond yield spread is the difference between a bond's yield to maturity and the yield of a synthetic risk-free bond that pays identical coupons, but that is priced at Treasury rates (Gürkaynak et al. 2007). The downside risk is a 5% VaR, i.e., the second lowest bond return in the previous 36 months, multiplied by -1. 'BPW illiquidity' is an illiquidity measure of Bao et al. (2011) (a negative covariance of daily price returns within each month). 'MMI illiquidity' is the inverse of a liquidity measure of Kyle and Obizhaeva (2016) and can be interpreted as a trading cost of an average-sized trade for a given bond and month (see details in Section 2). Bond beta is calculated with a rolling 36-month regression relative to the excess return of a value-weighted portfolio of all in-sample bonds (3-month Treasury yield is a reference riskless rate). For all bond-months when price-based measures are unavailable due to no trades, the most recent available measures from previous months are carried forward. The sample period is October 2004 to June 2019. Panel B presents time-series averages of per-month cross-sectional correlations (due to a 36-month lag in VaR calculations, the sample is Oct 2007 – Jun 2019 here).

Table 1 highlights the difference between BBW-like and our measure of imputed bond returns. According to both metrics, an average bond in our sample earns slightly more than 50 b.p. per month. Our measure of returns is less volatile in the cross-section than the BBW one and is available for all outstanding bond-months. The average bond in our sample is a BBB-rated 6%-coupon bond that matures in about 10 years and trades at a yield spread close to 250 b.p. It has an outstanding amount of close to $600 mln. Part (b) of Table 1 presents cross-correlations of main portfolio-sorting variables: credit rating, VaR (second lowest monthly return in a three-year backward-looking window), and the illiquidity measure of Bao et al. (2011). These sample correlations align with the results in Bai et al. (2019). We postpone the discussion of the cross-section of market microstructure invariance (MMI) illiquidity and implied bond transaction costs to Section 2.

In a recent work, van Binsbergen and Schwert (2022) attribute almost 90% of realized monthly corporate bond returns to changes in the term structure of risk-free rates. That is to say, a pure credit risk exposure has lately earned less than 10 b.p. per month in realized returns. We confirm these findings in our sample (unreported). However, this paper does not investigate the nature of risk that is or is not priced in the U.S. corporate bond market. We only evaluate the cost of risk transfer by means of bond trading, regardless of what the risks are.

Throughout the paper, we consider systematic corporate bond portfolios from Bai et al. (2019), Chordia et al. (2017), one multi-factor portfolio, and two broad market portfolios (see Table 2). If the underlying portfolios are long-short, we only consider a long leg. BBW portfolios are double-sorted, in different combinations, on historical VaR, credit rating, past return, and liquidity (see Table 2 for details). These are factor-mimicking portfolios of a four-factor model that prices the cross-section of US corporate bonds. The factors are 'default' (DEF, highest VaR bonds across rating quintiles), 'liquidity' (LIQ, most illiquid bonds across rating quintiles), 'reversal' (REV, past losers across rating quintiles), and 'credit' (CRD, lowest rated bonds across quintiles of VaR, liquidity, and past return). We merge DEF, LIQ, and CRD portfolios into a multi-factor portfolio (MFP) by equally weighting the three source signals. Chordia et al. (2017) portfolios considered here are two reversal strategies with superior gross returns (before trading cost adjustment). These two portfolios are univariate sorts on past bonds (R1D) and equity returns (REQ). Using the mutual fund industry terminology, a bond investor may view such rule-based portfolios as 'style' or 'smart-beta' strategies. Two broad market portfolios that we consider consist either of all sample bonds (MKT) or of investment-grade bonds (MIG) with an outstanding amount above $300 mln (the latter corresponds to a selection criterion of ICE BofA US Corporate Index, the major investment-grade corporate index benchmark).

Finding a better-performing portfolio is not the goal of this paper. We demonstrate how implementation costs affect on-paper profitable bond investment rules widely discussed in the literature hence a limited number of representative off-the-shelf strategies. There are many alternative systematic bond portfolios with significant excess return (see, for instance, Israel et al. 2018 and Bali et al. 2022). Our findings also apply to those portfolios because they consist of similar bonds and use comparable rebalancing principles. Also, we intentionally focus on long-only parts of systematic portfolios for the rest of the paper because short bond portfolios, on average, lose money (see Figure 3 in Appendix A).

When constructing systematic bond portfolios, we carry forward the latest available values of sorting variables for 'not-traded' bond-months (i.e. months when a bond does not contain a single trade in TRACE). For instance, consider a monthly-rebalanced portfolio that goes long illiquid bonds. Say a certain bond is traded in month $t$ and is included in the portfolio of month $t+1$ based on its illiquidity score of month $t$. Imagine this bond is not traded in month $t+1$, so its illiquidity score for this month can not be calculated. We still consider such bond for the portfolio of month $t + 2$ based on its illiquidity score of month $t$.[8]

Table 2 presents portfolio characteristics before any trading cost adjustment. Part (a) of the table presents full-sample portfolio characteristics, and part (b) zooms into a post-GFC period (Jan'2010 – Jun'2019). All considered strategies have relatively high gross risk-adjusted returns with annualized Sharpe ratios above one in the post-GFC period. Importantly, the strategies differ a lot in turnover. Reversal portfolios have the highest turnover; it stands above 80% for three reversal strategies considered here (i.e., 80% of the portfolio is sold and replaced with new bond holdings every month). The long-illiquidity portfolio (LIQ) also has a remarkably high turnover of about 42% monthly post-GFC. This reflects a low persistence of traditional illiquidity measures estimated for individual bonds on transactional data: liquid bonds may suddenly appear illiquid and vice-versa, which creates a high portfolio turnover. Portfolios that hold high-VaR and low-rated bonds (DEF and CRD, respectively, in Table 2) have three-four times lower turnover than the LIQ portfolio, thanks to slow-changing credit ratings and worst past returns. Remarkably, the multi-factor portfolio MFP that combines DEF, LIQ, and CRD signals delivers only mild improvements in turnover and the number of bond holdings. On average, the combined holdings of three source portfolios are at around 3.5 thousand individual bonds per month. The multi-factor portfolio contains about 2.9 thousand bonds, and its turnover is only marginally lower than the weighted average of source portfolio turnovers. Finally, on paper, market portfolios sell about 1.5–2.0% of their holdings monthly (we compare these numbers with the turnover of actual corporate bond mutual funds in Appendix E).

[8] Note that such bond is excluded from the illiquidity factor-mimicking portfolio of month $t + 2$ in Bai et al. (2019). From a portfolio management perspective, excluding bond-months without trades from systematic portfolios would mean using information not available at portfolio formation dates.

| | DEF | LIQ | REV | CRD | R1D | REQ | MFP | MKT | MIG |
|---|---|---|---|---|---|---|---|---|---|
| Mean return, % month | 0.76 | 0.64 | 0.88 | 0.79 | 1.03 | 0.31 | 0.75 | 0.53 | 0.47 |
| St. dev., % month | 2.92 | 2.17 | 2.22 | 2.22 | 2.87 | 1.87 | 2.43 | 1.38 | 1.40 |
| Sharpe (annualized) | 0.83 | 0.84 | 1.20 | 1.13 | 1.10 | 0.37 | 0.99 | 1.05 | 0.87 |
| Min return, % month | -11.85 | -10.10 | -8.06 | -9.34 | -9.93 | -9.45 | -9.40 | -5.97 | -6.61 |
| Max return, % month | 9.80 | 8.58 | 10.55 | 9.59 | 12.46 | 6.15 | 8.91 | 6.89 | 8.27 |
| Avg. turnover, % month | 10.87 | 43.46 | 82.65 | 13.87 | 86.10 | 88.31 | 21.18 | 1.58 | 1.98 |
| Avg. no. bonds | 900 | 1337 | 1411 | 1356 | 706 | 536 | 2874 | 7111 | 3712 |
| of them, not traded, % | 9 | 22 | 5 | 29 | 24 | 21 | 7 | 31 | 15 |

(a) Full sample (Oct 2004/2007 – Jun 2019)

| | DEF | LIQ | REV | CRD | R1D | REQ | MFP | MKT | MIG |
|---|---|---|---|---|---|---|---|---|---|
| Mean return, % month | 0.71 | 0.67 | 0.79 | 0.73 | 0.92 | 0.43 | 0.70 | 0.52 | 0.46 |
| St. dev., % month | 2.01 | 1.42 | 1.65 | 1.31 | 2.26 | 1.31 | 1.51 | 1.02 | 1.07 |
| Sharpe (annualized) | 1.15 | 1.52 | 1.56 | 1.79 | 1.35 | 1.02 | 1.50 | 1.60 | 1.34 |
| Min return, % month | -4.38 | -3.37 | -4.28 | -2.60 | -5.34 | -3.94 | -3.08 | -2.46 | -2.68 |
| Max return, % month | 8.22 | 5.34 | 6.05 | 4.78 | 9.98 | 3.90 | 6.12 | 3.19 | 2.70 |
| Avg. turnover, % month | 10.65 | 43.18 | 83.59 | 13.62 | 87.01 | 87.98 | 21.03 | 1.53 | 1.85 |
| Avg. no. bonds | 940 | 1507 | 1545 | 1422 | 773 | 595 | 3039 | 7799 | 4485 |
| of them, not traded, % | 9 | 24 | 4 | 29 | 21 | 16 | 7 | 28 | 14 |

(b) Post-GFC sample (Jan 2010 – Jun 2019)

Table 2: **Long-only portfolio performance before adjustment for trading costs.** Columns are different systematic portfolio strategies, monthly rebalanced. The first four columns (DEF, LIQ, REV, CRD) correspond to the long parts of Bai et al. (2019) double-sorted factor-mimicking portfolios. 'DEF' is a long 'default risk' portfolio (bonds with the highest VaR across credit rating quintiles). 'LIQ' is a long 'liquidity risk' portfolio (most illiquid bonds according to Bao et al. 2011 measure across rating quintiles). 'REV' is a long reversal portfolio (worst past performers across rating quintiles). 'CRD' is a long 'credit risk' portfolio (lowest rated bonds across quintiles of VaR, liquidity, and past return). The next two columns (R1D, REQ) are two better-performing factor-mimicking portfolios from Chordia et al. (2017). 'R1D' is a long reversal portfolio (lowest decile of past month's bond returns) and 'REQ' is a long equity-based reversal portfolio (lowest decile of past month's equity returns). 'MFP' is a 'multi-factor portfolio' representing an equally-weighted combination of DEF, LIQ, and CRD portfolios. 'MKT' is a value-weighted market portfolio of all bonds in our sample. 'MIG' is a value-weighted portfolio of investment-grade bonds with outstanding amounts greater than $300 mln. Sharpe ratio is based on excess returns relative to the 3-month Treasury yield. Turnover is the absolute value of the sum of all negative portfolio weight changes (i.e., the minimum of 0 corresponds to no bonds being sold, and the maximum of 1 corresponds to all bonds sold and hence an entirely new portfolio purchased). Bonds that do not have a single trade recorded in TRACE in a given month are labeled as 'not traded' (see the last line in the tables). Such a bond is still considered for systematic portfolios as long as it has a reading of a sorting variable that can be carried forward. A monthly return for such bond is its 'carry' (one-twelfth of its coupon rate). In table a), the earliest return observation for DEF, CRD and MFP portfolios is Oct 2007, and for other portfolios – Oct 2004. The sample extends to June 2019. In table b) the sample is from Jan 2010 to Jun 2019. For portfolio performance without imputed returns for non-traded bonds, see Table 10a in Appendix. Figure 3 in Appendix plots cumulative portfolio returns before transaction cost adjustment.

Table 2 also highlights an important characteristic of bond strategies that is rarely discussed in the literature. A substantial number of bonds that must be included in systematic portfolios do not trade. We have little understanding of their market prices, let alone trading costs in certain months. The fraction of such not-traded bonds varies from 5% of holdings for one of the reversal strategies to 30% for credit and broad market portfolios (both contain relatively many high-yield bonds that, on average, trade less frequently than investment-grade ones).

## 2 Invariance-implied corporate bond transaction costs

In this section, we adapt transaction cost functions of Kyle and Obizhaeva (2016) to individual corporate bonds and investigate implied rebalancing costs of systematic bond strategies discussed in the previous section. There is no lack of estimates of an explicit part of corporate bond transaction cost (bid-ask spread) in the literature (for instance, see Bao et al. 2011, Feldhütter 2012, Harris 2015, and Kargar et al. 2021). To estimate the capacity of systematic strategies, one needs an explicit (bid-ask spread) and an implicit part (price impact) of the transaction cost. Here the literature has been running into an obstacle: the estimates of price impact based on transaction data yield downward-sloping pricing functions (Edwards et al. 2007 and Reichenbacher and Schuster 2022). I.e., larger trades seem cheaper to execute than smaller trades (controlling for credit quality and exposure to systematic pricing factors). Such an effect is often explained by the prevalence of riskless-principal trades and client-dealer relationship motives among high-volume transactions (Green et al. 2007 and Pintér et al. 2022).[9] Does it imply that a systematic bond investor saves on implicit trading costs as her assets under management increase and, hence, the capacity of her strategies is effectively infinite? It does not because price impacts are likely still positive. We do not

[9]Bond dealers are capital-constrained and prefer not to hold large corporate bond inventory after the GFC. Hence, for large transactions, dealers tend to pre-negotiate two opposite-direction trades with two clients, effectively acting as a broker between them and holding bonds in inventory for a few minutes only. Such transactions, called 'riskless principal trades', have lower dealer markup than what it would have been if dealers were providing immediacy.

observe sufficiently many high-volume, high-immediacy trades to identify an upward-sloping pricing function. We can, however, construct upward-sloping pricing functions for individual corporate bonds using principles of market microstructure invariance.

## 2.1 Intuition behind MMI-implied T-cost estimates

Before we proceed with the calibration of T-cost functions, let us first present an intuition behind the invariance of transaction costs. The example below is similar to the one in Kyle and Obizhaeva (2016) but is adapted to corporate bonds rather than public equity. Consider bond $A$ traded at the par value of \$1000. Assume its daily return volatility is 60 b.p., and we observe on average 4 'independent' transactions or meta-orders in this bond per trading day.[10] Consider a buy order with a total par value of \$750'000 of bond $A$, and assume it comes from the $\alpha$-percentile of the bond-$A$ trade size distribution. Assume further that the total (explicit and implicit) cost of executing this transaction is 50 b.p. Based on these characteristics, what can we say about the transaction cost of another bond $B$ that is also traded at par, and has the same daily return volatility, but is only traded once a day on average? The MMI has an answer.

The first MMI hypothesis, the invariance of risk transfers, suggests that the distribution of the dollar amount of risk transferred per unit of business time (measured by the frequency at which meta-orders arrive) is invariant across financial securities. It implies that bond-$A$ and bond-$B$ orders that come from the same percentile of bond-specific order size distributions must transfer the same dollar amount of risk when adjusted for the difference in speed at which two markets operate:

$$\frac{\$1000 \times \$750'000 \times 60\text{b.p.}}{\sqrt{4}} = \frac{\$1000 \times Q_{\alpha}^{B} \times 60\text{b.p.}}{\sqrt{1}},$$

[10] Kyle and Obizhaeva (2016) call such independent trading decisions by portfolio managers 'bets'. It is plausible that TRACE-reported bond transactions are closer to independent bets than individual equity transactions on an exchange. Large bond meta-orders are rarely divided into smaller child orders for optimal execution because many smaller corporate bond transactions are typically priced worse than one large trade.

where $Q^B_\alpha$ is the $\alpha-$precentile meta-order in bond $B$. The invariance of risk transfers thus implies that $Q^B_\alpha = \$350\text{'}000$.

The second MMI hypothesis, the invariance of transaction costs, suggests that it costs the same (in dollar terms) to execute orders that transfer the same amount of dollar risk per unit of security-specific business time. Therefore:

$$\$750\text{'}000 \times 50\text{b.p.} = \$3750 = \$350\text{'}000 \times c^B_\alpha,$$

where $c^B_\alpha$ is the percentile cost of trading \$350'000 of bond $B$. Therefore, $c^B_\alpha = 100$ b.p.

Two microstructure invariance hypotheses thus link return volatility, trading volume, and trading costs across different securities. Kyle and Obizhaeva (2016) develop the concept further and demonstrate how to trace security-specific transaction cost functions based purely on average daily volume and return volatility estimates. We adapt this approach to corporate bonds.

## 2.2 MMI-implied T-cost functions

We construct MMI-implied bond trading costs as follows. Consider bond $i$ traded in month $t$. For every such bond, we calculate MMI illiquidity measure $1/L_{it}$ as:

$$\frac{1}{L_{it}} = \left(\frac{C\sigma^2_{it}}{\bar{V}_{it}m^2}\right)^{\frac{1}{3}}, \tag{1}$$

where $\bar{V}_{it}$ is the average daily (dollar) trading volume (ADV), and $\sigma_{it}$ is daily bond return volatility. $C = 2000$ and $m^2 = 0.25$ are MMI parameters estimated in Kyle and Obizhaeva (2016) and meant to be invariant across financial markets. $1/L_{it}$ represents the total cost (both explicit and implicit) of an average-volume trade in bond $i$ in month $t$. The more risk (as measured by return volatility) is transferred per dollar of an average trading volume, the higher the total cost of executing a trade. MMI states that the dollar cost of similar risk transfers (appropriately scaled) should be invariant across markets. Under such an assumption, certain illiquidity parameters estimated for risk transfers in equity trading apply to corporate bond transactions if that is the case.

MMI does not impose an exact functional form of the transaction cost function. Instead, it imposes restrictions on the parameters of a transaction cost function of choice. We consider both linear and square-root T-cost functions. The MMI-implied percentage cost of trading $X$ dollars of bond $i$ in month $t$ is then:

$$C_{it}^{\%,\text{lin}}(X) = \frac{1}{L_{it}} \left( \kappa + \frac{\lambda}{C L_{it}} X \right), \tag{2}$$

$$C_{it}^{\%,\text{sqrt}}(X) = \frac{1}{L_{it}} \left( \check{\kappa} + \frac{\check{\lambda}}{\sqrt{C L_{it}}} \sqrt{X} \right), \tag{3}$$

where $\kappa \approx 0.19272$, $\lambda \approx 0.06888$, $\check{\kappa} \approx 0.04883$, and $\check{\lambda} \approx 0.30721$ are implied by the estimations in Kyle and Obizhaeva (2016) and, under MMI, must be invariant across assets and time. Appendix B elaborates on the map between Kyle and Obizhaeva (2016) and T-cost functions (2) and (3). Equation (2) defines a time-varying bond-specific linear trading cost function in which the fixed part of the trading cost is proportional to illiquidity $1/L_{it}$, and the market impact is proportional to illiquidity squared $(1/L_{it})^2$. Since time-varying illiquidity is itself a function of volume and volatility, the parameters of the trading cost function (2) vary as bond return volatility and average trading volume change. Same applies to equation (3), which is a time-varying bond-specific square-root T-cost function.

The scarcity of corporate bond trading and high individual bond price dispersion complicate the evaluation of parameters of transaction cost function (2). Daily bond return volatility is estimated less precisely when there are only a few trading days a month. Individual bond trading volume is not persistent over time either. The ratio of the two may become very volatile, especially amid low trading volume, which would mean that an illiquid bond suddenly becomes very liquid and vice versa too often (as was the case for the Bao et al. 2011 illiquidity measure before). This result is likely counterfactual. To stabilize transaction cost estimates, we calculate MMI illiquidity and transaction costs for sample bonds in the following way:

1. We only calculate return volatility and average daily volume (hence, MMI illiquidity) for bonds that are traded for at least five business days a month.

2. We truncate 25% highest $1/L_{it}$ observations in the cross-section of bonds separately for each month $t$ (this right tale of illiquidity is predominantly due to very low trading volumes rather than extreme return volatility).

3. If, as a result, we miss the reading of $1/L_{it}$ for bond $i$ in month $t$, but there is an earlier illiquidity reading for this bond from a month before $t$, we carry it forward to month $t$ (these carried forward observations fill in months with no or little trading, and months with extreme illiquidity readings).

4. For each bond, we smooth out the time series of $\{1/L_{it}\}$ by taking a three-month backward-looking moving average.

| | N.obs. | Mean | Median | S.D. | 1st | 5th | 25th | 75th | 95th | 99th |
|---|---|---|---|---|---|---|---|---|---|---|
| Avg. daily volume if traded, \$ mn | 635438 | 3.09 | 1.68 | 4.16 | 0.05 | 0.12 | 0.64 | 3.78 | 10.95 | 25.00 |
| Daily volatility, b.p. | 635438 | 79.6 | 57.5 | 79.9 | 8.0 | 13.6 | 31.9 | 99.8 | 213.9 | 389.6 |
| MMI illiquidity: raw, b.p. | 635438 | 78.0 | 53.8 | 77.6 | 9.8 | 15.5 | 31.8 | 93.9 | 225.4 | 400.0 |
| MMI illiquidity: truncated, b.p. | 490293 | 47.3 | 42.8 | 25.3 | 9.2 | 14.2 | 27.5 | 63.2 | 95.6 | 117.2 |
| MMI illiquidity: truncated + LOCF, b.p. | 823516 | 58.1 | 55.1 | 29.9 | 10.5 | 17.2 | 35.8 | 76.2 | 108.8 | 140.3 |
| Linear fixed cost, b.p. | 823516 | 11.1 | 10.5 | 5.7 | 2.0 | 3.3 | 6.8 | 14.5 | 20.7 | 26.7 |
| Square-root fixed cost, b.p. | 823516 | 2.8 | 2.7 | 1.5 | 0.5 | 0.8 | 1.7 | 3.7 | 5.3 | 6.8 |
| Linear impact, b.p. per \$1 mn | 823516 | 14.4 | 10.2 | 16.1 | 0.4 | 1.0 | 4.3 | 19.5 | 39.8 | 66.3 |
| Square-root impact, b.p. per $\sqrt{\$1\text{ mn}}$ | 823516 | 33.4 | 28.1 | 26.1 | 2.3 | 4.9 | 14.7 | 45.7 | 78.0 | 114.2 |

Table 3: **Cross-sectional statistics of MMI illiquidity and implied transaction costs.** The linear fixed cost is $\frac{\kappa}{L_{it}}$, and the linear market impact is $\frac{\lambda}{CL_{it}^2}$ of equation (2). The square-root fixed cost is $\frac{\check{\kappa}}{L_{it}}$, and the square-root market impact is $\frac{\check{\lambda}}{\sqrt{CL_{it}^3}}$ of equation (3). The sample is from Jan 2010 to Jun 2019.

Following the above procedure, we assign individual transaction costs to the majority of bond-months in the sample. Table 3 presents cross-sectional characteristics of MMI-implied transaction costs and highlights the impact of steps two and three of the above procedure on these characteristics. An average bond that is traded at least five days a month has an average daily trading volume of about $3 mln, but the median trading volume is twice that lower. Such a bond has a daily return volatility of 80 b.p. (the standard deviation of daily price return, i.e., excluding accrued interest).[11] An average all-in transaction cost of a bond traded at least five days a month is about 78 b.p. (the median is 54 b.p.). Truncation of 25% highest illiquidity readings per month reduces the sample mean of MMI illiquidity to 47 b.p. More importantly, truncation reduces illiquidity readings in the right tale of the MMI illiquidity distribution from 200–400 b.p. down to 90–120 b.p. Rolling past illiquidity observations forward into missing and truncated bond-months increases the cross-sectional mean of the illiquidity to 58 b.p. with the right tale values around 110–140 b.p. Essentially, we claim that this is what the most 'expensive' of the average-sized liquidity-absorbing corporate bond trades cost.[12] For an average sample bond, under the linear T-cost model, our estimates imply a fixed trading cost (half-spread) of about 11 b.p. and the market impact of around 14 b.p. (per $1 mn of volume). Under the square-root T-cost, the average fixed cost is smaller at 3 b.p., but the price impact for a trade of $1 mn stands at around 33 b.p.

[11] In unreported results, we estimated return volatility as a bond-invariant constant plus duration-times-spread (Ben Dor et al. 2007) to get quantitatively similar results for bond-specific illiquidity, net returns, and capacity.

[12] According to Kargar et al. (2021), the most expensive risky-principal corporate bond transactions at the height of COVID-induced corporate bond sell-off in March 2020 cost a ballpark of 200 b.p.

| | Linear T-cost | | | | | | Square-root T-cost | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | IG bonds | | | HY bonds | | | IG bonds | | | HY bonds | | |
| Size ($1,000) | 1–5y | 5–15y | 15+y | 1–5y | 5–15y | 15+y | 1–5y | 5–15y | 15+y | 1–5y | 5–15y | 15+y |
| 10 | 4.5 | 6.4 | 9.1 | 7.5 | 7.7 | 9.7 | 2.1 | 3.1 | 4.7 | 3.8 | 3.9 | 5.1 |
| 100 | 4.8 | 6.9 | 10.0 | 8.1 | 8.3 | 10.6 | 4.1 | 6.3 | 10.0 | 7.8 | 8.0 | 10.8 |
| 200 | 5.1 | 7.4 | 10.9 | 8.8 | 9.0 | 11.6 | 5.3 | 8.3 | 13.1 | 10.3 | 10.5 | 14.2 |
| 500 | 5.9 | 8.9 | 13.6 | 10.9 | 11.0 | 14.7 | 7.7 | 12.1 | 19.4 | 15.2 | 15.4 | 21.1 |
| 1000 | 7.3 | 11.4 | 18.2 | 14.3 | 14.4 | 19.9 | 10.3 | 16.5 | 26.5 | 20.7 | 21.0 | 28.8 |
| 2000 | 10.1 | 16.5 | 27.4 | 21.1 | 21.3 | 30.2 | 14.2 | 22.7 | 36.5 | 28.4 | 28.9 | 39.7 |
| 5000 | 18.5 | 31.6 | 54.9 | 41.7 | 41.8 | 61.1 | 21.7 | 34.9 | 56.4 | 43.9 | 44.5 | 61.4 |
| 10000 | 32.6 | 56.8 | 100.8 | 75.9 | 75.9 | 112.5 | 30.2 | 48.6 | 78.8 | 61.2 | 62.1 | 85.8 |

Table 4: **Average MMI trading costs across rating and maturity classes**, in b.p. The linear transaction cost model is equation (2). The square-root model is (3). Column headers are bond maturity bins: '1–5y' is for bonds between 1 and 5 years to maturity, etc. 'IG' stands for investment-grade, 'HY' – for high-yield. T-costs are calculated by averaging (weighted by the ADV) the parameters of equations (2) and (3) across bonds within a given rating-maturity bucket, and then evaluating the costs for each transaction size. The sample is from Jan 2010 to Jun 2019.

Table 4 presents how MMI bond trading costs vary with bond credit quality and time to maturity. Among investment-grade bonds, long-duration bonds have considerably higher trading costs than short-duration bonds for all transaction sizes and both linear and square-root costs. For instance, it costs 1.5 times more to trade $1 mln of a 10-year than a 2-year-to-maturity corporate bond. Among high-yield bonds, the largest trading costs are also for the longest-maturity bonds; however, trading costs do not vary much for shorter maturities. Transaction costs are roughly twice higher for high-yield bonds with maturities of up to 15 years than for similar-maturity investment-grade bonds. Surprisingly, for maturities above 15 years, high-yield bonds seem almost as expensive to trade as investment-grade bonds. Comparing linear and square-root costs to one another across rating and maturity classes, the largest difference is expectedly found for the largest transactions. For large trades of $10 mn notional, square-root costs are roughly 10–30% lower than the linear ones.

Table 5 further documents that MMI liquidity improves for bonds with higher outstanding amounts, controlling for rating and maturity. However, the economic magnitude of the effect is limited: an extra $100 mn of the outstanding amount is associated, on average, with only 1–2 b.p. lower all-in trading cost. The effect was a bit stronger before the global financial crisis of

2008–2009. A similar pattern is also evident in the estimated loadings of other interaction variables in Table 5. For instance, post-GFC, extra ten years to maturity adds, on average, 9-9.5 b.p. of all-in trading cost. Pre-GFC, such an effect was 3 b.p. lower. The same applies to pre- and post-GFC sensitivity of the MMI illiquidity to credit ratings. These results suggest that corporate bond liquidity might have deteriorated in post-GFC years once we account for lower post-crisis trading volumes (Asquith et al. 2013 documented similar patterns).

| | Dependent variable: $1/L_{it}$, b.p. | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Intercept | 53.13*** | | | | 53.77*** | | | |
| | (1.65) | | | | (1.67) | | | |
| Size ($ mln) | −0.02*** | −0.01*** | −0.02*** | −0.01*** | −0.02*** | −0.01*** | −0.01*** | −0.01*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Maturity (years) | 0.92*** | 0.90*** | 0.93*** | 0.90*** | 0.89*** | 0.90*** | 0.97*** | 0.95*** |
| | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) |
| Rating (1 to 21) | 0.45*** | 0.94*** | 0.38*** | 0.86*** | 0.04 | 0.08 | 0.46*** | 0.87*** |
| | (0.09) | (0.25) | (0.08) | (0.13) | (0.11) | (0.20) | (0.08) | (0.11) |
| Size × Pre-GFC | | | | | 0.002* | −0.0002 | −0.003** | −0.003** |
| | | | | | (0.001) | (0.001) | (0.001) | (0.001) |
| Size × GFC | | | | | 0.001 | −0.001 | −0.01*** | −0.01*** |
| | | | | | (0.001) | (0.001) | (0.002) | (0.002) |
| Maturity × Pre-GFC | | | | | −0.23*** | −0.37*** | −0.38*** | −0.43*** |
| | | | | | (0.06) | (0.06) | (0.04) | (0.05) |
| Maturity × GFC | | | | | 0.91*** | 0.84*** | 0.21** | 0.20** |
| | | | | | (0.16) | (0.15) | (0.09) | (0.09) |
| Rating × Pre-GFC | | | | | 0.15 | 0.10 | −0.56*** | −0.38*** |
| | | | | | (0.12) | (0.15) | (0.12) | (0.14) |
| Rating × GFC | | | | | 3.49*** | 3.39*** | 0.45 | 0.58** |
| | | | | | (0.52) | (0.52) | (0.29) | (0.28) |
| Issuer FE | NO | YES | NO | YES | NO | YES | NO | YES |
| Year-month FE | NO | NO | YES | YES | NO | NO | YES | YES |
| Observations | 656,906 | 656,906 | 656,906 | 656,906 | 656,906 | 656,906 | 656,906 | 656,906 |
| Adjusted $R^2$ | 0.18 | 0.26 | 0.45 | 0.50 | 0.31 | 0.37 | 0.45 | 0.51 |
| *Note:* | *p<0.1; **p<0.05; ***p<0.01 | | | | | | | |

Table 5: **MMI illiquidity and bond characteristics.** Pre-GFC is Oct 2004 to May 2008, and GFC is Jun 2008 to Dec 2009. The standard errors are double-clustered in time and issuer.

There are, however, many more factors of corporate bond illiquidity than Table 5 considers. Some of those additional factors are, at best, only partially observed, like the structure of institutional ownership (which matters according to Mahanti et al. 2008). To highlight this point, Appendix D presents a small case study of trading activity and MMI illiquidity of three, on paper similar, corporate bonds issued by large tech firms that differ greatly in MMI-implied trading costs. This example emphasizes the importance of individual bond transaction cost measurement as opposed to metrics averaged across industries or bond characteristics.

In Appendix A, we also present comparative statistics between individual-bond MMI and alternative illiquidity measures. Table 9 compares the averages of cross-sectional correlations among MMI and BPW illiquidity (Bao et al. 2011), realized bond bid-ask, the percentage of no-trading days, and equity bid-ask for bond issuers. MMI illiquidity has an average cross-sectional correlation of 0.27–0.47 with other bond-specific illiquidity measures (the highest – with the realized bid-ask) except for equity bid-ask. Remarkably, MMI illiquidity has a comparably high correlation with both realized bid-ask and the percentage of zero trading days, while the latter is only weakly correlated with the realized bid-ask, as the literature has already documented (see Schestag et al. 2016 for exhaustive comparison of bond illiquidity measures beyond MMI). Figure 1 in Appendix A compares market illiquidity implied by individual-bond MMI and BPW measures. Both exhibit similar dynamics, especially during the GFC when market illiquidity jumps considerably. The key takeaway from this comparative analysis is that the MMI illiquidity is a reasonable individual-bond measure that, in principle, captures what other illiquidity measures capture too. The goal of this paper is not to propose a *better* illiquidity measure but to evaluate bond transaction costs coherently. Unlike other illiquidity measures, MMI illiquidity links to a full-fledged bond transaction cost model thanks to the microstructure invariance theory. The fact that the MMI measures average trading costs as reasonably as other measures is an additional and reassuring empirical observation.

An obvious shortcoming of MMI-implied transaction cost estimates is counterfactually low costs for small-sized transactions. In Table 4, 'retail-sized' trades (up to $100'000 notional) cost less than 10 b.p. Transaction-based estimated a-là Edwards et al. (2007) presented in Figure 1 suggest that the cost of such transactions is probably several times larger and stands, on average, at around 20–

30 b.p. The effect of such trading cost mismatch between EHP and MMI for small trades does not affect capacity estimates much because the capacity limit is primarily driven by the price impact for the largest transactions. Nonetheless, it is reasonable to consider transaction cost functions that blend EHP and MMI approaches. In Appendix C, we construct such cost function by averaging EHP and MMI estimates and call it a 'V-shape' T-cost model because of its convexity in trading size. We are not aware of a theoretical model that would generate a transaction cost function of such a shape hence we do not discuss the V-shape cost model more extensively in the paper. However, many market practitioners have confirmed to us that they see such trading cost convexity in their corporate bond trading.

## 3 Ex-cost systematic corporate bond returns and capacity

We now use MMI transaction costs to evaluate the net-of-cost performance of systematic bond strategies. Table 6 presents the results for a monthly-rebalanced fund that is fully invested in one of the considered systematic portfolios and has $500 mln assets under management (according to Appendix E, this is an above-median below-mean size of a corporate bond mutual fund). At this stage, we do not impose any additional rebalancing restrictions and assume that every single end-of-month rebalancing trade suggested by the investment strategy is carried out in full and, thus, bears a transaction cost.[13] If a portfolio bond misses the MMI illiquidity reading in a rebalancing month (which is still possible if the bond is not traded or its illiquidity reading was truncated and there is no prior illiquidity reading for this bond), then we assign it an average of illiquidity scores of all portfolio bonds in that month.

Expectedly, high-turnover reversal and illiquidity strategies suffer the most from trading cost adjustment. Their Sharpe ratios drop several times relative to a pre-cost case in Table 2. The

[13] Section 4 will relax this assumption and consider practical feasibility constraints.

| | DEF | LIQ | REV | CRD | R1D | REQ | MFP | MKT | MIG |
|---|---|---|---|---|---|---|---|---|---|
| (A) Ex-cost: Linear T-cost model | | | | | | | | | |
| Mean return, % month | 0.66 | 0.44 | 0.51 | 0.69 | 0.52 | 0.08 | 0.63 | 0.51 | 0.45 |
| St. dev., % month | 2.01 | 1.41 | 1.64 | 1.31 | 2.25 | 1.29 | 1.51 | 1.02 | 1.07 |
| Sharpe (annualized) | 1.07 | 0.98 | 0.98 | 1.70 | 0.74 | 0.11 | 1.35 | 1.59 | 1.32 |
| Min return, % month | -4.47 | -3.61 | -4.62 | -2.63 | -5.66 | -4.27 | -3.17 | -2.46 | -2.68 |
| Max return, % month | 8.19 | 5.09 | 5.78 | 4.75 | 9.59 | 3.54 | 6.04 | 3.18 | 2.69 |
| (B) Ex-cost: Square-root T-cost | | | | | | | | | |
| Mean return, % month | 0.65 | 0.36 | 0.41 | 0.68 | 0.36 | -0.05 | 0.62 | 0.51 | 0.45 |
| St. dev., % month | 2.02 | 1.41 | 1.63 | 1.31 | 2.24 | 1.29 | 1.51 | 1.02 | 1.07 |
| Sharpe (annualized) | 1.04 | 0.77 | 0.78 | 1.69 | 0.49 | -0.25 | 1.31 | 1.59 | 1.32 |
| Min return, % month | -4.50 | -3.71 | -4.73 | -2.63 | -5.80 | -4.39 | -3.19 | -2.46 | -2.68 |
| Max return, % month | 8.18 | 4.98 | 5.68 | 4.74 | 9.43 | 3.38 | 6.03 | 3.18 | 2.69 |
| (C) Memo: cum-cost characteristics | | | | | | | | | |
| Gross return, % per month | 0.71 | 0.67 | 0.79 | 0.73 | 0.92 | 0.43 | 0.70 | 0.52 | 0.46 |
| Gross st. dev., % per month | 2.01 | 1.42 | 1.65 | 1.31 | 2.26 | 1.31 | 1.51 | 1.02 | 1.07 |
| Gross Sharpe (annualized) | 1.15 | 1.52 | 1.56 | 1.79 | 1.35 | 1.02 | 1.50 | 1.60 | 1.34 |
| Avg. turnover, % month | 10.65 | 43.18 | 83.59 | 13.62 | 87.01 | 87.98 | 21.03 | 1.53 | 1.85 |
| Avg. no. bonds | 940 | 1507 | 1545 | 1422 | 773 | 595 | 3039 | 7799 | 4485 |
| of them, not traded, % | 8.98 | 23.79 | 4.38 | 28.77 | 21.01 | 16.42 | 7.03 | 27.80 | 13.53 |

Table 6: **Long-only portfolio performance after trading costs (AUM $500 mln).** The sample is Jan 2010–Jun 2019. Bond-specific time-varying trading costs are as in equations (2) and (3). The fund is of the unchanged size of $500 mln. The strategies are as in Table 2. The Sharpe ratio is based on excess returns relative to the 3-month Treasury yield. Figure 5 in the Appendix plots cumulative net returns over time.

reversal signal that is derived from the stock market (REQ) no longer generates positive mean returns assuming square-root transaction cost adjustment. However, LIQ and REV portfolios still have net Sharpe ratios close to 0.8 under the square-root model and almost 1.0 under the linear model – thanks to having around 1500 individual bond holdings and hence trading each of them in smaller amounts, which is cheaper under MMI costs (but that might be counterfactual, as discussed above).

Table 6 also reports a relatively mild drop in Sharpe ratios due to trading cost adjustment for credit (CRD) and default (DEF) portfolios. Both generate net Sharpe ratios above 1.0, with CRD being close to 1.7 under both linear and square-root costs. This result should probably be taken with a grain of salt for two reasons. Firstly, trading cost estimates are naturally the least reliable for the lowest-rated bonds that primarily constitute the CRD portfolio. Secondly, each month a large fraction of the CRD portfolio consists of bonds with no TRACE trade records, which adds to the inherent uncertainty of what it costs to trade the CRD strategy. The multi-factor portfolio (MFP), which is a union of LIQ, CRD, and DEF portfolios, inherits the robust net-of-cost performance of the original source portfolios. DeMiguel et al. (2020) demonstrate how multi-factor equity portfolios save on transaction costs by canceling out opposite-sign trades. This applies to the MFP bond portfolio only to a limited extent because the original signals do not have many overlapping holdings. In all cases that we consider below in the paper, the MFP portfolios have higher turnover and lower net Sharpe ratios than the CRD portfolios.

Market portfolios of \$500 mn AUM generated net risk-adjusted returns that are almost as high as the CRD portfolio. Market portfolios of this size do not lose much on transaction costs. Within our trading cost evaluation approach, this is due to broader diversification and, as a result, smaller-sized rebalancing trades. MMI-implied transaction costs seriously affect portfolio performance only when trades become large and market impact dominates fixed bid-ask cost that remains unchanged. This might not be the most realistic practical implication because bond trading costs estimated on transactional data suggest that costs are still sizeable even for small trades (see Figure 1). We likely underestimate small-trade costs when using MMI-implied trading cost functions. We address this issue in the next section by requiring rebalancing trades to be of institutional size (at least \$100k) and imposing additional practical turnover constraints.

It is also worth noting that, in our calculations, strategies with a large fraction of bonds without TRACE trade records tend to have lower return volatility mechanically due to the imputation of missing returns. Recall that we assume that the monthly return on a not-traded bond is its accrued interest which is $\frac{1}{12}^{\text{th}}$ of its coupon, and it does not vary from month to month since we only consider fixed-coupon bonds. Hence, the more months with no trades the bond has, the lower its return volatility is in our dataset. Bond portfolios that contain rarely- or not-traded bonds have lower volatility than they would have had if individual bonds were always traded.

This downward volatility bias is the strongest for CRD, LIQ, and MKT portfolios. Table 10 in Appendix A demonstrates how risk-adjusted cum- and ex-TC performance of bond strategies looks if, instead of individual-bond accrued interest, we impute the average return of the 'traded' part of the portfolio as the return of not-traded bonds. Under such an assumption, the ex-cost Sharpe ratio of the CRD portfolio drops by roughly a quarter. It becomes lower than the Sharpe ratio of the broad market portfolio MKT.

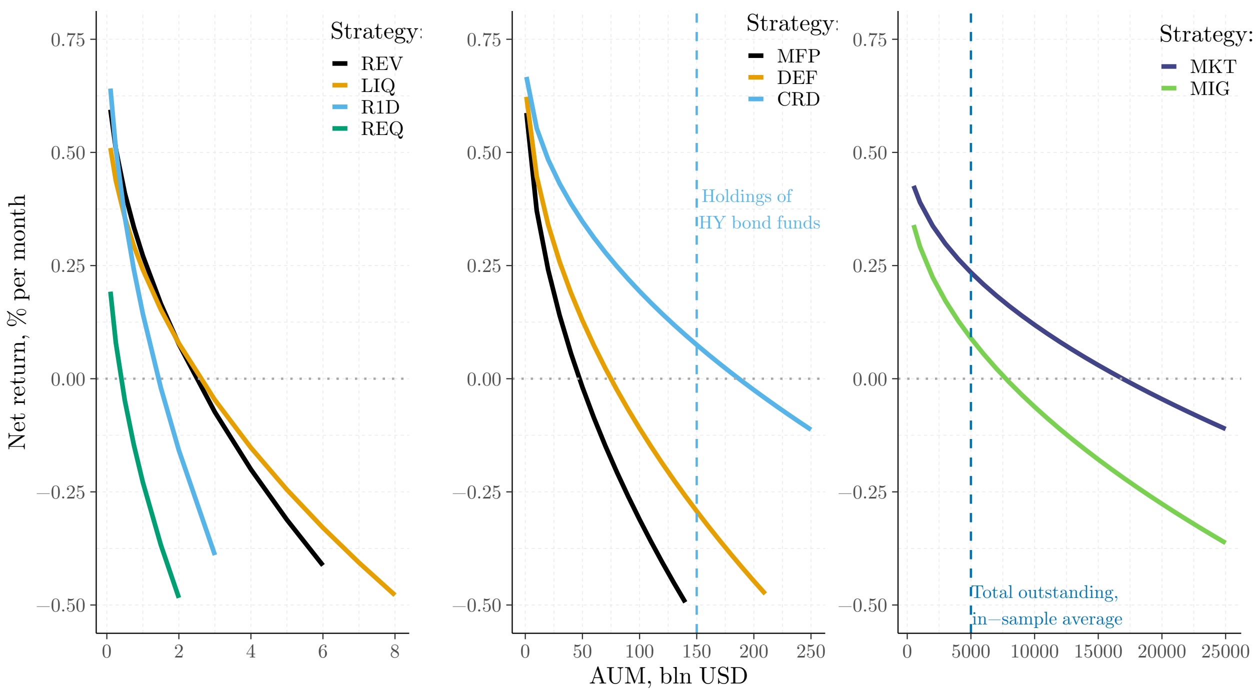


Figure 2: **Net systematic corporate bond return under square-root T-costs and fund size.** X-axis is the AUM, in $ bn. Y-axis is the average after-cost portfolio return. There are no turnover constraints imposed on the systematic strategies on this plot. The underlying square-root trading cost is in equation (3) and varies across bonds and months. The sample period is Jan 2010–Jun 2019.

Figure 2 depicts the scalability of systematic corporate bond strategies under square-root transaction costs. On the x-axis, we vary the fund size, and the y-axis traces the net-of-cost average monthly return. In our definition, the fund size at which the net return drops to zero is the capacity limit. Figure 2 shows that the capacity of reversal strategies with no turnover constraints is relatively limited and does not exceed $3 bn. This number should be interpreted as a combined size of funds that can be profitably invested in the strategy, assuming the funds trade and rebalance identically and at the same time.[14] DEF and CRD strategies are considerably more scalable, with capacity extending to $75 and $200 bn, respectively. The capacity of market strategies is at around $7-$17 tn (MIG and MKT, the latter being higher), which is above the total notional amount of all bonds currently outstanding. Capacity estimates are considerably lower under the linear transaction cost model (2) for broad market portfolios – we are comparing the estimates across T-cost specifications in more detail in Section 4.2.

# 4 Implementation constraints and capacity

In this section, we make our 'theoretical' bond portfolios more realistic by imposing several practically-motivated bond selection and rebalancing criteria. We describe these implementation constraints in the first part of the section. In the second part of the section, we vary the size of the fund to find the level at which each strategy no longer makes money after transaction costs, i.e., the capacity limit.

## 4.1 Implementation constraints

A relatively illiquid OTC corporate bond market is not the most suitable venue for high-turnover systematic trading. Theoretical bond portfolios are hard to replicate in practice because of implementation constraints, most of which relate to the infeasibility of trading a desired amount of a specific bond close to the target rebalancing date. Hence, bond investors often follow the rules designed to reduce portfolio turnover and 'excessive' trading. In this section, we integrate a few

[14] The competition among fund managers amid decreasing net alpha and implications for fund fees and optimal fund size are outside the scope of this paper. In the context of the Berk and Green (2004) model, this paper only tries to trace net alpha as a function of fund size for selected corporate bond strategies.

such rules into our systematic bond portfolios to better understand the ex-cost returns of (more) feasible bond strategies. The rules we consider are the following:

1. **No retail-sized trades**. If a rebalancing trade is of retail size (less than $100 th) it is not implemented, and the dollar position in such bond remains unchanged until the next rebalancing date. This is the rule that most large corporate bond investors follow because the benefit of a small portfolio adjustment (like a lower tracking error, if it's a benchmarked portfolio) does not overweight the cost (which, in principle, includes not only a monetary trading cost but also the effort of a fund trader to negotiate an OTC transaction). In our setting, such a rule also limits a possible 'underestimation' of the costs of small-sized trades. As discussed, MMI-implied transaction costs likely underestimate the fixed cost of small-sized trades (see Figure 1). By prohibiting retail-sized trades, we reduce the impact of such underestimation on ex-cost portfolio performance and capacity.

2. **Partial rebalancing**. We only implement the largest one-third of rebalancing sales and purchases suggested by the strategy. Partial rebalancing aims to reduce portfolio turnover at the cost of deviation from an original investment plan and dilution of the expected return signal. Fine-tuning a partial rebalancing rule in practice is 'more art than science,' one of the experienced bond traders told us. We opt for a simple 'one-third' rule because it still highlights the impact of partial rebalancing on bond portfolio performance and is yet straightforward to implement. Whenever a rebalancing trade does not pass a partial rebalancing cut-off, a dollar position in such bond remains unchanged until the next rebalancing date. The only exception to partial rebalancing (and also to the restriction on retail-sized trades) in this paper is when a bond drops out of the investment universe (because it reaches one year to maturity, for instance, or its outstanding amount falls below $100 mln due to a partial call). In this case, the position is closed regardless of trade size.

3. **Sampling**. We only consider half of the bonds with the largest portfolio weights in original systematic portfolios for inclusion into sampled portfolios (separately for each rebalancing month). Marginal benefits of diversification decrease with the number of securities held in a portfolio. This is particularly relevant for corporate bond portfolios because many issuers have multiple outstanding bonds, some of which do not differ much in size and maturity. Sampling aims to reduce excessive portfolio management costs without diluting the return signal.[15] Since bond portfolios in this paper are not equally weighted, 50% largest holdings represent 65 to 85% of the dollar value of original portfolios.

4. **Selection on past trading activity.** Corporate bonds trade infrequently, and bond portfolio managers often treat past trading activity as a relevant predictor of future bond liquidity.[16] Then, bonds with higher rather than lower past trading activity are selected into bond portfolios. Trading volume and the number of transactions both measure past trading activity. Anecdotally, the latter is preferred by bond managers because a) real-time TRACE records do not report transaction volumes above a regulatory cap, and b) a large isolated transaction, possibly between a core dealer and an infrequently-rebalancing institution, does not really make the bond liquid. Here, we restrict our portfolios to bonds that were traded for at least five business days in the previous month. Such selection criteria can be easily implemented by a fund manager observing real-time TRACE reports.

The introduction of such implementation constraints is motivated by not only anecdotal evidence from the asset management industry but also our analysis of observed fixed-income mutual fund portfolios (see Appendix E). We contrast our theoretical portfolios with the ones that bond mutual funds report and find that comparable observed portfolios have fewer holdings and lower turnover.

[15] Anecdotally, BlackRock claims in this note that it optimizes the tracking error in one of its high-yield corporate bond ETFs with only 40% of original index holdings.

[16] Ivashchenko and Neklyudov (2018) formally describe slow-moving waves of bond trading activity consistent with such a view.

We achieve similar characteristics in our portfolios with the introduction of implementation constraints.

The mechanic of rebalancing restrictions is as follows. For 'no retail-sized trades' and 'partial rebalancing', each month's target portfolio is the original unrestricted systematic portfolio from Table 2. In month $t$, a fund manager does not rebalance fully to the target portfolio of month $t$ because of turnover restrictions and ends up with an off-target portfolio. At the next rebalancing month $t+1$, an off-target portfolio from month $t$ is contrasted with an actual target of the month $t+1$, eligible rebalancing transactions are determined again, and so on. We implement 'no retail-sized trades' and 'partial rebalancing' sequentially, i.e., a partially-rebalanced portfolio first excludes retail-sized rebalancing trades. For 'sampling' and 'selection on past trading activity', the target portfolios change. In the former case, each month's target portfolio includes only half of the holdings of the original target portfolio. In the latter case, such sampled half-portfolio is further restricted to previously actively traded bonds. An actual portfolio of month $t$ is then contrasted with these revised targets of month $t$, and rebalancing trades that pass 'no retail-sized trades' and 'partial rebalancing' filters are implemented. That is to say, each constraint listed above nests all prior constraints.

| | DEF | LIQ | REV | CRD | R1D | REQ | MFP | MKT | MIG |
|---|---|---|---|---|---|---|---|---|---|
| (A) Unrestricted portfolios | | | | | | | | | |
| Avg. turnover, % month | 10.65 | 43.18 | 83.59 | 13.62 | 87.01 | 87.98 | 21.03 | 1.53 | 1.85 |
| Mean MMI illiquidity, b.p. | 64.57 | 80.10 | 54.40 | 48.36 | 60.08 | 47.51 | 64.17 | 47.23 | 44.82 |
| Gross mean return, % month | 0.71 | 0.67 | 0.79 | 0.73 | 0.92 | 0.43 | 0.70 | 0.52 | 0.46 |
| Net mean return, % month | 0.65 | 0.36 | 0.41 | 0.68 | 0.36 | -0.05 | 0.62 | 0.51 | 0.45 |
| Gross Sharpe (annualized) | 1.15 | 1.52 | 1.56 | 1.79 | 1.35 | 1.02 | 1.50 | 1.60 | 1.34 |
| Net Sharpe (annualized) | 1.04 | 0.77 | 0.78 | 1.69 | 0.49 | -0.25 | 1.31 | 1.59 | 1.32 |
| Avg. no. bonds | 940 | 1507 | 1545 | 1422 | 773 | 595 | 3039 | 7799 | 4485 |
| of them, not traded, % | 9 | 24 | 4 | 29 | 21 | 16 | 7 | 28 | 14 |
| (B) No retail-sized trades | | | | | | | | | |
| Avg. turnover, % month | 9.48 | 40.71 | 81.79 | 9.99 | 86.56 | 87.79 | 11.79 | 1.35 | 1.45 |
| Mean MMI illiquidity, b.p. | 64.82 | 80.32 | 53.98 | 48.55 | 60.14 | 47.52 | 64.08 | 43.90 | 44.57 |
| Gross mean return, % month | 0.72 | 0.66 | 0.78 | 0.73 | 0.92 | 0.43 | 0.70 | 0.52 | 0.46 |
| Net mean return, % month | 0.66 | 0.37 | 0.40 | 0.69 | 0.36 | -0.05 | 0.65 | 0.51 | 0.46 |
| Gross Sharpe (annualized) | 1.16 | 1.52 | 1.55 | 1.80 | 1.35 | 1.02 | 1.62 | 1.56 | 1.36 |
| Net Sharpe (annualized) | 1.05 | 0.80 | 0.77 | 1.71 | 0.49 | -0.24 | 1.49 | 1.55 | 1.34 |
| Avg. no. bonds | 941 | 1492 | 1404 | 1408 | 779 | 595 | 3063 | 3172 | 2887 |
| of them, not traded, % | 11 | 26 | 11 | 32 | 10 | 14 | 27 | 45 | 11 |
| (C) As in B + partial rebalancing | | | | | | | | | |
| Avg. turnover, % month | 6.85 | 22.34 | 29.07 | 6.45 | 29.95 | 30.50 | 10.72 | 1.35 | 1.47 |
| Mean MMI illiquidity, b.p. | 64.36 | 76.45 | 52.63 | 47.99 | 58.92 | 46.27 | 63.23 | 43.90 | 44.15 |
| Gross mean return, % month | 0.73 | 0.64 | 0.67 | 0.73 | 0.71 | 0.48 | 0.71 | 0.52 | 0.46 |
| Net mean return, % month | 0.68 | 0.46 | 0.52 | 0.71 | 0.52 | 0.33 | 0.66 | 0.51 | 0.45 |
| Gross Sharpe (annualized) | 1.18 | 1.55 | 1.45 | 1.79 | 1.27 | 1.30 | 1.53 | 1.56 | 1.34 |
| Net Sharpe (annualized) | 1.09 | 1.08 | 1.12 | 1.72 | 0.91 | 0.87 | 1.41 | 1.55 | 1.33 |
| Avg. no. bonds | 799 | 904 | 795 | 1207 | 456 | 342 | 2259 | 3172 | 2802 |
| of them, not traded, % | 14 | 45 | 19 | 38 | 18 | 26 | 35 | 45 | 12 |
| (D) As in C + sampling on size | | | | | | | | | |
| Avg. turnover, % month | 7.39 | 23.04 | 29.38 | 7.73 | 30.03 | 30.54 | 11.39 | 1.32 | 1.61 |
| Mean MMI illiquidity, b.p. | 60.66 | 73.89 | 49.39 | 44.23 | 54.51 | 42.94 | 61.88 | 42.75 | 39.25 |
| Gross mean return, % month | 0.70 | 0.64 | 0.69 | 0.70 | 0.72 | 0.48 | 0.72 | 0.51 | 0.45 |
| Net mean return, % month | 0.64 | 0.41 | 0.52 | 0.66 | 0.51 | 0.32 | 0.65 | 0.50 | 0.44 |
| Gross Sharpe (annualized) | 1.09 | 1.40 | 1.43 | 1.70 | 1.23 | 1.24 | 1.41 | 1.49 | 1.25 |
| Net Sharpe (annualized) | 0.99 | 0.88 | 1.07 | 1.60 | 0.85 | 0.78 | 1.28 | 1.47 | 1.24 |
| Avg. no. bonds | 424 | 535 | 487 | 615 | 264 | 210 | 1253 | 3032 | 2269 |
| of them, not traded, % | 7 | 23 | 13 | 35 | 11 | 11 | 23 | 12 | 5 |
| (E) As in D + restriction on past T-cost | | | | | | | | | |
| Avg. turnover, % month | 5.79 | 19.60 | 21.55 | 4.87 | 24.11 | 29.18 | 8.29 | 1.39 | 1.66 |
| Mean MMI illiquidity, b.p. | 62.37 | 71.75 | 48.83 | 44.32 | 54.06 | 43.10 | 61.54 | 42.61 | 38.59 |
| Gross mean return, % month | 0.70 | 0.62 | 0.67 | 0.71 | 0.73 | 0.48 | 0.71 | 0.51 | 0.44 |
| Net mean return, % month | 0.66 | 0.44 | 0.55 | 0.68 | 0.57 | 0.32 | 0.67 | 0.50 | 0.44 |
| Gross Sharpe (annualized) | 1.19 | 1.45 | 1.53 | 1.76 | 1.36 | 1.24 | 1.50 | 1.48 | 1.23 |
| Net Sharpe (annualized) | 1.11 | 1.00 | 1.26 | 1.69 | 1.05 | 0.80 | 1.40 | 1.47 | 1.22 |
| Avg. no. bonds | 541 | 634 | 624 | 673 | 320 | 214 | 1430 | 2975 | 2118 |
| of them, not traded, % | 11 | 23 | 15 | 38 | 12 | 12 | 23 | 13 | 6 |

Table 7: **Performance of systematic strategies under turnover constraints and square-root T-cost.** The sample is Jan 2010–Jun 2019. Trading costs are as in equation (3). The fund size is $500 mn. The strategies are as in Table 2. Part A of the table contains previously reported performance characteristics from Table 6. Part B prohibits rebalancing trades smaller than $100 th notional. Part C, on top of that, restricts rebalancing to only one-third of the largest portfolio adjustments. Part D starts with portfolios that contain only the largest half of portfolio holdings each month and then introduces the same turnover constraints as in Part C. Part E, on top of all previous constraints, restricts portfolio holdings to bonds that were traded at least five business days in the previous month. Mean MMI illiquidity is the average of individual bond MMI illiquidity weighted by portfolio weights of respective bonds. Table 11 in Appendix presents analogous results for $V-$shape T-costs.

Table 7 presents key portfolio performance characteristics by sequentially adding implementation constraints to our benchmark $500 mln AUM systematic funds. Part B of Table 7 restricts trade size to institutional (the unrestricted performance is in Part A). No retail-sized rebalancing means that the smallest of new holdings are not making it into the portfolio. Therefore, the portfolios most affected by this constraint are the ones that have many such small holdings: MKT and MIG. For instance, the average number of bond holdings in the broad market portfolio (MKT) drops from 8 thousand to approximately 3 thousand after the restriction on retail-sized rebalancing. The turnover of market portfolios also drops, but it has a moderate impact on the performance of MKT and MIG portfolios since they are well-diversified even with 40% of the original holdings. The impact of the retail-sized trading restriction on other systematic portfolios is moderate, except for the MFP portfolio; its net Sharpe ratio grows from about 1.3 to almost 1.5 amid a two-times drop in turnover. Portfolios with high unrestricted turnover and relatively few holdings (like the R1D and REQ reversal portfolios) see virtually no impact of the retail-sized trading restriction. Such portfolios are rebalanced in institutional-sized trading amounts already in the unrestricted case.

In Part C of Table 7, we impose the partial rebalancing constraint on top of the retail-sized trading restriction. This constraint effectively removes rebalancing trades that are large enough to be of institutional size but are not large enough to make it to the top third of rebalancing trades in a given month. Relative to the no-retail-sized trading, such a constraint must strongly affect the strategies with high turnover and fewer holdings. So it does: for all reversal strategies and the LIQ portfolio, the turnover drops almost by two-thirds to levels close to 30% a month.[17] Importantly, the turnover reduction does not affect the performance of reversal and liquidity portfolios even

[17] Restricting rebalancing to one-third of the largest trades does not automatically reduce average strategy turnover by two-thirds relative to an unrestricted case. Firstly, a 'natural' turnover must be implemented (if the bond becomes less than one year to maturity or its outstanding amount falls below the threshold due to a partial call or a tender offer). Secondly, a restricted portfolio carried from month $t-1$ contains some positions that have not been sold out in the past due to the same trade-size filters. These previously unsold positions will eventually sell when the signal is strong enough. Such delayed sales create an additional turnover.

on a cum-cost basis – the reversal signal is not being diluted. Ex-cost Sharpe ratios increase for all reversal and liquidity strategies in Part C of Table 7 (relative to Part B of the same table). The same applies to credit and default portfolios (CRD and DEF), though the impact is moderate here. For the MFP portfolio, partial rebalancing seems to increase return volatility (amid another considerable drop in holdings), negatively affecting risk-adjusted performance. Remarkably, partial rebalancing tilts portfolios to rarely traded bonds across the board, and this is likely not a desirable portfolio feature. Finally, partial rebalancing has almost no effect on market portfolios on top of the no-retail-trades constraint. This is because, for a market portfolio of $500 mln AUM, some of the largest rebalancing trades are retail-sized and have already been filtered out at a previous step.

In Part D of Table 7, we impose constraints on retail-sized trades and partial rebalancing on sampled portfolios, i.e., portfolios that contain only the largest half of original portfolio holdings. Relative to Part C, where full portfolios were considered, sampling reduces portfolio holdings across the board. Also, it considerably reduces the fraction of non-traded bonds in portfolios. However, having fewer holdings while keeping fund size fixed means having more turnover and smaller net returns. As a result, net Sharpe ratios of all portfolios are smaller in Part D of Table 7 than in Part C. Comparing sampled and constrained portfolios with original unrestricted portfolios (Part A), one finds that ex-cost risk-adjusted performance either reduces marginally (DEF, CRD, MFP, MKT, MIG) or improves (LIQ, REV, R1D, REQ).

In Part E of Table 7, target portfolios of Part D are further restricted to only include bonds that were actively traded in the past. One universal consequence of this restriction for all portfolios (except for two market portfolios) is an additional drop in turnover. This is likely a consequence of a relatively persistent trading frequency of individual corporate bonds. The list of bonds traded more than five business days a month does not change much from month to month. For instance, the turnover of CRD and DEF portfolios is now around 5%, which is close to the average reported monthly turnover of corporate bond mutual funds in the CRSP Mutual Funds dataset (see Table 13 in Appendix). Lower turnover yields higher (or unchanged) net returns, translating into higher net Sharpe ratios for all portfolios except the MIG. Given these results, we consider portfolios in Part E of Table 7 superior to portfolios in Parts A–D in practical feasibility and performance.

Constrained portfolios discussed in this section stop short of explicitly optimizing portfolios with respect to transaction costs. Gârleanu and Pedersen (2013) consider theoretical TC-optimized portfolios, and DeMiguel et al. (2020) demonstrate how to incorporate some of these ideas in multi-factor equity portfolios. Corporate bond transaction costs are not as well researched as equity trading costs yet and we attempt to advance the understanding of the impact of individual bond transaction costs on the performance of feasible systematic portfolios. Optimizing portfolios explicitly to bond T-costs is a venue for future research once the consensus on individual bond trading costs is reached.

### 4.2 Capacity

This section has only considered constrained portfolios of a fixed size of $500 mln so far. We now turn to discuss the capacity limits of constrained systematic bond strategies. Capacity limits arise because relative transaction costs increase in trade size (like in Equation 2). Consider two funds, A and B, with the same holdings and rebalancing schedules, but fund B is twice as large as fund A. Every trade fund B executes will cost more than a respective trade of fund A. Gross returns are identical for the two funds. Since fund B pays more in transaction costs than fund A, its net return will be lower. Now imagine fund B grows in size to the extent at which its gross returns are equal to transaction costs; hence, its net returns are down to zero. We call such fund size a ‘capacity limit’ or a ‘capacity constraint’.

To estimate the capacity, we vary the size of a hypothetical corporate bond fund using the post-GFC part of our corporate bond sample to evaluate returns and transaction costs. For a given strategy, the capacity limit is the size of the fund at which the average monthly net return in 2010–2019 drops to zero. We assume, as before, that the total fund size remains unchanged from one month to another and that the fund is fully invested in U.S. corporate bonds. We consider both unrestricted portfolios and portfolios with rebalancing constraints. There are still many practical economic aspects that we abstract away from in our capacity evaluation. For instance, we run estimation for a single-fund industry (as if assets of multiple funds are pooled together and rebalancing happens at once). We also disregard any possible changes in the investment approach as the fund gets bigger. Having multiple funds, each adapting dynamically to increased assets under management, would likely push capacity limits up.

| | DEF | LIQ | REV | CRD | R1D | REQ | MFP | MKT | MIG |
|---|---|---|---|---|---|---|---|---|---|
| (A) Unrestricted turnover | 15.6 | 2.7 | 2.8 | 31.6 | 1.8 | 0.7 | 20.9 | 526 | 310 |
| (B) Inst. trades only | 15.6 | 2.7 | 2.8 | 31.6 | 1.8 | 0.7 | 20.9 | 527 | 310 |
| (C) As B, and partial rebalancing | 18.8 | 4.0 | 4.9 | 39.2 | 3.5 | 2.9 | 27.8 | 525 | 310 |
| (D) As C, and sampling | 12.2 | 2.6 | 3.8 | 21.9 | 2.6 | 2.2 | 19.2 | 451 | 261 |
| (E) As D, and most actively traded bonds | 17.5 | 3.3 | 5.5 | 28.3 | 3.7 | 2.3 | 28.1 | 470 | 266 |

(a) **Linear cost**

| | DEF | LIQ | REV | CRD | R1D | REQ | MFP | MKT | MIG |
|---|---|---|---|---|---|---|---|---|---|
| (A) Unrestricted turnover | 74.8 | 2.6 | 2.5 | 186.9 | 1.4 | 0.4 | 47.4 | 16913 | 7741 |
| (B) Inst. trades only | 74.8 | 2.6 | 2.5 | 186.9 | 1.4 | 0.4 | 47.4 | 16913 | 7741 |
| (C) As B, and partial rebalancing | 136.2 | 6.8 | 12.2 | 466.0 | 7.7 | 5.8 | 116.0 | 16327 | 7556 |
| (D) As C, and sampling | 78.0 | 4.4 | 9.8 | 195.9 | 6.2 | 4.6 | 77.0 | 13969 | 6955 |
| (E) As D, and most actively traded bonds | 146.1 | 6.4 | 19.7 | 422.2 | 11.2 | 5.1 | 157.4 | 15003 | 7271 |

(b) **Square-root cost**

Table 8: **The capacity of systematic strategies ($ bn) under different T-cost models**. The linear cost is as in (2); the square-root model is in (3). Implementation constraints correspond to those in Table 7. The sample period is Jan 2010 – Jun 2019.

Table 8 reports capacity estimates obtained by solving numerically for a single-fund AUM that zeroes out ex-cost returns of respective strategies. Part a) presents the results for a linear transaction cost model, and part b) uses the square-root model. The top line of part b) reports capacity limits for unrestricted portfolios plotted previously in Figure 2. Capacity limits under a linear T-cost assumption are lower than under the square-root model (except for reversal strategies, which have similar scalability no matter which model is used). We consider the square-root model a more realistic one, and we will comment primarily on part b) of Table 8.

- **Reversal and illiquidity strategies** (LIQ, REV, R1D, and REQ) see their capacity growing thanks to implementation constraints. Here, we start with \$0.4-2.6 bn capacity in an unrestricted case and increase it to \$5.1-19.7 bn under the most constrained case (line E in part b) of Table 8). Partial rebalancing and past trading activity restrictions help to push the capacity higher.

- **Default, credit, and multi-factor strategies** (DEF, CRD, and MFP) also see the capacity grow 2–4 times thanks to implementation constraints. As for reversal portfolios, partial rebalancing (line C) is the constraint that provides a strong boost to capacity. Importantly, sampling (line D) destroys some of the gains of partial rebalancing. The fewer bonds a fund manager holds, the sooner the capacity limit is reached, other things equal. However, the restriction on bond trading activity (line E) allows recovering what sampling destroys and pushes the capacity even higher than in a pure partial rebalancing case. The capacity limit for these strategies stands at around \$150 bn for DEF and MFP portfolios and above \$400 bn for the CRD portfolio.

- **Market portfolios'** capacity is rather incensitive to implementation constraints. The unrestricted capacity of about \$8 tn for the MIG and \$17 tn for the MKT remain stable and even decrease slightly under the most elaborate feasibility constraints. This is due to the fact that market portfolios here are very broadly diversified and have a low turnover already in the unrestricted case. Reducing the number of holdings in market portfolios may not hurt the performance but does eventually hurt the capacity as the fund grows sufficiently large.

Overall, the capacity estimates in Table 8 suggest that there is still considerable room for growth in systematic corporate bond investment. Even reversal strategies can withstand several $ bn of assets under management if the portfolio is tilted towards more liquid bonds and the turnover is optimized. Low-turnover portfolios consisting of bonds with a high default or credit risk can generate positive net-of-cost returns up to several hundreds of $ bn of assets under management. Multi-factor portfolios combining such factors do not save much on transaction costs because the aforementioned signals are only mildly correlated and imply largely non-overlapping bond holdings. Finally, the corporate bond market risk premia are not absorbed by transaction costs even in the largest possible market portfolios.

## Conclusion

We apply principles of market microstructure invariance to evaluate corporate bond transaction costs and use these empirical estimates to rank systematic corporate bond long-only investment strategies by their capacity. Unlike prevailing transaction-based estimates of bond trading costs, pricing functions implied by microstructure invariance have a positive market impact. As the size of the bond fund increases, the market impact part of transaction costs drives net return down to zero. High-turnover strategies that exploit reversal and illiquidity signals reach capacities up to $ 20 bn. Low-turnover strategies targeting credit risk premia have capacities up to $400 bn. These capacity limits are achieved under restrictions on portfolio rebalancing. A broad market portfolio has a capacity several times higher than the current market size, suggesting that transaction costs do not fully offset corporate bond risk premia. Our capacity estimates have further implications for investors and regulators of systematic corporate bond strategies.

There are several interesting avenues for future research. First, recent machine learning approaches (Bali et al. 2022) to corporate bond return predictability have generated impressive performance gains. The MMI estimates from our paper could be extended to answer the question of whether such predictability leads to portfolios that generate statistically and economically significant performance after transaction cost adjustments. Second, our transaction cost estimates could be compared to those from alternative approaches such as those of Patton and Weller (2020). Third, incorporating ESG and carbon emissions considerations in investment portfolios is a very important recent area of research (Diep et al. 2022). Understanding the capacity constraints of such approaches is of great interest to investors and regulators overseeing these markets.

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# Appendix A Additional Tables and Charts

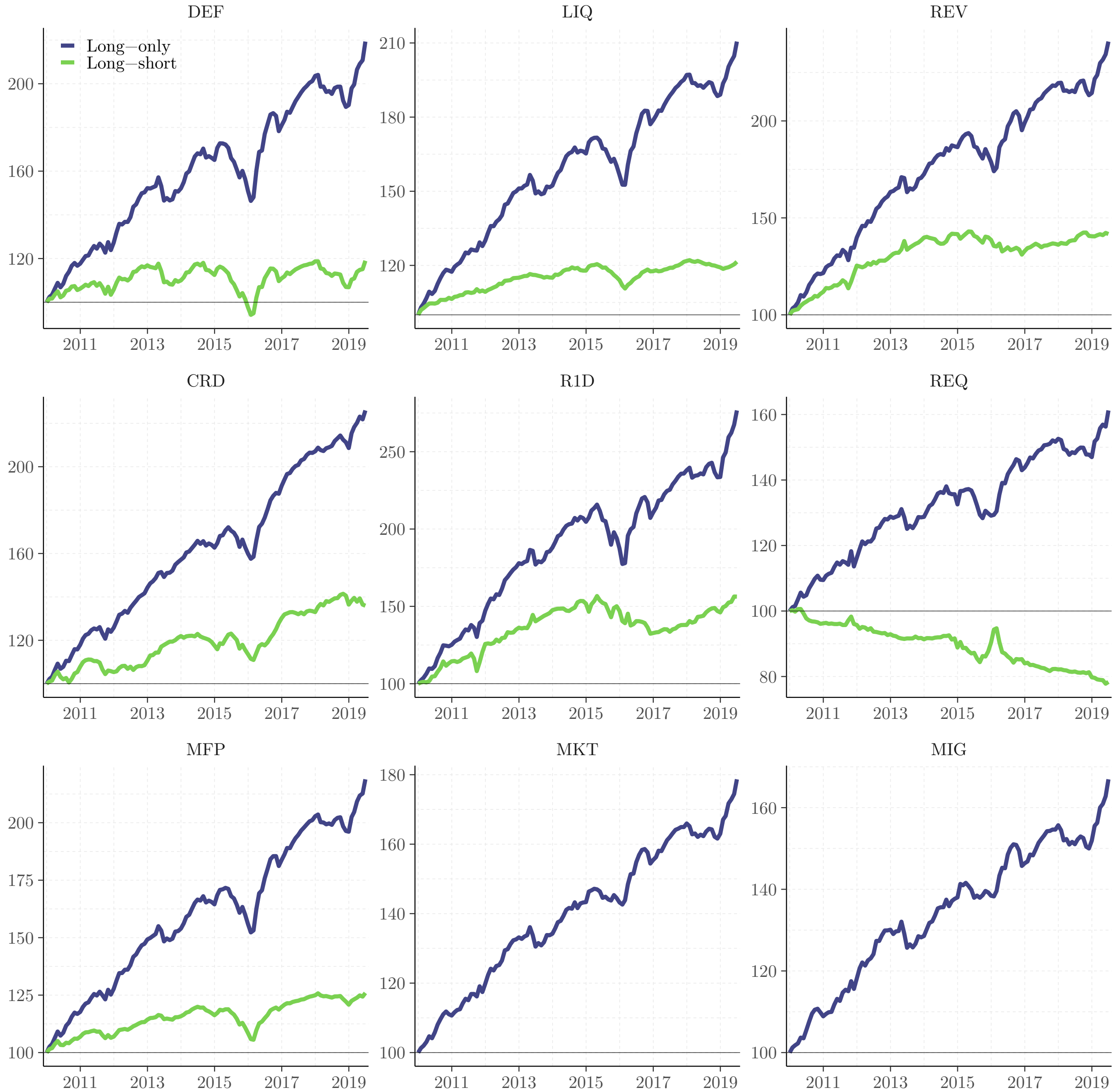


Figure 3: **Cumulative performance of long-only and long-short strategies before TC adjustment.** Portfolios are worth 100 at inception, which is Dec 2009. For portfolio description, see Table 2. Long-short portfolios are as constructed in Bai et al. (2019) and Chordia et al. (2017), long-only portfolios are their subsets with positive individual bond weights. Trading costs are not accounted for.

| | MMI illiquidity | BPW illiquidity | Realized bid-ask | Zero trading days | Equity bid-ask |
|---|---|---|---|---|---|
| MMI illiquidity | 1 | 0.272 | 0.473 | 0.443 | 0.046 |
| BPW illiquidity | | 1 | 0.324 | 0.177 | 0.097 |
| Realized bid-ask | | | 1 | -0.000 | 0.113 |
| Zero trading days | | | | 1 | -0.013 |
| Equity bid-ask | | | | | 1 |

Table 9: **Cross-sectional correlation among bond illiquidity measures**. The correlation matrix is estimated month by month (Jan 2010 – Jun 2019) in the cross-section of bonds, then averaged across months. The MMI illiquidity is as in equation (1) (after truncation but before rolling past values forward). The BPW illiquidity is the Roll's measure calculated as in Bao et al. (2011). Realized bid-ask is the difference between volume-weighted average buy and sell prices, as a % of the average of the two. Zero trading days is the % of business days within a month the bond is not traded. Equity bid-ask is from CRSP, averaged across days within a month (only calculated for bonds issued by public firms).

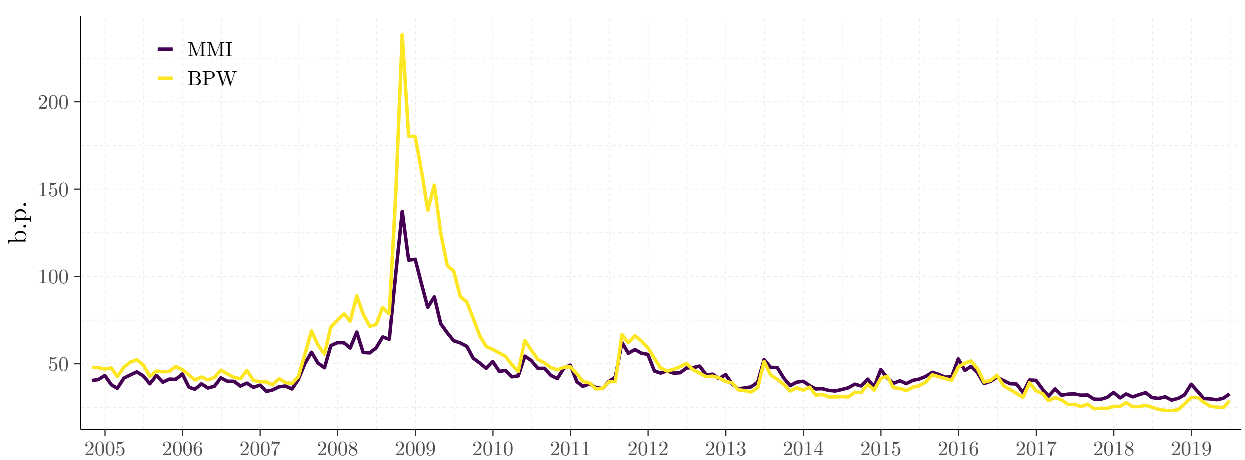


Figure 4: **Bond market illiquidity**. MMI illiquidity is $1/L_t$ of Kyle and Obizhaeva (2016), BPW is the square-root of the illiquidity measure of Bao et al. (2011). For each month, cross-sectional means are value-weighted.

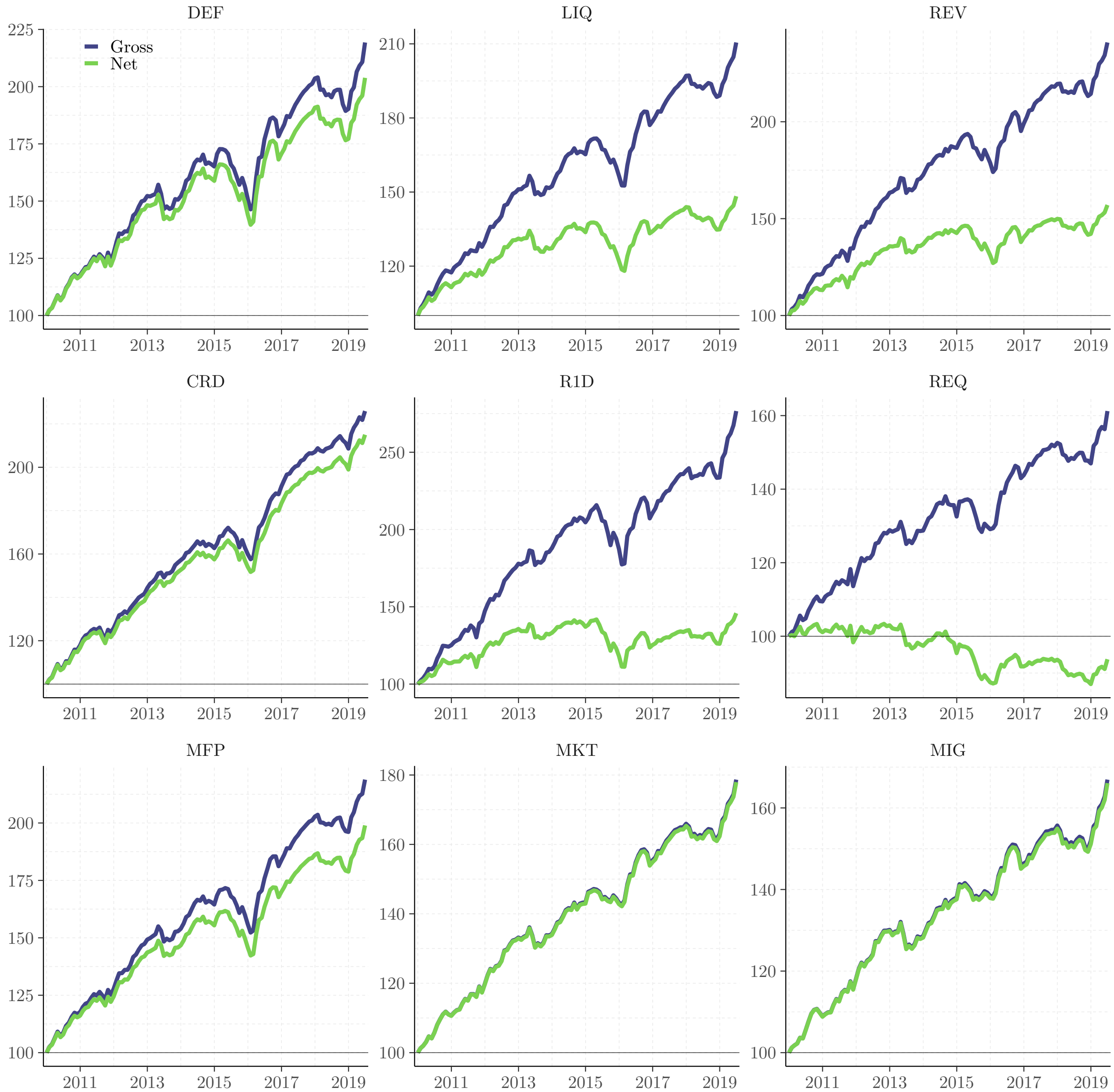


Figure 5: **Cumulative performance of long-only strategies before and after TC adjustment** for a fixed fund size of $500 mln AUM. Portfolios are worth 100 at inception, which is Dec 2009. For portfolio description, see Table 2. Trading costs are square-root MMI-implied costs of equation (3).

| | DEF | LIQ | REV | CRD | R1D | REQ | MFP | MKT | MIG |
|---|---|---|---|---|---|---|---|---|---|
| | | | | With imputed returns | | | | | |
| Mean return, % month | 0.71 | 0.67 | 0.79 | 0.73 | 0.92 | 0.43 | 0.70 | 0.52 | 0.46 |
| St. dev., % month | 2.01 | 1.42 | 1.65 | 1.31 | 2.26 | 1.31 | 1.51 | 1.02 | 1.07 |
| Sharpe (annualized) | 1.15 | 1.52 | 1.56 | 1.79 | 1.35 | 1.02 | 1.50 | 1.60 | 1.34 |
| | | | | Only observed returns | | | | | |
| Mean return, % month | 0.71 | 0.64 | 0.87 | 0.71 | 1.03 | 0.42 | 0.69 | 0.50 | 0.45 |
| St. dev., % month | 2.11 | 1.68 | 1.69 | 1.66 | 2.29 | 1.35 | 1.74 | 1.12 | 1.12 |
| Sharpe (annualized) | 1.10 | 1.24 | 1.70 | 1.39 | 1.49 | 0.96 | 1.29 | 1.39 | 1.24 |

(a) Before trading cost adjustment

| | DEF | LIQ | REV | CRD | R1D | REQ | MFP | MKT | MIG |
|---|---|---|---|---|---|---|---|---|---|
| | | | | With imputed returns | | | | | |
| Mean return (% month) | 0.65 | 0.36 | 0.41 | 0.68 | 0.36 | -0.05 | 0.62 | 0.51 | 0.45 |
| St. dev. (% month) | 2.02 | 1.41 | 1.63 | 1.31 | 2.24 | 1.29 | 1.51 | 1.02 | 1.07 |
| Sharpe (annualized) | 1.04 | 0.77 | 0.78 | 1.69 | 0.49 | -0.25 | 1.31 | 1.59 | 1.32 |
| | | | | Only observed returns | | | | | |
| Mean return (% month) | 0.65 | 0.33 | 0.49 | 0.67 | 0.46 | -0.06 | 0.60 | 0.49 | 0.44 |
| St. dev. (% month) | 2.12 | 1.67 | 1.67 | 1.66 | 2.27 | 1.33 | 1.73 | 1.12 | 1.12 |
| Sharpe (annualized) | 0.99 | 0.60 | 0.94 | 1.30 | 0.64 | -0.27 | 1.12 | 1.38 | 1.23 |

(b) After trading cost adjustment

Table 10: **Comparison of portfolio performance with and without the imputation of returns for non-traded bonds**. The upper part of sub-table a) is identical to Table 2. The lower part only uses traded bond returns to calculate performance, assuming that the non-traded part, as a whole, has the same return as the traded part. Sub-table b) presents similar calculations but for ex-trading-costs portfolio returns. Here, the trading cost is the square-root MMI-implied cost as in Table 6. The AUM is $500 mn and the sample period is from Jan 2010 to Jun 2019.

| | DEF | LIQ | REV | CRD | R1D | REQ | MFP | MKT | MIG |
|---|---|---|---|---|---|---|---|---|---|
| (A) Unrestricted portfolios | | | | | | | | | |
| Avg. turnover, % month | 10.65 | 43.18 | 83.59 | 13.62 | 87.01 | 87.98 | 21.03 | 1.53 | 1.85 |
| Mean MMI illiquidity, b.p. | 64.57 | 80.10 | 54.40 | 48.36 | 60.08 | 47.51 | 64.17 | 47.23 | 44.82 |
| Gross mean return, % month | 0.71 | 0.67 | 0.79 | 0.73 | 0.92 | 0.43 | 0.70 | 0.52 | 0.46 |
| Net mean return, % month | 0.65 | 0.39 | 0.40 | 0.66 | 0.44 | 0.03 | 0.59 | 0.51 | 0.45 |
| Gross Sharpe (annualized) | 1.15 | 1.52 | 1.56 | 1.79 | 1.35 | 1.02 | 1.50 | 1.60 | 1.34 |
| Net Sharpe (annualized) | 1.04 | 0.85 | 0.76 | 1.63 | 0.61 | -0.02 | 1.24 | 1.58 | 1.31 |
| Avg. no. bonds | 940 | 1507 | 1545 | 1422 | 773 | 595 | 3039 | 7799 | 4485 |
| of them, not traded, % | 9 | 24 | 4 | 29 | 21 | 16 | 7 | 28 | 14 |
| (B) No retail-sized trades | | | | | | | | | |
| Avg. turnover, % month | 9.48 | 40.71 | 81.79 | 9.99 | 86.56 | 87.79 | 11.79 | 1.35 | 1.45 |
| Mean MMI illiquidity, b.p. | 64.82 | 80.32 | 53.98 | 48.55 | 60.14 | 47.52 | 64.08 | 43.90 | 44.57 |
| Gross mean return, % month | 0.72 | 0.66 | 0.78 | 0.73 | 0.92 | 0.43 | 0.70 | 0.52 | 0.46 |
| Net mean return, % month | 0.66 | 0.41 | 0.40 | 0.68 | 0.44 | 0.04 | 0.63 | 0.51 | 0.46 |
| Gross Sharpe (annualized) | 1.16 | 1.52 | 1.55 | 1.80 | 1.35 | 1.02 | 1.62 | 1.56 | 1.36 |
| Net Sharpe (annualized) | 1.05 | 0.90 | 0.76 | 1.68 | 0.62 | -0.02 | 1.46 | 1.55 | 1.34 |
| Avg. no. bonds | 941 | 1492 | 1404 | 1408 | 779 | 595 | 3063 | 3172 | 2887 |
| of them, not traded, % | 11 | 26 | 11 | 32 | 10 | 14 | 27 | 45 | 11 |
| (C) As in B + partial rebalancing | | | | | | | | | |
| Avg. turnover, % month | 6.85 | 22.34 | 29.07 | 6.45 | 29.95 | 30.50 | 10.72 | 1.35 | 1.47 |
| Mean MMI illiquidity, b.p. | 64.36 | 76.45 | 52.63 | 47.99 | 58.92 | 46.27 | 63.23 | 43.90 | 44.15 |
| Gross mean return, % month | 0.73 | 0.64 | 0.67 | 0.73 | 0.71 | 0.48 | 0.71 | 0.52 | 0.46 |
| Net mean return, % month | 0.69 | 0.50 | 0.54 | 0.70 | 0.56 | 0.37 | 0.65 | 0.51 | 0.45 |
| Gross Sharpe (annualized) | 1.18 | 1.55 | 1.45 | 1.79 | 1.27 | 1.30 | 1.53 | 1.56 | 1.34 |
| Net Sharpe (annualized) | 1.11 | 1.17 | 1.15 | 1.72 | 0.99 | 0.97 | 1.40 | 1.55 | 1.32 |
| Avg. no. bonds | 799 | 904 | 795 | 1207 | 456 | 342 | 2259 | 3172 | 2802 |
| of them, not traded, % | 14 | 45 | 19 | 38 | 18 | 26 | 35 | 45 | 12 |
| (D) As in C + sampling on size | | | | | | | | | |
| Avg. turnover, % month | 7.39 | 23.04 | 29.38 | 7.73 | 30.03 | 30.54 | 11.39 | 1.32 | 1.61 |
| Mean MMI illiquidity, b.p. | 60.66 | 73.89 | 49.39 | 44.23 | 54.51 | 42.94 | 61.88 | 42.75 | 39.25 |
| Gross mean return, % month | 0.70 | 0.64 | 0.69 | 0.70 | 0.72 | 0.48 | 0.72 | 0.51 | 0.45 |
| Net mean return, % month | 0.65 | 0.47 | 0.56 | 0.66 | 0.57 | 0.36 | 0.65 | 0.50 | 0.44 |
| Gross Sharpe (annualized) | 1.09 | 1.40 | 1.43 | 1.70 | 1.23 | 1.24 | 1.41 | 1.49 | 1.25 |
| Net Sharpe (annualized) | 1.01 | 1.02 | 1.14 | 1.61 | 0.96 | 0.92 | 1.28 | 1.47 | 1.23 |
| Avg. no. bonds | 424 | 535 | 487 | 615 | 264 | 210 | 1253 | 3032 | 2269 |
| of them, not traded, % | 7 | 23 | 13 | 35 | 11 | 11 | 23 | 12 | 5 |
| (E) As in D + restriction on past T-cost | | | | | | | | | |
| Avg. turnover, % month | 5.79 | 19.60 | 21.55 | 4.87 | 24.11 | 29.18 | 8.29 | 1.39 | 1.66 |
| Mean MMI illiquidity, b.p. | 62.37 | 71.75 | 48.83 | 44.32 | 54.06 | 43.10 | 61.54 | 42.61 | 38.59 |
| Gross mean return, % month | 0.70 | 0.62 | 0.67 | 0.71 | 0.73 | 0.48 | 0.71 | 0.51 | 0.44 |
| Net mean return, % month | 0.66 | 0.48 | 0.57 | 0.69 | 0.61 | 0.37 | 0.67 | 0.50 | 0.44 |
| Gross Sharpe (annualized) | 1.19 | 1.45 | 1.53 | 1.76 | 1.36 | 1.24 | 1.50 | 1.48 | 1.23 |
| Net Sharpe (annualized) | 1.13 | 1.11 | 1.30 | 1.70 | 1.13 | 0.93 | 1.40 | 1.46 | 1.21 |
| Avg. no. bonds | 541 | 634 | 624 | 673 | 320 | 214 | 1430 | 2975 | 2118 |
| of them, not traded, % | 11 | 23 | 15 | 38 | 12 | 12 | 23 | 13 | 6 |

Table 11: **Performance of systematic strategies under turnover constraints and $V-$shape transaction costs**. This is the analog of Table 7 but with different transaction costs. Here, bond-specific time-varying trading costs are the average of the square-root MMI and the EHP, as in Figure 6. The fund is of the unchanged size of $500 mln.

## Appendix B Recover bond TCs from Kyle and Obizhaeva (2016)

Kyle and Obizhaeva (2016) test microstructure invariance hypotheses using non-public equity portfolio transitions data that allows separating portfolio meta-orders from individual trades implemented by a transition manager. Meta-orders proxy for 'bets' – a cornerstone concept of the microstructure invariance theory. The invariance of the distribution of the dollar amount of risk transferred by bets and the distribution of cost associated with such risk transfer are two invariance hypotheses put forward in Kyle and Obizhaeva (2016). If the invariance hypotheses hold, the transaction costs estimated from the equity portfolio transition bets must also apply to other asset classes. Here, we demonstrate how one can re-write cost functions from Section 6 of Kyle and Obizhaeva (2016) to make them applicable to corporate bonds.

Equity portfolio transitions imply the following transaction cost functions:[18]

$$C_{it}^{\%,\text{lin}}(Q) = \frac{\sigma_{it}}{0.02}\left(\frac{8.21}{10^4}\left[\frac{W_{it}}{(0.02)(40)(10^6)}\right]^{-\frac{1}{3}} + \frac{2.50}{10^4}\left[\frac{W_{it}}{(0.02)(40)(10^6)}\right]^{\frac{1}{3}}\frac{Q}{(0.01)V_{it}}\right),$$

$$C_{it}^{\%,\text{sqrt}}(Q) = \frac{\sigma_{it}}{0.02}\left(\frac{2.08}{10^4}\left[\frac{W_{it}}{(0.02)(40)(10^6)}\right]^{-\frac{1}{3}} + \frac{12.08}{10^4}\left[\frac{Q}{(0.01)V_{it}}\right]^{\frac{1}{2}}\right),$$

where $\sigma_{it}$ and $V_{it}$ are daily volatility and trading volume (in the number of shares) for stock $i$ on day $t$, $W_{it} \equiv \sigma_{it}P_{it}V_{it}$ is the dollar size of risk transfer per calendar day, and $Q$ is the trade size (also in the number of shares). These cost functions have been scaled to a typical stock in the Kyle and Obizhaeva (2016) sample. Such stock has a 2% daily volatility, a price of \$40, and an average daily trading volume (ADV) of 1 mn shares; call the dollar size of daily risk transfer in such stock $\alpha = 0.02 \times 40 \times 10^6$. Executing a trade amounting to the 1% of the ADV in such stock then costs 10.71 b.p., of which 8.21 b.p. is the explicit cost (half bid-ask spread), and 2.50 b.p. is the market

[18] Formulas 37 and 38 in Kyle and Obizhaeva (2016). These are relative transaction cost functions, i.e., the measurement unit is the fraction of the traded amount.

impact, according to the linear cost function above. For the square-root model, the explicit and implicit costs of a similar trade are estimated at 2.08 and 12.08 b.p., respectively.

MMI does not restrict the shape of the cost function per se, so both linear and square-root models are, in principle, consistent with the MMI. But to use them for corporate bonds, one must first re-scale the cost functions appropriately. Here is how we adapt the linear function:

$$
\begin{aligned}
C_{it}^{\%,\text{lin}}(Q) &= \frac{\sigma_{it}}{0.02}\left(\frac{8.21}{10^4}\left[\frac{W_{it}}{(0.02)(40)(10^6)}\right]^{-\frac{1}{3}} + \frac{2.50}{10^4}\left[\frac{W_{it}}{(0.02)(40)(10^6)}\right]^{\frac{1}{3}}\frac{Q}{(0.01)V_{it}}\right) = \\
&= \underbrace{\left[\sigma_{it}W_{it}^{-\frac{1}{3}}Ci^2\right]}_{\frac{1}{L_{it}}}\left(\frac{1}{0.02}\frac{1}{Ci^2}\frac{8.21}{10^4}\alpha^{\frac{1}{3}} + \frac{1}{0.02}\frac{1}{Ci^2}\frac{2.50}{10^4}\alpha^{-\frac{1}{3}}\frac{1}{0.01}\underbrace{\sigma_{it}W_{it}^{-\frac{1}{3}}}_{\frac{W_{it}^{\frac{2}{3}}}{P_{it}V_{it}}}P_{it}Q\right) = \\
&= \frac{1}{L_{it}}\left(\underbrace{\frac{1}{0.02}\frac{1}{Ci^2}\frac{8.21}{10^4}\alpha^{\frac{1}{3}}}_{\kappa} + \underbrace{\frac{1}{0.02}\frac{C}{(Ci^2)^2}\frac{2.50}{10^4}\alpha^{-\frac{1}{3}}\frac{1}{0.01}}_{\lambda}\frac{1}{CL_{it}}(P_{it}Q)\right) \Rightarrow \\
C_{it}^{\%,\text{lin}}(X) &= \frac{1}{L_{it}}\left(\kappa + \lambda\frac{1}{CL_{it}}X\right),
\end{aligned}
$$

where $C$ and $i^2$ are invariant parameters estimated in Kyle and Obizhaeva (2016), and $X \equiv PQ$ is the dollar size of the transaction. $i^2 \approx 0.009886$ is the mean of the log-normal distribution of scaled bet sizes, and $C \approx \$2000$ is the cost of executing an average-sized bet. The direct calculation yields $\kappa \approx 0.19272$ and $\lambda \approx 0.06888$. We keep these parameters unchanged for all individual bonds in our sample, as MMI suggests one should do under the invariance assumption. Notice that the explicit and implicit costs would still vary from bond to bond as the MMI illiquidity $\frac{1}{L_{it}}$ varies.

Following similar steps, the square-root function re-writes as:

$$C_{it}^{\%,\mathrm{sqrt}}(X) = \frac{1}{L_{it}}\left(\breve{\kappa} + \check{\lambda}\frac{1}{\sqrt{CL_{it}}}\sqrt{X}\right),$$
$$\breve{\kappa} = \frac{1}{0.02}\frac{1}{Ci^2}\frac{2.08}{10^4}\alpha^{\frac{1}{3}} \approx 0.04883,$$
$$\check{\lambda} = \frac{1}{0.02}\frac{1}{Ci^{\frac{3}{2}}}\frac{12.08}{10^4}\frac{1}{\sqrt{0.01}} \approx 0.30721.$$

Kyle and Obizhaeva (2020) also discuss how to adapt linear MMI-implied T-cost functions to fixed-income markets. They likewise derive the linear cost function for corporate bonds, which is similar (but not identical) to (2) in its numeric parameters. We are not aware of adaptions of the square-root MMI cost function to corporate bonds in the literature.

# Appendix C $V-$shape transaction costs

In this section, we hypothesize that implicit corporate bond transaction costs may, in fact, contain both a positive market impact component (as proxied by the MMI market impact) and a volume discount component (as identified in transactional data by Edwards et al. 2007, 'EHP' transaction costs henceforth). We blend the two approaches by equally weighting MMI (square-root) and EHP transaction cost functions for individual bonds in what becomes a 'V-shape' transaction cost function. Our goal here is to refine the estimates of capacity limits in systematic trading strategies with hypothetical transaction cost functions that might better represent documented corporate bond market frictions and characteristics. We do not test the validity of our V-shape-cost hypothesis.

We estimate EHP transaction costs with minor changes relative to the Edwards et al. (2007) approach. We estimate with the iterated weighted least squares method the following model for individual corporate bonds (in the same post-GFC sample as in the rest of the paper):

$$r_{ts} = \underbrace{c_0(Q_t - Q_s) + c_1\left(Q_t\frac{1}{S_t} - Q_s\frac{1}{S_s}\right) + c_2\left(Q_t \log S_t - Q_s \log S_s\right)}_{\text{Transcation cost}} + \underbrace{\alpha \text{Days}_{ts} + \beta \text{MKT}_{ts}}_{\text{Carry and systematic return}} + \eta_{ts}, \tag{4}$$

where $r_{ts}$ is the total bond return between two consecutive transactions on days $s$ (the former of the two transactions) and $t$ (the latter). $Q_t$ is the trade direction (1 if clients buy from dealers, -1 if sell to dealers, and 0 for inter-dealer trades), $S_t$ is the dollar-size of the trade, $\text{Days}_{ts}$ is the number of calendar days between $s$ and $t$, and $\text{MKT}_{ts}$ is the total return on the market portfolio between days $s$ and $t$. Two latter factors represent bond-specific carry and systematic return components.[19]

[19] The results are similar when we use Bai et al. (2019) factors rather than the market model to account for a systematic return component.

$\eta_{ts}$ is a mean-zero error term with variance $\sigma^2_{ts}$ that equals to:

$$\sigma^2_{ts} = N^{\text{sessions}}_{ts} \sigma^2_{\text{Sessions}} + D_{ts}\sigma^2_{\delta} + (2 - D_{ts})\,\sigma^2_{\kappa}, \tag{5}$$

where $N^{\text{sessions}}_{ts}$ is the number of trading days between $s$ and $t$, $\sigma^2_{\text{sessions}}$ is the variance of zero-mean idiosyncratic component of bond valuation, $\sigma^2_{\delta}$ is the variance of zero-mean price concessions in inter-dealer trades, and $\sigma^2_{\kappa}$ is the variance of zero-mean idiosyncratic variation in individual bond transaction costs. The variances in (5) are estimated in a pooled bond sample using the same iterated constrained least-squares procedure as in Edwards et al. (2007). Given the estimated variances, the model for individual bonds (4) is re-estimated with weighted OLS using the inverse of $\sigma^2_{ts}$ as the weights.

We use granular rating-maturity buckets to regularize individual-bond transaction cost functions

$$\hat{c}(S) = \hat{c}_0 + \hat{c}_1 \frac{1}{S} + \hat{c}_2 \log S \tag{6}$$

in the cross-section of similar bonds. We consider eight credit rating bins (letter-level grouping from AAA to D, merging ratings from CC to D into one category) and seven maturity bins (breakpoints are 1, 3, 5, 7, and 15 years to maturity) that yield 56 rating-maturity buckets. In each bucket, we evaluate the cross-sectional average transaction cost function by weighting individual bond transaction cost functions with the inverse of the estimated error variance

$$\mathbb{V}\left(\hat{c}(S)\right) = \begin{bmatrix} 1 & \frac{1}{S} & \log S \end{bmatrix} \hat{\Sigma}_c \begin{bmatrix} 1 & \frac{1}{S} & \log S \end{bmatrix}',$$

where $\hat{\Sigma}_c$ is the estimated variance-covariance matrix in (4). For subsequent analysis, we assign the same estimated EHP transaction cost function to all bonds within the same rating-maturity bucket.

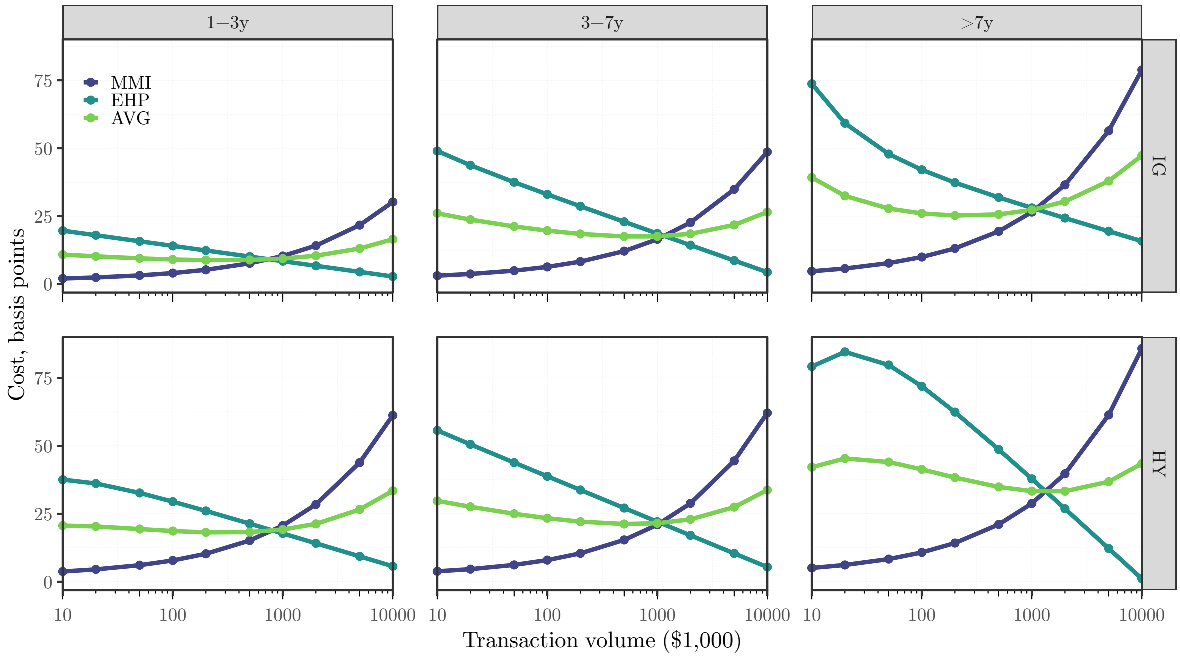


Figure 6: **Average corporate bond transaction cost functions by bond maturity and credit rating.** 'MMI' are microstructure-invariance-implied square-root transaction cost functions. 'EHP' are trade-based transaction cost functions estimated as in Edwards et al. (2007). Horizontal axes have a log scale. 'AVG' is the average between the two. The top row of the charts is for investment-grade bonds (IG); the bottom row is for high-yield bonds (HY). The leftmost column is for the bonds with maturity between 1 and 3 years, the middle – between 3 and 7 years, the rightmost – more than 7 years. 'EHP' estimates are not at the individual bond level but within granular rating-maturity buckets (56 groups: 7 by maturity × 8 by rating). Each bond within a bucket is assigned the same estimated EHP transaction cost function. For presentation purposes, in this figure, 56 buckets are further aggregated into 6 groups.

Figure 6 presents estimated EHP, MMI-implied, and averaged V-shape transaction cost functions. As previously discussed, EHP functions are downward-sloping.[20] EHP and MMI functions yield similar transaction costs for trade sizes around $1 mln. EHP transaction costs are higher for high-yield bonds than investment-grade ones, except for bonds with the longest maturity. Remarkably,

[20]The function in (6) may turn negative. Whenever this happens, we set the EHP component to zero in the weighted V-shape transaction cost function. In other words, we effectively set the V-shape cost for extremely large trade sizes (>$10 mln) to half of the MMI-implied cost.

the EHP model prices small transactions ($10-100 thousand) at 20-75 b.p. (depending on maturity and rating), which is similar to the levels at which MMI prices large bond transactions ($1-10 mln). Aggregating EHP and MMI functions into a compound transaction cost measure (by taking the equally-weighted average of the two) yields a V-shaped relationship between trading volume and transaction cost. It illustrates the hypothesis that a systematic investor (i.e., a liquidity consumer with little discretion about which trades to implement) would benefit from OTC volume discounts only to a certain point, after which further increases in transaction volume would be associated with a growing market impact.

| | DEF | LIQ | REV | CRD | R1D | REQ | MFP | MKT | MIG |
|---|---|---|---|---|---|---|---|---|---|
| (A) Unrestricted turnover | 256.8 | 9.4 | 8.7 | 901.9 | 4.8 | 0.8 | 187.8 | 51896 | 24282 |
| (B) Inst. trades only | 256.8 | 9.4 | 8.7 | 901.9 | 4.8 | 0.8 | 187.8 | 51896 | 24282 |
| (C) As B, and partial rebalancing | 428.5 | 26.9 | 51.6 | 2549.0 | 29.0 | 23.4 | 448.0 | 50338 | 23655 |
| (D) As C, and sampling | 251.8 | 17.4 | 41.5 | 1007.6 | 22.8 | 18.7 | 299.6 | 38938 | 19072 |
| (E) As D, and most actively traded bonds | 453.6 | 25.5 | 84.2 | 2486.4 | 40.3 | 20.7 | 597.7 | 39788 | 18592 |

Table 12: **Capacity of systematic strategies ($ bn) under V-shape T-cost**. Implementation constraints correspond to those in Table 7. The sample period is Jan 2010 – Jun 2019.

Table 12 presents capacity estimates under the V-shape cost. They are considerably higher than those in Table 8. This might be counterfactual because the V-shape cost likely underestimates the cost of large transactions (by averaging between a reasonable MMI-implied cost and a close-to-zero EHP-implied cost). Nonetheless, the V-shape T-cost function might be a reasonable transaction cost approximation for an average-sized institutional bond portfolio that does not rebalance in tens of millions of dollars. The V-shape hypothesis is worth future research.

## Appendix D Case-study of three tech-sector bonds

Individual corporate bond transaction prices can vary substantially within a short period of time, and often there are no informational reasons behind that. Since bonds are traded over-the-counter (OTC), there is a number of market frictions that come into play when prices are determined. Counterparty search frictions (Feldhütter 2012), relationship trading (Hendershott et al. 2020), bond ownership structure (Mahanti et al. 2008) are among the factors of bond prices and liquidity that the literature discusses. In this note, we illustrate transaction price dispersion for several corporate bonds that are similar in headline bond and issuer characteristics and yet differ strikingly in trading activity and trading cost. We then demonstrate that the illiquidity measure suggested by market microstructure invariance (MMI) of Kyle and Obizhaeva (2016) captures time-varying trading conditions in these bonds well.

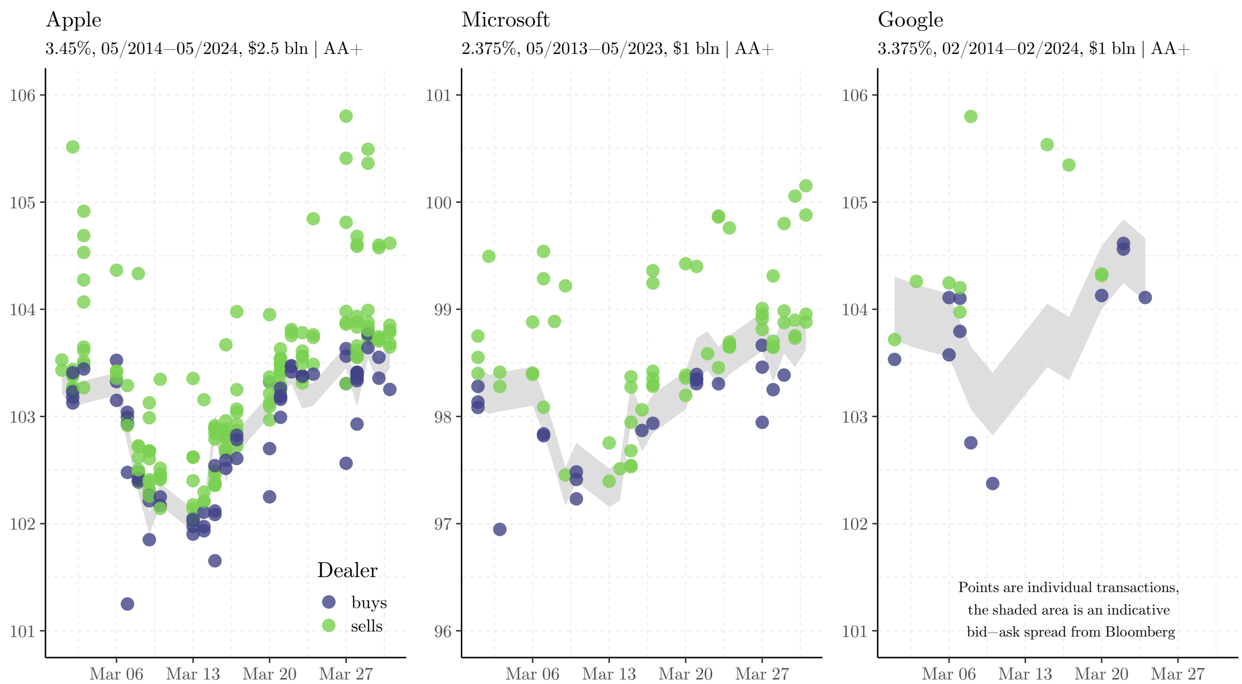


Figure 7: **Bond transaction prices and indicative Bloomberg bid-offers** for three tech sector bonds in March 2017. Clean bond price is on the vertical axis. Points are individual transactions in TRACE. The shaded area is the indicative Bloomberg bid-offer.

Figure 7 presents a snapshot of trading activity in three bonds issued by tech sector firms. The bonds were issued by Apple, Microsoft, and Google (at issuance, now Alphabet), all within one year of each other in 2013–2014. All three bonds had ten years to maturity at issuance and at least $1 bn outstanding amount, which places all three bonds in the top quartile of size distribution in our sample (see Table 1). We plot all customer-to-dealer transactions in these three bonds in March 2017. Bonds were rated AA+ at that time. Moving from the leftmost panel (Apple bond) to the rightmost one (Google), we notice a substantial drop in trading activity. The Apple bond was traded 236 times (excluding inter-dealer trades and trades smaller than $10k in size) in March 2017, the Microsoft bond – 86 times, and the Google bond – 21 times. We rarely observed more than one transaction per trading day for the latter bond. When we did observe both buy and sell transactions of the Google bond on the same day, the difference between the volume-weighted buy and sell prices (which can be viewed as a proxy for a realized bid-ask spread) varied between 20 and 300 b.p. Remarkably, only one business day separated a 20 b.p. realized-bid-ask day from a 300 b.p. one. Speaking of the latter, on Mar 8, 2017, a dealer bought $50k worth of the Google bond at 102.75 and sold the same amount at 105.80. That buy price was the lowest in this bond in the entire month, and the selling price was the highest.

The Microsoft bond was traded considerably more actively in March 2017 than the Google bond. Nonetheless, the realized bid-ask spread in this bond was not necessarily lower than that of the Google bond. The minimum of the realized bid-ask was close to 20 b.p. too, but the average stood at 75 b.p., with the maximum extending to 150 b.p. Such acute transaction price dispersion is visible on the middle plot of Figure 7 on the days when purple and green lines diverge a lot. Indicative Bloomberg bid-offers, also plotted in Figure 7, are several times narrower than the realized bid-ask spreads. This emphasizes a practical importance of higher-quality proxies for bond trading costs (like the MMI-implied estimates) compared to indicative quotes behaving largely as dealers' marketing devices.

The Apple bond, the most actively traded of the three, did not avoid large price differences between the almost-simultaneous buy and sell transactions either. On Mar 27, 2017, dealers were buying the bond, on average, at 103.55 and selling at 104.60, with the minimum buy price being 102.56 and the maximum sell price – 105.41. That was a rather isolated 'illiquidity' event; all other days realized bid-ask in the Apple bond stayed within 5 to 60 b.p. bounds. It showed us, however, that even historically ample trading with tight spreads in a particular corporate bond is not a guarantee of good trade execution in such a bond in the near future.

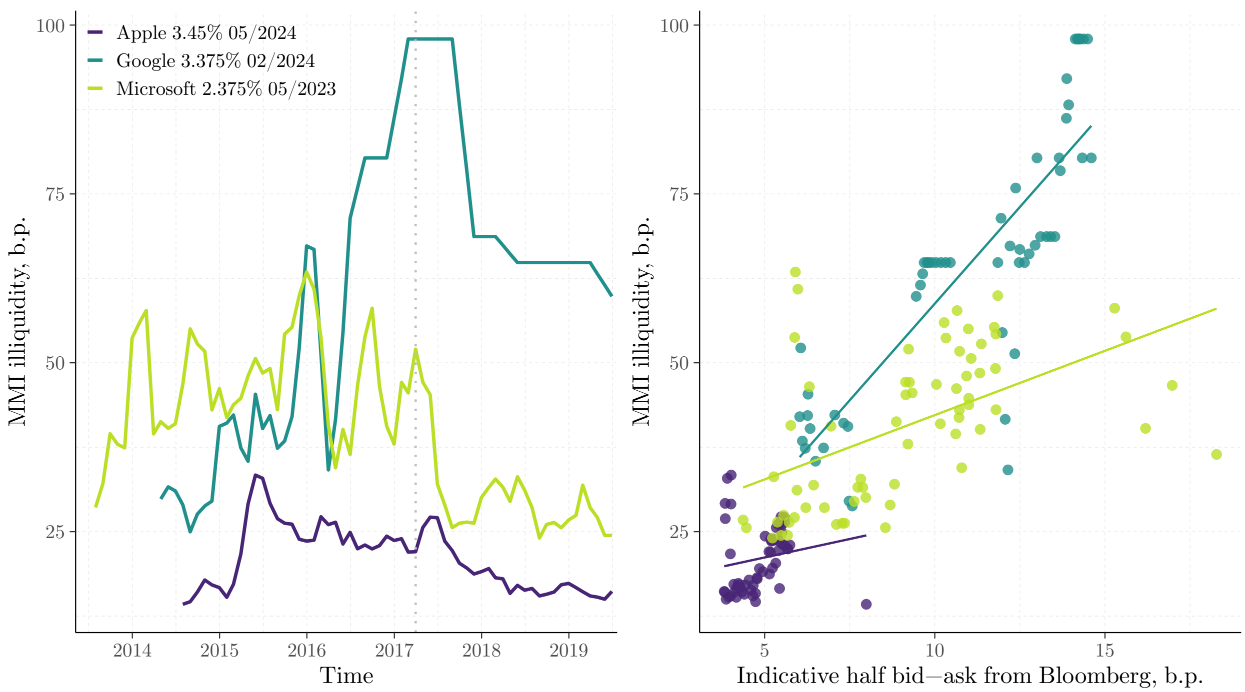


Figure 8: **MMI illiquidity (b.p.)** for three tech bonds of similar credit quality, issue size, and maturity. The vertical line is Mar 2017 which corresponds to Figure 7.

MMI illiquidity in (1) is a monthly bond-specific liquidity characteristic that depends on bond return volatility and average daily trading volume. It represents a total transaction cost (explicit and implicit) of an average-volume trade. The main advantage of the MMI illiquidity over other illiquidity proxies, for the sake of this paper, is a theoretically-founded map from illiquidity to explicit and implicit trading costs as in (2). In Figure 8, we attempt to investigate qualitatively whether the MMI illiquidity dynamic for our three tech bonds is reasonable. The dashed line on the plot refers to Mar 2017, which was analyzed in more detail in Figure 8. At that dashed line, the cost of an average executed trade in the Google bond is close to 100 b.p., which is twice the cost of trading the Microsoft bond. The MMI illiquidity of the Google bond would have been even higher if it was not truncated and replaced with an earlier value, as represented by a horizontal segment of the Google line on the chart.

The Google bond used to have the MMI illiquidity similar to the Microsoft bond until early 2016 – but then the two decoupled. There had been no changes in the outstanding amount or the rating of the Google bond prior to the drop in liquidity; neither had there been any abnormal trading volume. As of the end of 2019, the Google bond has not recovered to the levels of liquidity of 2014–2016. The MMI illiquidity dynamics of two other bonds, on the contrary, look stationary with a level shift (permanent improvement in liquidity) around mid-2017. The Apple bond, with average-volume trade costs of around 20 b.p., remains more liquid than the Microsoft bond in the entire sample period.

Key takeaways from this brief analysis of individual bond MMI illiquidity are as follows. Bonds that look very similar in key issue and issuer characteristics can have considerably different liquidity. MMI illiquidity metric adequately captures liquidity differences both in the cross-section and in the times series for individual bonds. As with many other transaction-price-based liquidity measures, MMI illiquidity is quite volatile for individual corporate bonds. Truncation of extreme observations and smoothing of abrupt illiquidity changes results in reasonably stable MMI illiquidity estimates.

## Appendix E Mutual fund transaction costs

The corporate bond portfolios we analyze in this paper are 'theoretical' and thus may differ considerably from the strategies that bond mutual funds follow in practice. Except for index-tracking funds, the rebalancing rules for actual bond mutual funds are unobserved. Therefore, we are not able to test our transaction cost models on observed corporate bond portfolios. Instead, in this note, we document key cross-sectional characteristics of bond mutual funds and use these characteristics to motivate and justify implementation constraints that we impose in Section 4.

We work with fund holdings from CRSP Mutual Funds dataset. 'Bond funds' are funds with the Lipper objective code A, BBB, HY, SII, SID, or IID, or the CRSP objective code starting with IC (as in Choi et al. 2020). The CRSP MF dataset distinguishes between 'portfolios' and 'funds': there are, in principle, multiple 'funds' per 'portfolio' representing different share classes (they have identical holdings but may differ in costs). We only retain the largest share class (by average AUM calculated over the entire fund life), i.e., there is a unique fund per bond portfolio in our sample. We also restrict our analysis to funds that have, on average, at least 50% of their holdings in TRACE-eligible corporate bonds. The remainder is, most of the time, either US government bonds or non-US instruments. We do not observe the characteristics and returns of those individual non-TRACE securities and disregard them in our analysis. So, we analyze the characteristics of sub-portfolios of TRACE bonds within broader corporate bond funds and assign the characteristics of these sub-portfolios to the entire funds they belong to. The higher the fraction of non-TRACE bonds, the bigger the 'error' we make when we extrapolate TRACE-bond-based characteristics onto entire mutual fund portfolios. Further, we require at least 20 individual corporate bonds among fund holdings. Finally, we only look at monthly-reporting funds to facilitate the comparison with the monthly-rebalanced strategies we consider in the paper.

| | N.obs. | Mean | Median | S.D. | 1st | 5th | 25th | 75th | 95th | 99th |
|---|---|---|---|---|---|---|---|---|---|---|
| AUM, mln $ | 5129 | 927 | 184 | 2436 | 1 | 8 | 48 | 874 | 4089 | 12603 |
| No. bonds | 5139 | 357 | 193 | 595 | 25 | 36 | 107 | 373 | 1029 | 3098 |
| of them, not traded | 5139 | 2 | 1 | 6 | 0 | 0 | 0 | 2 | 10 | 28 |
| Turnover (reported), % per month | 5127 | 5.52 | 4.08 | 5.15 | 0.25 | 0.67 | 2.42 | 6.83 | 15.92 | 24.17 |
| Turnover (estimated), % per month | 4784 | 8.02 | 6.31 | 6.69 | 0.25 | 1.55 | 3.94 | 10.18 | 19.39 | 32.69 |
| MMI illiquidity, b.p. | 5139 | 21.41 | 21.05 | 8.97 | 5.16 | 7.92 | 14.32 | 27.19 | 37.30 | 45.06 |
| Transaction cost (estimated), b.p. per month | 4770 | 5.41 | 1.94 | 13.38 | 0.03 | 0.22 | 0.87 | 4.52 | 18.47 | 78.93 |
| Expense ratio (reported), b.p. per month | 5093 | 5.25 | 5.33 | 2.40 | 0.08 | 0.83 | 3.83 | 6.67 | 9.00 | 11.33 |
| Gross return (estimated), % m-o-m | 5139 | 0.27 | 0.22 | 0.76 | -1.76 | -0.98 | -0.09 | 0.63 | 1.60 | 2.36 |
| Net return (estimated), % m-o-m | 4770 | 0.20 | 0.18 | 0.84 | -2.01 | -1.13 | -0.15 | 0.58 | 1.53 | 2.33 |
| Net return (reported), % m-o-m | 5139 | 0.38 | 0.36 | 1.24 | -2.91 | -1.66 | -0.23 | 1.02 | 2.44 | 3.68 |

(a) Non-ETFs

| | N.obs. | Mean | Median | S.D. | 1st | 5th | 25th | 75th | 95th | 99th |
|---|---|---|---|---|---|---|---|---|---|---|
| AUM, mln $ | 3886 | 3020 | 180 | 7483 | 5 | 9 | 44 | 1257 | 18605 | 36971 |
| No. bonds | 3886 | 830 | 358 | 1033 | 55 | 98 | 206 | 1039 | 2985 | 5057 |
| of them, not traded | 3886 | 7 | 1 | 14 | 0 | 0 | 0 | 5 | 38 | 70 |
| Turnover (reported), % per month | 3886 | 3.54 | 1.83 | 5.17 | 0.08 | 0.33 | 0.92 | 3.83 | 12.17 | 29.92 |
| Turnover (estimated), % per month | 3611 | 8.14 | 5.82 | 8.09 | 0.30 | 0.94 | 3.49 | 9.74 | 24.09 | 40.53 |
| MMI illiquidity, b.p. | 3886 | 24.84 | 25.43 | 10.92 | 5.24 | 6.97 | 16.22 | 32.15 | 43.45 | 48.66 |
| Transaction cost (estimated), b.p. per month | 3607 | 5.38 | 1.27 | 16.66 | 0.03 | 0.11 | 0.53 | 3.14 | 20.04 | 121.51 |
| Expense ratio (reported), b.p. per month | 3886 | 1.85 | 1.67 | 1.13 | 0.42 | 0.58 | 0.92 | 2.33 | 4.17 | 4.58 |
| Gross return (estimated), % m-o-m | 3886 | 0.26 | 0.18 | 0.90 | -2.25 | -1.12 | -0.12 | 0.62 | 1.89 | 2.94 |
| Net return (estimated), % m-o-m | 3607 | 0.11 | 0.16 | 2.13 | -3.80 | -1.41 | -0.19 | 0.61 | 1.83 | 2.93 |
| Net return (reported), % m-o-m | 3886 | 0.31 | 0.25 | 1.15 | -2.92 | -1.59 | -0.23 | 0.87 | 2.28 | 3.68 |

(b) ETFs

Table 13: **Transactions costs of bond mutual funds.** Unit observation is at the portfolio–month level. Fund holdings and performance are from the CRSP Mutual Funds dataset. The sample period is Oct 2004 – Dec 2019. 'Bond funds' here are funds with the Lipper objective code A, BBB, HY, SII, SID, or IID or the CRSP objective code starting with IC, as in Choi et al. (2020). Only funds that a) report monthly, b) allocate at least 50% of their holdings to TRACE-eligible US corporate bonds, and c) hold at least 20 individual bonds are included in the sample. If there are multiple share classes/subfunds for a given fund portfolio, we retain in our sample only the largest subfund (by AUM). Estimated fund returns and turnover are for sub-portfolios of TRACE bonds. They deviate from reported return and turnover the more the lower is the fraction of US corporate bonds in fund holdings.

Table 13 reports cross-sectional (portfolio–month) corporate bond mutual fund characteristics focusing on the metrics of size and implementation costs. We split the sample into exchange-traded funds (part B of the table) and non-ETFs (part A). ETFs are three times larger in terms of assets under management and have two and a half times as many holdings as non-ETFs. The largest ETFs (all are funds replicating broad market indices) have several thousand holdings, and, remarkably, only 1–1.5% of them are non-traded (i.e., there are no dealer–customer transactions in this bond in a month when holding is reported). Our theoretical market portfolios have 15–30% non-traded holdings before implementation constraints (Table 6) and 7–16% after sampling (Table 7). Part of this discrepancy in the number of illiquid holdings between theoretical and actual market funds is due to more elaborate actual index inclusion criteria than what we implement here. We only restrict maturity and outstanding amount, while actual benchmarks often include further eligibility criteria. Some of them may vaguely target liquidity as, for instance, this broad Bloomberg US Corporate Bond Index that excludes '*illiquid securities with no available internal or third-party pricing source*'. Non-ETFs in our dataset also have few non-traded holdings, which suggests that corporate bond funds systematically avoid investing in bonds that are traded very infrequently. Related, actual corporate bond mutual funds with the most illiquid holdings have a weighted MMI illiquidity of 40–50 b.p. Our default, illiquidity, and reversal strategies (Table 7) have a considerably higher average holding illiquidity.

Corporate bond mutual funds (that report monthly) have relatively modest turnover. The average reported turnover stands at 3.5% for ETFs and at 5.5% for non-ETFs. Our estimation of funds' turnover using reported holdings yields an average of 8% per month for both ETFs and non-ETFs, but this number is based only on TRACE bonds. One can reconcile two sets of numbers by assuming that non-TRACE holdings have below-average turnover (which is a realistic assumption given the sizeable cash and money-market positions of many bond funds). Notably, even the funds that trade the most actively report a monthly turnover of around 30%. We get close to these levels in our actively-managed theoretical portfolios with restrictions on retail-sized trades and partial rebalancing (see Part C of Table 7). Low average holding illiquidity of actual bond mutual funds does not mean that the funds are not exposed to idiosyncratic illiquidity risk at all. Figure 9 demonstrates that the least liquid bonds are still found in about 5% of actual portfolios, on average.

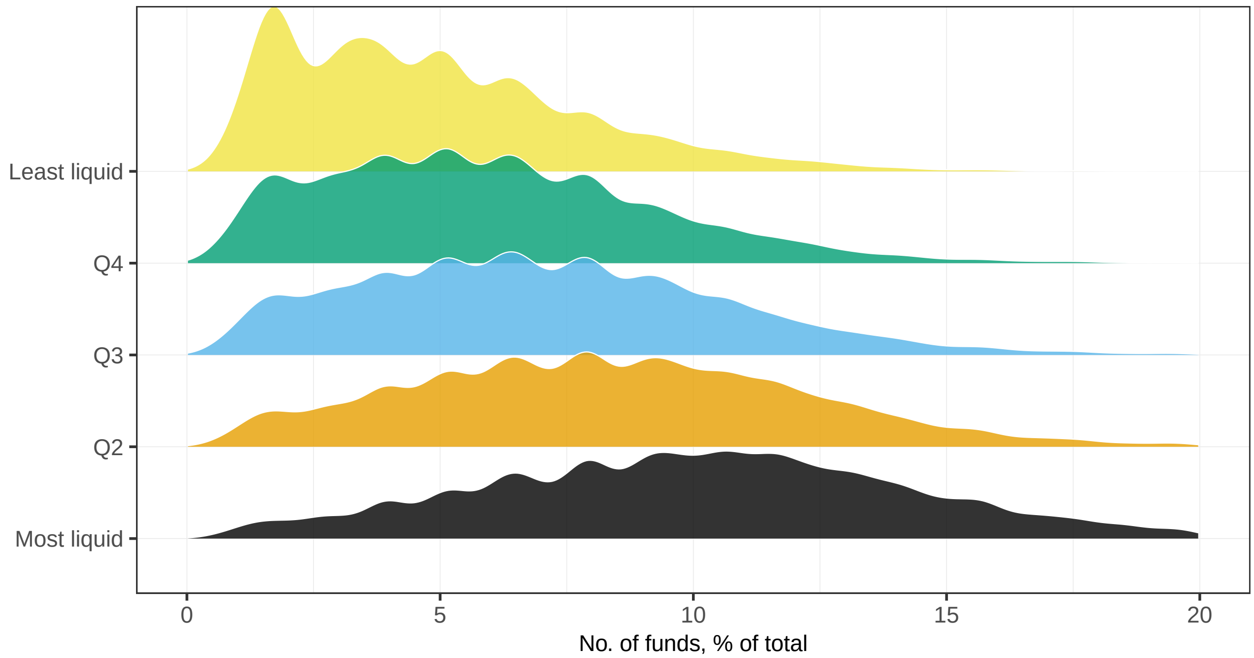


Figure 9: **Number of bond mutual funds that own the bond depending on its illiquidity.** The x-axis is the percentage of the total number of fund portfolios that the bond belongs to (per calendar month). The y-axis is the quintiles of MMI illiquidity.

We estimate transaction costs for actual mutual funds using observed corporate bond holdings and MMI trading costs.[21] For non-ETFs, our estimated transaction costs are close to reported expense ratios, on average, and stand at around 5 b.p. per month. As discussed above, we overestimate turnover, especially in the right tale of the cross-sectional turnover distribution – same mechanically applies to transaction costs. Reported right-tale fund expense ratios are around 10 b.p. for non-ETFs and 5 b.p. for ETFs – we are not able to match these numbers with MMI transaction costs. Likewise, our estimates of net fund returns are lower than the reported ones.

Figure 10 plots how MMI-implied transaction costs vary with the average fund AUM, turnover, or illiquidity of holdings. Here, we average out all variables across time for a given fund, i.e., we plot the cross-section of average portfolio characteristics (unlike in Table 13 and Figure 9 where a unit

[21]Since we only observe TRACE corporate bond transactions we are able to calculate MMI illiquidity only for TRACE bonds which constitute $> 50\%$ but $< 100\%$ of funds holdings. We make an assumption that percentage transaction costs for non-TRACE parts of fund portfolios are equal to those of TRACE sub-portfolios.

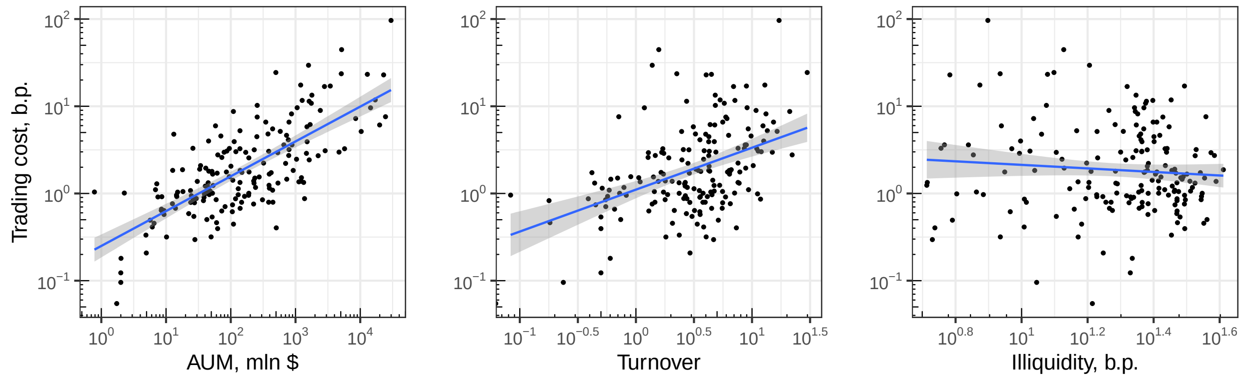


Figure 10: **MMI-implied average trading costs in the cross-section of bond mutual funds.** Each point represents a fund. AUM, turnover, MMI illiquidity, and MMI-implied trading costs are averaged across reporting periods for each individual bond fund. 'Illiquidity' in the rightmost panel is a value-weighted average MMI illiquidity across fund holdings. All scales are in logs.

observation was portfolio–month). Since percentage transaction costs increase with trade size, there is a strong positive relationship between fund size and MMI-implied trading cost. Likewise, funds with high turnover mechanically have higher transaction costs. Interestingly, there is no significant statistical relationship between fund holdings' average illiquidity (weighted) and fund transaction costs. This suggests that portfolios invested in less liquid bonds tend to have smaller sizes and/or lower turnover. In other words, fund managers are optimizing rebalancing schedules to limit the impact of illiquid holdings on fund performance. We attempt to account for such cost-management behavior in our theoretical portfolios with the introduction of rebalancing constraints in Section 4.