# Transaction costs and capacity of systematic corporate bond strategies

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**Abstract**

Can systematic corporate bond investments generate attractive returns net of costs? To answer this question, we apply the principle of market microstructure invariance and obtain bond transaction costs increasing in trade size. As the size of the bond fund increases, the market impact reduces net returns to zero. High-turnover strategies hit capacity constraints fast. Low-turnover credit-risk-focused strategies have much higher capacities that can be further increased by constraining portfolio rebalancing in realistic ways. Transaction costs do not absorb the corporate bond risk premium 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.

In industry, index providers such as MSCI offer multi-factor and ESG corporate bond indices, several large asset managers such as Blackrock, Robeco, and Amundi sell corporate bond ETFs, and asset management companies promote the concept of systematic corporate bond strategies.[1] The electronification of corporate bond trading has reached levels of around 50 percent,[2] and the share of portfolio trading is reaching double digit percentages,[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 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]

Due to the limitations of extant data sets and methodologies, there are at least two important unanswered questions in the corporate bond pricing literature. First, do systematic corporate bond

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

[2] According to the Financial Times article 'Corporate bond trading enters the 20th century'.

[3] According to the Financial Times article 'Bond Trading 3.0'.

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

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 (the relationship between dollar trade size and the percentage cost of executing a trade) 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 trading cost functions estimated on transactional corporate bond data (TRACE) typically have a negative slope (larger trades are cheaper to execute). This poses a problem because, with downward-sloping cost functions, the capacity of any systematic bond strategy (with positive gross returns) is, in principle, infinite. Logically, the larger the fund, the larger the rebalancing trades, and the lower the costs of each transaction would be.

The reason for such 'volume discounts' is that relationship motives often result in large corporate bond trades being priced more favorably. Large investors and investors that trade often receive the best prices from bond dealers. However, in the TRACE data, one never observes investor identity. Pooling trades across unobserved tiers of investors results in volume discounts in TRACE-based cost estimates. The lack of information on intended trades that did not go through because of unfavorable dealer prices further biases the estimates. Using the most recent TRACE data, we confirm the classic result on a negative slope of a bond trading cost function and illustrate it in Figure 1, using the EHP (Edwards et al. 2007) cost function. However, as we show in the paper, the volume discount is at odds with the expense ratios of individual corporate bond mutual funds and trading costs inferred from their reported portfolios. This is indirect evidence that controlling for investor identity, bond trading costs do not decrease monotonically in trade size.[5]

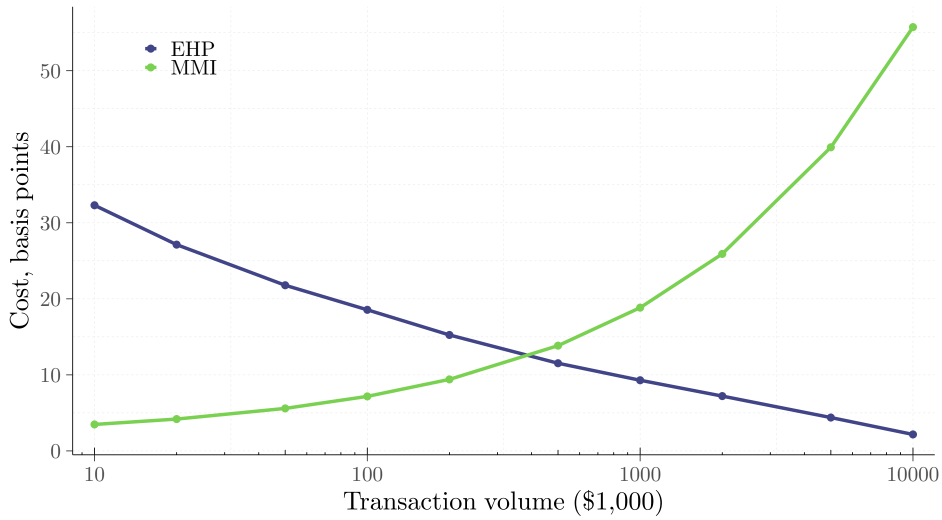


Figure 1: **Average MMI-implied and transaction-based corporate bond trading costs.** The MMI-implied function is a square-root cost of Kyle and Obizhaeva (2016) adapted to individual corporate bonds. The plotted average MMI cost is trading-volume-weighted across bonds. The EHP is a transaction cost 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 Dec 2022. 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 the negative slopes of transactions-based cost functions, 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). We show that such upward-sloping cost functions, unlike the downward-sloping ones, reconcile

[5] Pintér et al. (2024) arrive at a similar conclusion studying a regulatory un-anonymized dataset of OTC transactions in the UK.

corporate bond funds' expense ratios with the trading cost implied by reported fund holdings. Building on the MMI-implied price impacts, we estimate the capacity of systematic bond strategies. We hypothesize that the MMI estimates represent the cost of large trades for an investor who absorbs corporate bond liquidity (without discretion on which trades to execute and which not to execute based on the cost suggested by a bond dealer) better than the TRACE-based ones. An asset manager who follows a rule-based rebalancing strategy is a prime example of such a liquidity price-taker.

Recognizing the limitations of both the MMI and the transaction-based approaches to the evaluation of bond trading costs, we posit a compound cost function by weighting the MMI and the EHP functions differentially across trade sizes. Such a compound cost function has a V-shaped (the cost decreases for trades up to $2m and then increases gradually). We use such V-shaped functions to refine the estimates of net returns and capacity of systematic corporate bond strategies. For capacity estimates, the V-shaped and the MMI cost functions deliver very close results.

To make our results comparable to the existing literature, we follow established portfolio construction approaches to represent systematic bond portfolio strategies. We consider several portfolios that are double-sorted, in different combinations, on historical VaR (Value-at-Risk), credit rating, past return, and liquidity (Dickerson et al. 2023b and Dick-Nielsen et al. 2023 discuss the properties of such portfolios before transaction cost adjustment). We also use the reversal portfolio of Chordia et al. (2017) and its adjusted version of Dickerson et al. (2023c). These two portfolios are constructed with univariate sorts on past bond returns and differ in how the end-of-month transactions are treated. Unlike the empirical bond pricing literature, we consider exclusively *long-only* portfolios. Using the mutual fund industry terminology, a bond investor may view such rule-based long-only portfolios as 'style' or 'smart-beta' portfolios. We also include two broad market portfolios and one multi-factor portfolio in our set of systematic strategies.

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 (≈ high-yield portfolios), default (≈ high drawdown portfolio), then (il)liquidity (long illiquid bonds), followed by several strategies based on 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 is no longer profitable after transaction costs. Our capacity estimates for market portfolios range from $4.5tr to $11tr under both MMI and V-shaped 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 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. Bali et al. (2022) apply machine learning to show superior performance compared to univariate bond-implied predictors. Dickerson et al. (2023b), Dickerson et al. (2023c), and Dick-Nielsen et al. (2023) challenge some of the previous cross-sectional bond pricing literature and argue that candidate long-short bond factor portfolios exhibit smaller and less significant risk premia. Dickerson et al. (2023a) provide a Bayesian perspective on the corporate bond 'factor zoo'. Our contribution to this literature is that we provide net-of-transaction-cost performance and capacity estimates for *long-only* systematic bond portfolios documented in the literature. Without taking a stance on the factor structure in bond returns, we quantify what fraction of return premia associated with candidate portfolios is attainable after implementation frictions are accounted for.

Second, our work is related to the market microstructure and bond transaction costs literature.[6] 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.

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

[6] 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), Kargar et al. (2021), Li et al. (2023) and Cabrol et al. (2023). Specifically on implicit trading costs (market impact), Guo et al. (2022) use the technique of propagator functions to estimate changes in inter-dealer corporate bond prices following dealer-to-customer transactions (which is an alternative definition of the market impact) in the most liquid bonds. They find a positive market impact that decays fast in the number of follow-up trades.

strategies designed to reduce transaction costs and increase capacity. We extend this literature by studying implementation constraints and ways to increase capacity in systematic corporate bond strategies.

The rest of the paper is structured as follows. Section 1 describes the data and the sample. Section 2 reports MMI trading costs vis-a-vis alternative trading cost metrics, studies cost characteristics across individual bonds and bond mutual funds, and constructs a compound V-shaped cost function. In Sections 3 and 4, we discuss net returns and capacity estimates for systematic bond strategies for different trading cost functions and various implementation constraints. Section 5 concludes.

# 1 Bond sample and systematic bond portfolios

## 1.1 Data and sample

We largely follow the previous literature (Dickerson et al. 2023b and earlier work) 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 December 2022. Bond transactions are from TRACE (excluding trades less than $10k notional), bond characteristics – from Mergent FISD, and issuer characteristics (if it is a traded company) – from CRSP and Compustat. Our sample differs from a typical one in the cross-sectional bond pricing literature in two aspects. Firstly, we only sample bonds with an outstanding amount of at least $100m. 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.[7] Secondly, for the evaluation of portfolio returns, we recognize returns of infrequently traded bonds differently.

It is standard in the academic literature to recognize month-$t$ return 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 $t$. We call such an approach 'last-five' in what follows. These are strict criteria for securities that trade as infrequently as US corporate bonds. Our sample of plain-vanilla US corporate bonds contains about 1.6 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 last-five approach reduces the sample to 1.1 million bond-month observations, roughly two-thirds of an original sample of all eligible outstanding bonds.

While the last-five 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 the last-five returns with 'imputed' total expected returns calculated as the bond coupon rate divided by twelve for bond-months with few or no trades.[8] We use imputed returns only for the evaluation of portfolio performance and construct price-based signals using the last-five returns.

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

[8] For portfolio performance without imputed returns, see Table A1 in Appendix.

| | N.obs. | Mean | Median | S.D. | 1st | 5th | 25th | 75th | 95th | 99th |
|---|---|---|---|---|---|---|---|---|---|---|
| Bond return, imputed (%) | 1581352 | 0.45 | 0.48 | 3.49 | -9.67 | -3.64 | -0.31 | 1.12 | 4.54 | 10.47 |
| Bond return, last-five (%) | 1118108 | 0.41 | 0.31 | 3.85 | -10.73 | -4.18 | -0.57 | 1.42 | 5.03 | 11.52 |
| Rating | 1580551 | 8.89 | 8.00 | 3.81 | 1.00 | 4.00 | 6.00 | 10.00 | 16.00 | 21.00 |
| Time to maturity (years) | 1581352 | 10.28 | 6.48 | 10.47 | 1.10 | 1.49 | 3.51 | 14.42 | 28.44 | 36.28 |
| Size ($ mn) | 1581352 | 605.9 | 400.0 | 605.5 | 100.0 | 125.0 | 250.0 | 750.0 | 1750.0 | 3000.0 |
| Coupon rate (%) | 1581352 | 5.66 | 5.65 | 2.12 | 1.20 | 2.38 | 4.12 | 7.00 | 9.25 | 11.12 |
| Downside risk (5% VaR) | 808654 | 3.72 | 2.66 | 4.69 | -3.64 | -0.02 | 1.37 | 4.76 | 11.00 | 25.61 |
| BPW illiquidity | 1104433 | 42.56 | 27.32 | 66.74 | -93.66 | -31.23 | 10.09 | 59.25 | 161.86 | 346.90 |
| MMI illiquidity (b.p.) | 845654 | 50.23 | 44.20 | 30.23 | 9.41 | 14.79 | 28.48 | 65.24 | 103.30 | 153.69 |
| Bond market beta | 805229 | 1.03 | 0.83 | 1.38 | -1.73 | -0.13 | 0.41 | 1.50 | 2.83 | 4.76 |

(a) Pooled bond-month sample: descriptive statistics (Oct 2004 – Dec 2022)

| | Return | Rating | Maturity | Size | VaR | BPW illiq | MMI illiq | Bond beta |
|---|---|---|---|---|---|---|---|---|
| Return | 1 | 0.083 | 0.043 | -0.013 | 0.086 | 0.046 | 0.025 | 0.094 |
| Rating | | 1 | -0.091 | -0.214 | 0.422 | 0.094 | 0.078 | 0.239 |
| Maturity | | | 1 | 0.136 | 0.411 | 0.158 | 0.353 | 0.529 |
| Size | | | | 1 | 0.036 | -0.170 | -0.379 | 0.112 |
| VaR | | | | | 1 | 0.139 | 0.264 | 0.650 |
| BPW illiq | | | | | | 1 | 0.426 | 0.115 |
| MMI illiq | | | | | | | 1 | 0.226 |
| Bond beta | | | | | | | | 1 |

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

Table 1: **Descriptive statistics.** 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 $100m outstanding amount. Bond transactions are from TRACE (excl. trades <$10k), and bond characteristics are from Mergent FISD. Panel A presents full-sample descriptive statistics. The last-five bond return is the return 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 last-five 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. To construct 'imputed' bond returns (top line in the table), we complement last-five return observations by bond carry for bond-months when last-five returns are not available. Credit rating is on a numerical scale (1 is AAA, 2 is AA+, ... , 21 is C). Defaulted bonds drop from the sample the moment their rating is downgraded to D. Size is an outstanding notional amount. 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 a signed square root of an absolute value of the illiquidity measure of Bao et al. (2011), expressed in b.p. A negative observation of BPW illiquidity means that the covariance of daily prices was positive for that bond and 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). The sample period is October 2004 to December 2022. Panel B presents time-series averages of per-month cross-sectional correlations. Return here is the imputed return metric.

Table 1 highlights the difference between the last-five and our measure of imputed bond returns. According to both metrics, an average bond in our sample earns slightly more than 40 b.p. per month. Our measure of returns is less volatile in the cross-section 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. It has an outstanding amount of close to $600m. 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 Table A2 in Dickerson et al. (2023b). 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 et al. (2023) 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.

### 1.2 Rule-based bond portfolios

Throughout the paper, we consider systematic corporate bond portfolios that attracted much attention in the academic literature. All our portfolios are *long-only*,[9] size-weighted (unless specified explicitly), and monthly-rebalanced. Using the mutual fund industry terminology, a bond investor may view such rule-based portfolios as 'style' or 'smart-beta' strategies. The portfolios are:

- MKT – a broad market portfolio (all bonds in the sample, both IG and HY);

[9]Figure A1 in the Appendix shows that the short legs of such portfolios would all lose money in the sample period.

- MIG – a broad investment-grade bond portfolio (all IG bonds with at least \$250m (before Apr 2017) or \$300m (after Apr 2017) outstanding – corresponding to a selection criterion of ICE BofA US Corporate Index);
- CRD – a high credit risk portfolio (lowest credit rating quintile, equally weighted across quintiles of VaR, liquidity, and past return);
- VAR – a high historical drawdown portfolio (top historical VaR quintile, equally weighted across credit rating quintiles);
- LIQ – a high liquidity risk portfolio (top BPW illiquidity quintile, equally weighted across credit rating quintiles);
- MFP – a multi-factor portfolio that combines CRD, VAR, and LIQ in equal proportion;
- REV – a reversal portfolio of past losers balanced across credit classes (bottom quintile of month $t-1$ last-five return, equally weighted across credit rating quintiles);
- R1D – a univariate reversal portfolio (bottom decile of month $t-1$ last-five return);
- REX – an adjusted univariate reversal portfolio (bottom decile of month $t-1$ last-five return calculated excluding the latest trading day for each candidate bond).

The long-short versions of CRD, VAR, LIQ, and REV are discussed in much detail in Dickerson et al. (2023b) and the earlier literature. The R1D and the REX are due to Chordia et al. (2017) and Dickerson et al. (2023c), respectively. The difference between the latter two portfolios is whether the price movement on the latest business day of the sorting month is taken into account or not when estimating the reversal signal.

Finding a better-performing portfolio is not the goal of this paper. We demonstrate how implementation costs affect on-paper profitable bond investment rules, hence a limited number of representative strategies that are commonly used in the extant literature. There are many alternative systematic bond portfolios with significant cum-cost excess return (see, for instance, Israel et al. 2018, Bali et al. 2022, and Bartram et al. 2023). Our findings also apply to those portfolios because they consist of similar bonds and use comparable rebalancing principles.

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 $t$.

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 – Dec 2022).[10] 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 70% for three reversal strategies considered here (i.e., 70% of the portfolio is sold and replaced with new bond holdings every month). The illiquidity portfolio (LIQ) also has a remarkably high turnover of about 43% monthly post-GFC. Portfolios that hold high-VaR and low-rated bonds (VAR and CRD, respectively, in Table 2) have several times lower turnover than the LIQ portfolio, thanks to slow-changing credit ratings and historical drawdown. The multi-factor portfolio MFP that combines VAR, LIQ, and CRD signals delivers relatively limited improvements in turnover and the

[10]In the remainder of the paper, we will use the post-GFC sample (Jan 2010 – Dec 2022) to illustrate our results on the ex-cost performance and capacity of bond strategies. The primary reason behind this is the stability of both bond transaction costs and portfolio-sorting signals post-GFC.

number of bond holdings as compared to equity multi-factor portfolios analyzed in DeMiguel et al. (2020). On average, the combined holdings of three source portfolios are at around 3.7 thousand individual bonds per month. The MFP contains about 3 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.

| | MKT | MIG | CRD | VAR | LIQ | MFP | REV | R1D | REX |
|---|---|---|---|---|---|---|---|---|---|
| Mean return, % month | 0.44 | 0.36 | 0.72 | 0.75 | 0.69 | 0.73 | 0.76 | 0.88 | 0.75 |
| St. dev., % month | 1.62 | 1.64 | 2.18 | 3.03 | 2.28 | 2.47 | 2.50 | 3.18 | 3.12 |
| Sharpe (annualized) | 0.71 | 0.53 | 1.05 | 0.78 | 0.88 | 0.94 | 0.90 | 0.84 | 0.71 |
| Min return, % month | -6.13 | -6.27 | -8.87 | -11.35 | -8.85 | -9.17 | -11.60 | -15.58 | -15.03 |
| Max return, % month | 7.16 | 8.33 | 8.86 | 11.66 | 8.91 | 8.71 | 10.92 | 13.93 | 13.89 |
| Avg. turnover, % month | 1.57 | 1.94 | 13.38 | 10.18 | 43.56 | 20.93 | 72.84 | 70.62 | 72.44 |
| Avg. no. bonds | 7254 | 4460 | 1301 | 931 | 1376 | 2875 | 1397 | 699 | 694 |
| of them, not traded, % | 29 | 16 | 30 | 9 | 22 | 7 | 17 | 39 | 34 |

(a) Full sample (Oct 2004/2007 – Dec 2022)

| | MKT | MIG | CRD | VAR | LIQ | MFP | REV | R1D | REX |
|---|---|---|---|---|---|---|---|---|---|
| Mean return, % month | 0.38 | 0.32 | 0.68 | 0.61 | 0.62 | 0.63 | 0.64 | 0.72 | 0.65 |
| St. dev., % month | 1.50 | 1.55 | 1.57 | 2.62 | 1.99 | 1.99 | 2.35 | 2.98 | 3.01 |
| Sharpe (annualized) | 0.76 | 0.59 | 1.36 | 0.73 | 0.98 | 1.01 | 0.86 | 0.78 | 0.69 |
| Min return, % month | -6.13 | -5.71 | -7.31 | -11.35 | -8.85 | -9.17 | -11.60 | -15.58 | -15.03 |
| Max return, % month | 4.88 | 4.81 | 5.18 | 8.30 | 7.84 | 6.78 | 10.92 | 13.93 | 13.89 |
| Avg. turnover, % month | 1.52 | 1.83 | 13.15 | 9.79 | 43.44 | 20.74 | 75.00 | 72.39 | 73.69 |
| Avg. no. bonds | 7847 | 5157 | 1336 | 968 | 1522 | 2998 | 1535 | 768 | 764 |
| of them, not traded, % | 26 | 15 | 30 | 9 | 24 | 7 | 17 | 38 | 33 |

(b) Post-GFC sample (Jan 2010 – Dec 2022)

Table 2: **Long-only portfolio performance before adjustment for trading costs.** Columns are different systematic portfolio strategies, monthly rebalanced. MKT is a value-weighted market portfolio of all bonds in our sample. MIG is a value-weighted portfolio of investment-grade bonds. CRD, VAR, LIQ, and REV are the long parts of double-sorted bond portfolios, as in Dickerson et al. (2023b). CRD is a long-credit-risk portfolio (lowest-rated bonds across quintiles of VaR, liquidity, and past return). VAR is a long-value-at-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). R1D is a univariate reversal portfolio (lowest decile of past month's bond returns) of Chordia et al. (2017). REX is an analogue of R1D but the reversal signal is adjusted for last-day price movements as in Dickerson et al. (2023c). MFP (a multi-factor portfolio) is an equally-weighted combination of VAR, LIQ, and CRD portfolios. 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. Not-traded bonds are portfolio bonds that do not have a single trade in TRACE in a holding month. A monthly return for such bonds is 'carry' (one-twelfth of the coupon rate). In table a), the earliest return observation for VAR, CRD, and MFP portfolios is Oct 2007, and for other portfolios – Oct 2004. The sample extends to December 2022. In table b) the sample is from Jan 2010 to Dec 2022.

Table 2 also highlights an important characteristic of bond strategies that is rarely discussed in the literature. A substantial number of bonds that are in systematic portfolios as of month $t$ are not traded in month $t+1$. The fraction of such non-traded holdings can be as high as 40%. We have little understanding of their market prices, let alone trading costs in certain months. A systematic investor would nonetheless have to trade in such bonds if the investment rule suggests so.

## 2 Invariance-implied corporate bond transaction costs

In this section, we adapt the transaction cost functions of Kyle and Obizhaeva (2016) to individual corporate bonds and contrast the estimates with alternative approaches. We then reconcile MMI-implied costs with expense ratios of bond mutual funds and suggest a compound bond transaction cost function that blends the MMI and transaction-based estimates.

There is no lack of estimates of a bid-ask spread component of corporate bond transaction cost 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 also needs a price impact component of the 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). Larger trades seem cheaper to execute than smaller trades. Such an effect is often explained by client-dealer relationship motives (Green et al. 2007 and Pintér et al. 2024). Top-tier clients (large and actively trading) receive the best prices from dealers, but the transactions data like TRACE pools transactions from all tiers of clients.[11] Does it imply that a systematic bond investor saves inexhaustibly on price impact 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 increasing for the largest trade sizes (we provide indirect

[11] Unique customer ID is not available even in the regulatory version of TRACE.

evidence for this in Section 2.3). We do not observe either investor identities or sufficiently many high-volume, high-immediacy trades to identify an upward-sloping pricing function.[12] 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

We use the MMI in this paper as a formal tool to compare trade order sizes and associated trading costs. A dollar amount is not an exhaustive characteristic of the trade size. A $1m trade in a security that typically trades in fractions of this amount is allegedly a 'larger' order than the same $1m trade in a security that routinely trades in such dollar amounts, other things equal. Likewise, between two securities always traded in $1m orders, one of them once a day and another one ten times a day, the arrival of a new order is a 'larger' market event in the former rather than the latter security. The example below, similar to the one in Kyle and Obizhaeva (2016) but adapted to corporate bonds, develops the intuition and demonstrates an application to trading costs.

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 meta-orders ('bets' in Kyle and Obizhaeva 2016) independent from each other in this bond each day. Consider a buy order for 750 units of bond $A$, and assume it comes from the $\alpha$-percentile of the bond-$A$ trade size distribution. That is to say, if $\alpha = 90\%$, there is only a 10% chance of encountering an order larger than 750 units. Assume further that the total cost (including the price impact) 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.

[12] Transactions-based T-cost functions in Reichenbacher and Schuster (2022) show a small uptick in costs for trade sizes above $10m, particularly during the COVID crisis.

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:

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

where $Q_\alpha^B$ is the $\alpha-$precentile meta-order in bond $B$. The invariance of risk transfers thus implies that $Q_\alpha^B = 375$ (i.e., there is a $1 - \alpha$ chance to encounter a bond-B order larger than 375 units).

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 dollar amount of risk per unit of security-specific business time. Therefore:

$$\$750\text{'}000 \times 50\text{b.p.} = \$3750 = \$375\text{'}000 \times c_\alpha^B,$$

where $c_\alpha^B$ is the percentile cost of trading \$375'000 of bond $B$. Therefore, $c_\alpha^B = 100$ 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 on invariance principles. We adapt this approach to corporate bonds. In our bond transaction cost functions, we estimate bond-specific parameters with the TRACE data, and we borrow the invariant parameters from the equity market estimates in Kyle and Obizhaeva (2016).

The MMI does not discuss the exact economic mechanism that equates the dollar cost of risk transfer per unit of business time across markets. Intuitively, one would expect MMI-like effects if the preferences of marginal investors across different markets were close to one another. Therefore, we expect the MMI to work better across more integrated markets. The MMI was corroborated originally on large institutional equity portfolio transitions, which points to a class of investors that is likely among the largest corporate bond traders, too.

## 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 first calculate MMI illiquidity measure $1/L_{it}$ as:

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

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 calibrated in Kyle and Obizhaeva (2016) and meant to be invariant across financial markets.[13] $1/L_{it}$ represents the total cost (both the bid-ask spread and the price impact) 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, once 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.

[13] Kyle and Obizhaeva (2020) mention but do not implement a possible adjustment of $C$, which represents a dollar cost of a reference trade, for inflation. We do not adjust $C$ in this study for the overall price level as well because we do not have access to the original equity portfolio transition data data for re-calibration of invariant parameters. Also, the MMI illiquidity is relatively insensitive to small changes in $C$: it would take a 6% increase in $C$ to increase the cost of an average-sized corporate bond transaction by 1 b.p.

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. In this paper, we consider the square-root T-cost function.[14] The MMI-implied percentage cost of trading $\$X$m of bond $i$ in month $t$ is then:

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

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

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. 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.

[14] In the analysis of the cost of equity portfolio transitions in Kyle and Obizhaeva (2016), the square-root model is a better fit to the data.

2. We truncate the 25% highest $1/L_{it}$ observations in the cross-section of bonds separately for each month $t$ (this right tail of illiquidity is predominantly due to very low trading volumes rather than extreme return volatility).[15]

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.

| | Mean | Med. | S.D. | 1st | 5th | 25th | 75th | 95th | 99th | N.obs. |
|---|---|---|---|---|---|---|---|---|---|---|
| Avg. daily volume, if traded, \$ mn | 2.9 | 1.6 | 3.9 | 0.0 | 0.1 | 0.7 | 3.6 | 10.2 | 22.3 | 896122 |
| Daily volatility, b.p. | 79.8 | 57.0 | 81.2 | 7.1 | 12.7 | 30.6 | 100.2 | 217.4 | 429.3 | 896122 |
| MMI illiq.: raw, b.p. | 76.8 | 53.3 | 75.9 | 9.7 | 15.5 | 31.6 | 92.8 | 219.4 | 391.3 | 896122 |
| MMI illiq.: truncated, b.p. | 46.9 | 42.1 | 26.2 | 9.1 | 14.2 | 27.2 | 61.9 | 94.7 | 120.7 | 684859 |
| MMI illiq.: trunc. + LOCF, b.p. | 56.6 | 53.6 | 29.4 | 10.0 | 16.8 | 34.8 | 73.2 | 106.7 | 143.9 | 1153127 |
| Fixed cost, b.p. | 2.8 | 2.6 | 1.4 | 0.5 | 0.8 | 1.7 | 3.6 | 5.2 | 7.0 | 1153127 |
| Price impact, b.p. per $\sqrt{\$1 \text{ mn}}$ | 32.1 | 26.9 | 25.6 | 2.2 | 4.7 | 14.1 | 43.1 | 75.7 | 118.6 | 1153127 |

Table 3: **Cross-sectional statistics of MMI illiquidity and implied transaction costs.** The fixed cost is $\frac{\kappa}{L_{it}}$ and the price impact is $\frac{\lambda}{\sqrt{CL_{it}^3}}$ of equation (2). 'LOCF' stands for 'last observation carried forward' which is the procedure we use to fill in missing or truncated MMI illiquidity readings. The sample is from Jan 2010 to Dec 2022.

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

[15]Figure A2 in Appendix shows the dynamic of the median truncated $1/L_{it}$ vis-a-vis the inter-quartile range (IQR) of the untruncated MMI across bond rating, maturity, and size categories. The figure demonstrates that truncation primarily applies to small-size long-maturity bonds, which is to be expected given their high duration (hence, high return volatility) and low dollar trading volumes. For larger-size, shorter-maturity bonds, the IQR is relatively tight, suggesting little cross-sectional variation in individual-bond MMI illiquidity. Truncation also does not affect the time-series properties of the cross-sectional median $1/L_{it}$: the correlation between the two series is statistically indistinguishable from one. Figure A3 in the Appendix further compares average MMI cost functions across different truncation levels.

volume of about \$3m, 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).[16] An average all-in transaction cost of a bond traded at least five days a month is about 77 b.p. (the median is 53 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 tail of the MMI illiquidity distribution from 220–390 b.p. down to 95–120 b.p. Rolling past illiquidity observations forward into missing and truncated bond-months increases the cross-sectional mean of the illiquidity to 57 b.p. with the right tail values around 105–150 b.p.[17] This yields the average fixed cost (half bid-ask) at a modest 3 b.p., but the price impact stands at 32 b.p. per $\sqrt{\$1\text{ mn}}$ traded.

| | MMI T-cost | | | | | | EHP T-cost | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | IG bonds | | | HY bonds | | | IG bonds | | | HY bonds | | |
| Size (\$1,000) | 1–3y | 3–7y | 7+y | 1–3y | 3–7y | 7+y | 1–3y | 3–7y | 7+y | 1–3y | 3–7y | 7+y |
| 10 | 2.3 | 3.5 | 5.0 | 3.9 | 4.0 | 4.6 | 17.3 | 36.4 | 75.7 | 39.5 | 60.1 | 85.5 |
| 100 | 4.6 | 7.3 | 10.5 | 8.2 | 8.4 | 9.7 | 11.9 | 23.6 | 43.4 | 26.1 | 33.4 | 49.3 |
| 200 | 6.0 | 9.5 | 13.9 | 10.8 | 11.1 | 12.8 | 10.0 | 19.4 | 34.8 | 21.4 | 26.5 | 37.9 |
| 500 | 8.8 | 14.0 | 20.5 | 15.9 | 16.3 | 18.9 | 7.6 | 14.4 | 24.7 | 15.6 | 18.3 | 24.2 |
| 1000 | 11.9 | 19.1 | 28.0 | 21.7 | 22.3 | 25.8 | 6.1 | 11.4 | 19.0 | 12.2 | 13.9 | 17.1 |
| 2000 | 16.4 | 26.2 | 38.7 | 29.9 | 30.7 | 35.5 | 4.7 | 8.6 | 14.4 | 9.2 | 10.3 | 11.8 |
| 5000 | 25.2 | 40.4 | 59.7 | 46.2 | 47.3 | 54.8 | 3.0 | 5.1 | 8.7 | 5.3 | 5.5 | 5.0 |
| 10000 | 35.1 | 56.4 | 83.5 | 64.5 | 66.1 | 76.6 | 1.6 | 2.4 | 4.2 | 2.1 | 1.7 | 0.0 |

Table 4: **Average MMI and EHP trading costs across rating and maturity classes**, in b.p. The MMI cost is the square-root function in equation (2). The EHP cost is the transaction-based estimate similar to Edwards et al. (2007) (see Appendix B for estimation details). Column headers are bond maturity bins: '1–3y' is for bonds between 1 and 3 years to maturity, etc. 'IG' stands for investment-grade, 'HY' – for high-yield. MMI T-costs are calculated by averaging (weighted by the ADV) the parameters of equation (2) across bonds within a given rating-maturity bucket, and then evaluating the costs for each transaction size. The EHP costs are precision-weighted averages within each rating-maturity bucket. The sample is from Jan 2010 to Dec 2022.

[16] 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.

[17] 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.

Table 4 presents how MMI bond trading costs vary with bond credit quality and time to maturity and contrasts MMI costs with transaction-based estimates similar to Edwards et al. (2007).[18] Among investment-grade bonds, long-duration bonds have considerably higher MMI trading costs than short-duration bonds for all transaction sizes. For instance, the MMI cost of trading $1m of a 10-years-to-maturity corporate bond is at 21 b.p. while the same trade costs only 9 b.p. for a 2-year-to-maturity bond. Among high-yield bonds, the largest trading costs are also for the longest-maturity bonds. For trade sizes around $500k (which is close to the average trade size in the TRACE data), the MMI and the EHP costs are at comparable levels, but they diverge at small and large trade sizes. The EHP cost is higher for small than for large trade sizes, as the literature has extensively documented. The MMI cost, on the opposite, is counterfactually low for small trade sizes but increases to 30-80 b.p. for $10-mn-size trades due to a positive price impact embedded in the MMI assumptions. Remarkably, both the MMI and the EHP suggest that it is cheaper to trade long-duration HY than IG bonds.

| | MMI illiquidity | BPW illiquidity | Realized bid-ask | Zero trading days | Equity bid-ask |
|---|---|---|---|---|---|
| MMI illiquidity | 1 | 0.405 | 0.400 | 0.388 | 0.037 |
| BPW illiquidity | | 1 | 0.214 | 0.163 | 0.042 |
| Realized bid-ask | | | 1 | -0.125 | 0.107 |
| Zero trading days | | | | 1 | -0.004 |
| Equity bid-ask | | | | | 1 |

Table 5: **Cross-sectional correlation among bond illiquidity measures**. The correlation matrix is estimated month by month (Jan 2010 – Dec 2022) in the cross-section of bonds, then averaged across months. The MMI illiquidity is as in equation (1) (after 25% truncation but before rolling past values forward). The BPW illiquidity (Bao et al., 2011) is the negative covariance of daily clean-price log returns. The 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 are the % of business days within a month the bond is not traded. Equity bid-ask is from CRSP, averaged within a month (only calculated for bonds issued by public firms). All correlation coefficients in this table are statistically different from zero at a 99% confidence level (Newey-West standard errors) except for the equity bid-ask/zero trading days correlation, which is insignificantly different from zero.

[18]Table A2 in the Appendix provides a more formal analysis of MMI illiquidity in a bond-month panel and finds, in line with the previous literature (Asquith et al., 2013), that corporate bond liquidity deteriorated in post-GFC years. The table also shows that liquidity improves for bonds with higher outstanding amounts.

Table 5 further shows that the MMI illiquidity metric, central to constructing the MMI transaction cost functions, has positive cross-sectional correlations with other bond illiquidity measures (BPW illiquidity of Bao et al. 2011, realized bond bid-ask, the percentage of no-trading days, and equity bid-ask for bond issuers).[19] Remarkably, the MMI illiquidity is twice as strongly correlated with realized bond bid-asks as the BPW illiquidity. Also of interest, the MMI illiquidity has a comparably high correlation with both the 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.[20]

The key takeaway from this comparative analysis is that the MMI illiquidity is a reasonable individual-bond illiquidity metric. 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 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 a counterfactually low cost for small-sized transactions. We address this issue by constructing, in Section 2.4, a compound bond transaction cost function that blends the MMI and the EHP T-costs.

### 2.3 MMI-implied transaction costs and expense ratios of bond funds

To further highlight the practical relevance of the MMI transaction cost, we demonstrate that it yields a positive link between total expense ratios (TER) reported by corporate bond mutual funds

[19]Figure A4 in the Appendix further shows that the time series of market-wide MMI illiquidity is strongly correlated with the market BPW illiquidity.

[20]See Schestag et al. 2016 for exhaustive comparison of bond illiquidity measures beyond MMI.

and their implied trading cost derived from reported portfolio rebalancing. The EHP cost, on the contrary, yields lower implied costs for high-TER funds.

For the analysis in this section, we use fund holdings and fund characteristics reported in the CRSP Survivor-Bias-Free US Mutual Fund Database. We focus on the funds that invest at least 50% of their assets in TRACE bonds that constitute the main bond sample of the paper (Table 1). The sample period here, like in the main analysis of the paper, extends from Jan 2010 to Dec 2022. We derive our estimates of fund trading costs from actual changes in fund holdings between consecutive reporting periods under the MMI and the EHP cost function assumptions. Our objective is to compare implied costs and reported TERs in the cross-section of funds. For this, we calculate time-series averages of costs and TERs for each fund in the sample period.

| | Mean | Med. | S.D. | 1st | 5th | 25th | 75th | 95th | 99th | N.obs. |
|---|---|---|---|---|---|---|---|---|---|---|
| Total net assets, $ mn | 1137 | 136 | 3710 | 4 | 9 | 39 | 629 | 4066 | 22540 | 279 |
| Monthly turnover, % | 7.7 | 6.7 | 3.9 | 1.1 | 3.2 | 5.0 | 9.4 | 14.1 | 23.1 | 279 |
| Monthly expense ratio, b.p. | 3.7 | 3.3 | 2.6 | 0.8 | 0.8 | 1.5 | 5.4 | 8.3 | 11.4 | 279 |
| MMI cost, b.p. per month | 12.0 | 2.4 | 24.6 | 0.0 | 0.3 | 0.8 | 10.3 | 50.2 | 148.0 | 279 |
| EHP cost, b.p. per month | 3.2 | 2.9 | 2.0 | 0.3 | 0.5 | 1.6 | 4.6 | 7.1 | 8.6 | 279 |
| Monthly return, % | 0.1 | 0.2 | 0.4 | -1.0 | -0.4 | 0.0 | 0.3 | 0.6 | 1.1 | 279 |
| No. reporting periods | 61 | 49 | 40 | 10 | 12 | 27 | 86 | 140 | 144 | 279 |

Table 6: **Summary statistics of the cross-section of corporate bond funds**. Fund characteristics and holdings are from the CRSP Survivor-Bias-Free US Mutual Fund Database. The fund sample consists of funds with Lipper's objective codes 'A', 'BBB', 'HY', 'SII', 'SID', and 'IID' that a) invest at least 50% of their assets in bonds that constitute the main sample of the paper (Table 1), b) report above-zero TERs, and c) have reported holdings at least ten times within the sample period, which is from Jan 2010 to Dec 2022. The reporting frequency for holdings is either monthly (approx. 75% of funds) or quarterly. For each fund, we calculate the MMI and the EHP transaction costs implied by reported holdings (for funds reporting on a quarterly basis, we divide the cost by 3 to get a monthly estimate). We assume that the transaction cost for non-TRACE portfolio holdings is the average of the fund's TRACE bonds T-costs. For each fund, we then calculate the time-series averages of variables of interest to yield a cross-section of fund characteristics presented in this table.

Table 6 summarizes the cross-section of funds. A median fund in the sample has about $140 mn net assets (the mean is considerably larger at $1.2 bn), and its monthly turnover is close to 7%. The median fund's TER is approximately 40 b.p. per year (3.3 b.p. per month). A quarter of the sample funds report average net returns at or below zero. The implied MMI and EHP costs for the median fund are similar and stand at around 30-35 b.p. per year (2.4 and 2.9 b.p. per month, respectively). The average MMI cost is considerably higher than the EHP-implied one amid a large difference in implied cost estimates in the right tails of the MMI and the EHP cost distributions. Such difference is expected given the divergence of the two cost functions for the largest trade sizes reported in Table 4.

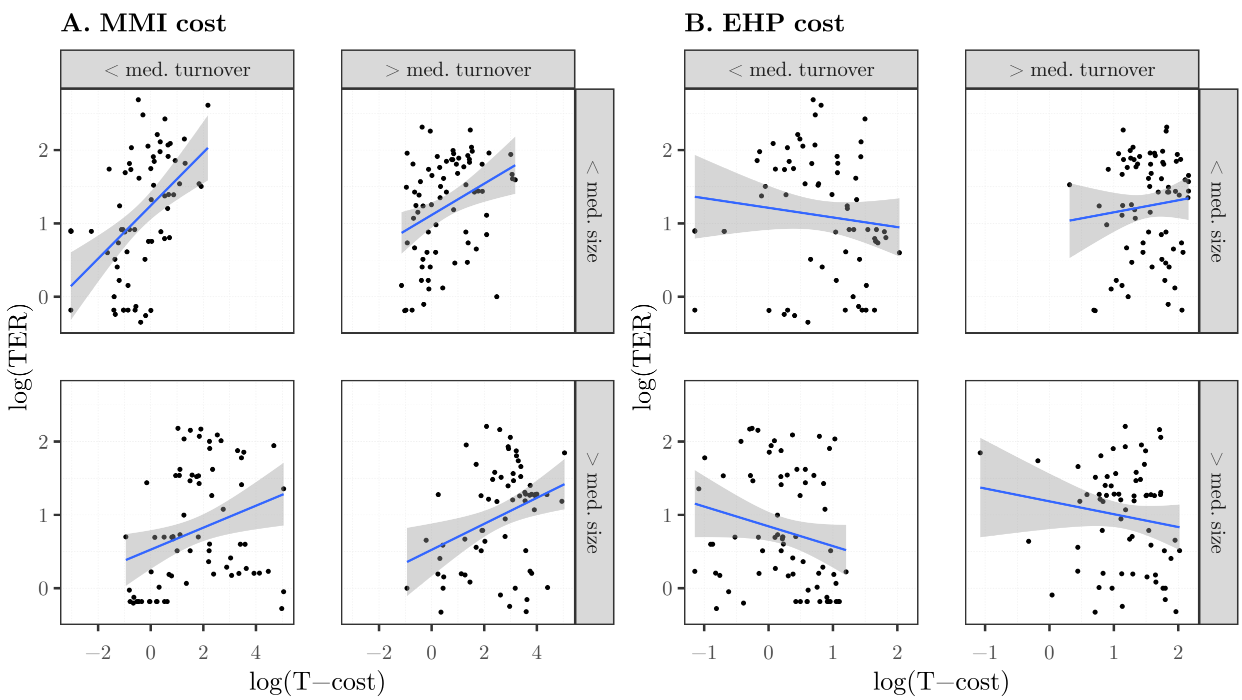


Figure 2: **Average implied fund T-costs and reported TERs**. Here, a dot is a bond mutual fund. The blue lines are linear regressions, and the shaded areas are 95% confidence bands. Both costs and expense ratios, before taking the log, are per month, and in b.p. Panel A is for the square-root MMI-implied transaction cost of equation (2). Panel B is for the EHP cost (see details in Appendix B. The median monthly turnover is 6.7% per month. The funds with below-median turnover are in the left-hand-side plots in Panels A and B. The median size is \$136m. The funds of below-median size are in the top row. The sample is from Jan 2010 to Dec 2022.

In Figure 2, we plot average implied fund trading costs vis-a-vis reported fund TERs. Since both costs and TERs are positive by construction, we apply the log transformation. We further split the funds into four categories based on their size and turnover using median values from Table 6 as the cutoffs.[21] Economically, the funds are closer to one another within than between the four size-turnover categories. The MMI cost assumption yields a positive link between average fund trading costs and expense ratios within all size-turnover categories, as Panel A in Figure 6 shows. The EHP cost implies a negative link between costs and TERs in all but one size-turnover category, and in neither category is the relation statistically significant. It is plausible, in equilibrium, to expect a positive relation between the trading cost and the TER, especially in such an illiquid and costly-to-trade asset class as corporate bonds. Therefore, the MMI, unlike the EHP, yields a result well aligned with economic intuition.[22]

Is there a contradiction between transaction-based EHP costs being downward-sloping and upward-sloping MMI costs being a better fit to mutual fund TERs? Both facts are consistent with each other. Per-bond EHP estimates are derived from transactions pooled across heterogeneous investors. It is very likely that small and large transactions in the pooled sample are not executed by the same investor. Larger investors get better execution, hence the 'volume discount' in EHP cost estimates. Yet, each investor possibly observes a positive price impact when she attempts to trade larger lots. If this is the case, then the MMI must indeed provide a better fit to the cross-section of fund TERs – and it does.

### 2.4 Compound transaction cost function

Each of the trading cost evaluation approaches discussed above has its advantages and disadvantages. The EHP costs are data-driven and likely capture the costs of small bond trades well but lack an increasing price impact for large trade sizes. The MMI costs yield an increasing price impact by construction and help explain the cross-section of corporate bond mutual funds expense

[21] In unreported results, in a pooled sample, we find that the MMI still yields a stronger positive link between the implied cost and the reported TER than the EHP measure, but both lack statistical significance.

[22] Yan (2020) establishes that corporate bond funds' alpha is hump-shaped in fund size, which is consistent with the evidence presented in this section.

ratios, but are at odds with the data for small trade sizes. To enhance the practical relevance of our net-of-cost bond performance evaluation, we posit a compound transaction cost function that blends the advantages of both the EHP and the MMI approaches.

Our compound transaction cost function, also called the 'V-shaped cost' in the rest of the paper, is a weighted average of the MMI and the EHP cost functions. For a given trade size $X$ (in \$m), the V-shaped cost is:

$$C^{\%,\text{V-shaped}}(X) = \left(1 - e^{-\frac{X}{\gamma}}\right) C^{\%,\text{sqrt}}(X) + e^{-\frac{X}{\gamma}} C^{\%,\text{EHP}}(X), \tag{3}$$

where $\gamma$ is the constant to be calibrated. We set $\gamma = 7$ in the rest of the paper.[23] Under such parametrization, the weight of the EHP component in the compound cost decreases from 0.98 at \$100k transaction size to 0.86 at \$1m. The two components have approximately equal weights at \$5m, and at \$10m, the MMI dominates with a weight of 0.75. Individual-bond EHP cost estimates are sensitive to the idiosyncratic estimation noise. Following the original approach of Edwards et al. (2007), we consider EHP costs averaged across bonds of similar maturity, rating, and outstanding amount. Therefore, in equation (3), the MMI component is bond-specific, while the EHP component is specific to a maturity-rating-size bin.

Figure 3 traces the cost functions for maturity-rating-size bins. For trades up to \$1m, the V-shaped cost is only negligibly different from the EHP cost. For these trade sizes and within all maturity-rating-size bins, there is a 'volume discount': it is cheaper to trade \$1m than \$100k. For trade sizes larger than \$1m, the weight of the MMI component increases and ultimately yields an upward-sloping cost function for trades above \$2m. At \$10m, the V-shaped cost of trading (one

[23] Our choice is guided by feedback from industry participants and an anonymous referee on the realistic levels of transaction costs at different trade sizes. The estimation of $\gamma$ would require trading or implementation shortfall data from a large bond investor (ideally, including considered transactions that did not go through). We do not have access to such data but would be delighted to collaborate with an industry participant if the opportunity arises.

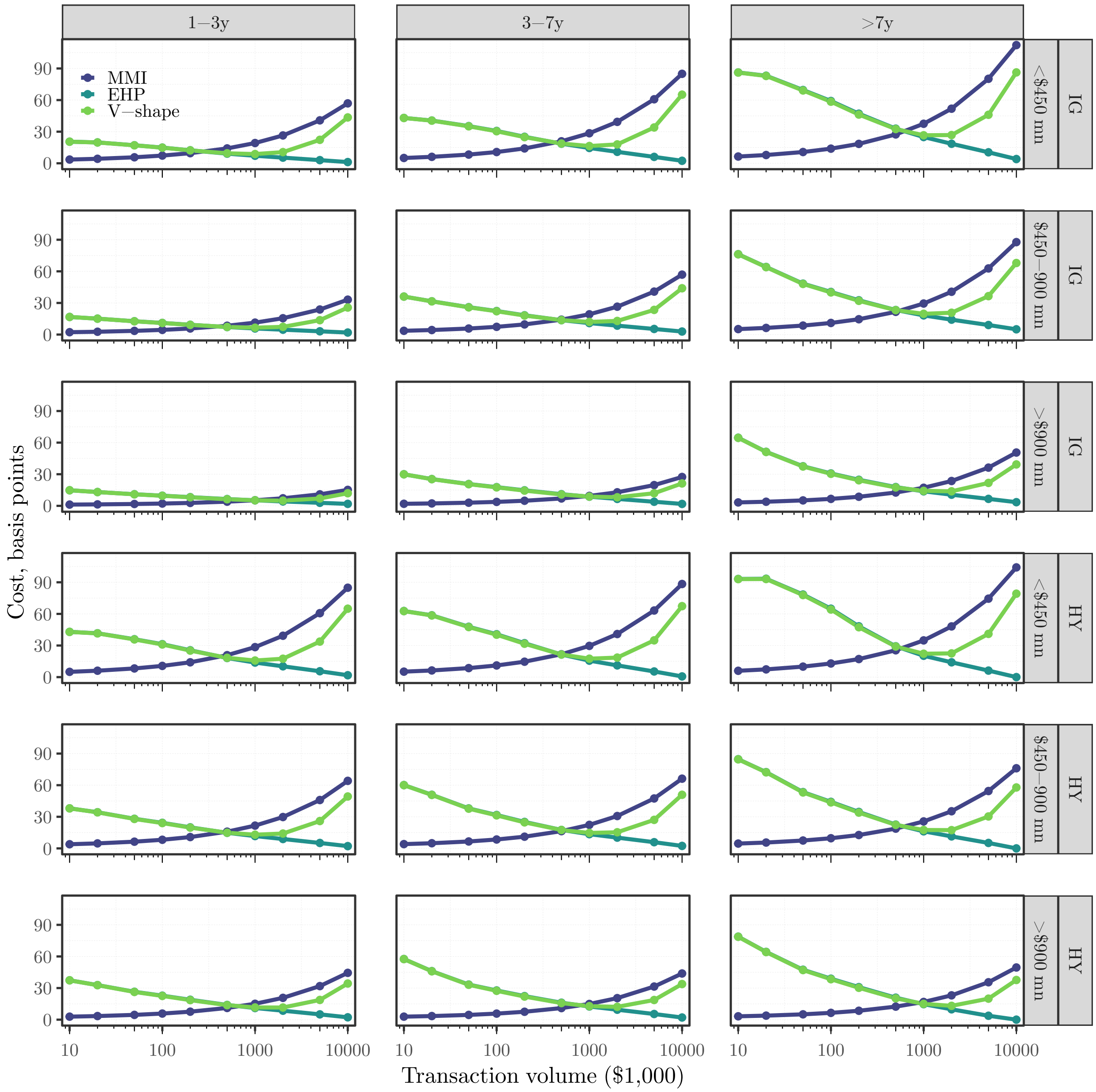


Figure 3: **Corporate bond transaction cost functions by bond maturity, credit rating, and size.** 'MMI' are microstructure-invariance-implied square-root transaction cost functions. 'EHP' are trade-based transaction cost functions estimated as in Edwards et al. (2007). 'V-shaped' is the weighted average between the MMI and the EHP, calculated as in (3). The transaction volume on the horizontal axes is in $ th, and the axes have a log scale. Bond maturities (1 to 3, 3 to 7, and above 7 years) differ across columns of figures. Credit class (investment-grade, 'IG', and high-yield, 'HY') and the outstanding amount vary across rows. The EHP functions are precision-weighted averages of individual-bond estimates in each maturity-rating-size bin (see Appendix B for the details). The MMI functions are volume-weighted averages of individual bond estimates.

way) a short-maturity investment-grade bond with a large outstanding amount is at around 15 b.p. – about six times smaller than the cost of trading the same amount of a long-maturity small-size IG bond. For a given trade size, in line with the economic intuition, the costs (both EHP and MMI, and the V-shaped by extension) increase with maturity and credit risk, and decrease with the bond outstanding amount.

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

We now turn to the evaluation of the net-of-cost performance of systematic bond strategies from Table 2. At this stage, we do not impose any additional rebalancing restrictions and assume that every single end-of-month rebalancing trade suggested by the strategy is carried out and, thus, bears a full transaction cost. 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.

Table 7 presents the results for a monthly-rebalanced fund that is fully invested in one of the systematic portfolios and has \$500m assets under management.[24] As expected, high-turnover reversal and illiquidity strategies suffer the most from trading cost adjustment. Their Sharpe ratios drop several times relative to a cum-cost case. LIQ portfolio fares better than other strategies in this category with a net-of-cost Sharpe ratio near 0.5. The reversal strategy adjusted for the microstructure noise (REX) performs the worst of the group with Sharpe ratios between 0.12 (MMI cost) and 0.28 (EHP cost). The fact that the MMI cost for the REX is considerably higher than the EHP cost suggests that a typical rebalancing trade of the strategy is larger than \$500k (at this trade size, the MMI and the EHP costs are close to one another).

[24]Figure A5 in the Appendix plots cumulative net returns over time.

| | MKT | MIG | CRD | VAR | LIQ | MFP | REV | R1D | REX |
|---|---|---|---|---|---|---|---|---|---|
| (A) Ex-cost: MMI T-cost | | | | | | | | | |
| Mean return, % month | 0.38 | 0.31 | 0.64 | 0.55 | 0.31 | 0.55 | 0.29 | 0.22 | 0.16 |
| St. dev., % month | 1.50 | 1.55 | 1.57 | 2.61 | 1.96 | 1.98 | 2.33 | 2.96 | 2.99 |
| Sharpe (annualized) | 0.76 | 0.58 | 1.28 | 0.66 | 0.46 | 0.87 | 0.35 | 0.19 | 0.12 |
| Min return, % month | -6.14 | -5.71 | -7.40 | -11.39 | -9.18 | -9.26 | -12.03 | -16.01 | -15.50 |
| Max return, % month | 4.87 | 4.80 | 5.08 | 8.22 | 7.10 | 6.54 | 10.29 | 13.33 | 13.23 |
| (B) Ex-cost: EHP T-cost | | | | | | | | | |
| Mean return, % month | 0.37 | 0.30 | 0.59 | 0.55 | 0.35 | 0.48 | 0.26 | 0.37 | 0.30 |
| St. dev., % month | 1.50 | 1.55 | 1.57 | 2.62 | 1.98 | 1.99 | 2.35 | 2.98 | 3.02 |
| Sharpe (annualized) | 0.73 | 0.56 | 1.18 | 0.66 | 0.51 | 0.74 | 0.30 | 0.37 | 0.28 |
| Min return, % month | -6.15 | -5.72 | -7.43 | -11.39 | -9.10 | -9.32 | -11.90 | -15.85 | -15.31 |
| Max return, % month | 4.86 | 4.79 | 5.05 | 8.21 | 7.36 | 6.49 | 10.55 | 13.65 | 13.59 |
| (C) Ex-cost: V-shape T-cost | | | | | | | | | |
| Mean return, % month | 0.37 | 0.30 | 0.59 | 0.54 | 0.33 | 0.48 | 0.25 | 0.33 | 0.26 |
| St. dev., % month | 1.50 | 1.55 | 1.57 | 2.62 | 1.98 | 1.99 | 2.35 | 2.98 | 3.01 |
| Sharpe (annualized) | 0.73 | 0.56 | 1.18 | 0.65 | 0.49 | 0.74 | 0.28 | 0.32 | 0.23 |
| Min return, % month | -6.15 | -5.72 | -7.43 | -11.39 | -9.12 | -9.32 | -11.93 | -15.89 | -15.36 |
| Max return, % month | 4.86 | 4.79 | 5.05 | 8.20 | 7.32 | 6.49 | 10.49 | 13.60 | 13.53 |
| (D) Memo: cum-cost characteristics | | | | | | | | | |
| Gross return, % per month | 0.38 | 0.32 | 0.68 | 0.61 | 0.62 | 0.63 | 0.64 | 0.72 | 0.65 |
| Gross st. dev., % per month | 1.50 | 1.55 | 1.57 | 2.62 | 1.99 | 1.99 | 2.35 | 2.98 | 3.01 |
| Gross Sharpe (annualized) | 0.76 | 0.59 | 1.36 | 0.73 | 0.98 | 1.01 | 0.86 | 0.78 | 0.69 |
| Avg. turnover, % month | 1.52 | 1.83 | 13.15 | 9.79 | 43.44 | 20.74 | 75.00 | 72.39 | 73.69 |
| Avg. no. bonds | 7847 | 5157 | 1336 | 968 | 1522 | 2998 | 1535 | 768 | 764 |
| of them, not traded, % | 26 | 15 | 30 | 9 | 24 | 7 | 17 | 38 | 33 |

Table 7: **Long-only portfolio performance after trading costs (AUM $500m).** The strategies are as in Table 2. The trading costs are MMI, EHP, and V-shaped in panels A, B, and C, respectively. Panel D presents the characteristics of the strategies prior to trading cost adjustment. The fund is of an unchanged size of $500m. The Sharpe ratio is based on excess returns relative to the 3-month Treasury yield. The sample is from Jan 2010 to Dec 2022.

Table 7 reports a milder drop in Sharpe ratios due to trading cost adjustment for credit (CRD) and value-at-risk (VAR) portfolios compared to reversal portfolios. Both strategies generate net Sharpe ratios above 0.6, with CRD being above 1. 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 blend of LIQ, CRD, and VAR 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 portfolios 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 portfolio.

Market portfolios (MKT and MIG) of $500m AUM generated net risk-adjusted performance comparable to riskier VAR and MFP portfolios thanks to a low turnover that stands at around 1.5-1.8% per month. At such a turnover level and for such fund size, the impact of transaction costs on performance is negligibly small, even if smaller rebalancing trades are priced unfavorably, as in the EHP and the V-shaped T-cost models.

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. Hence, the more no-trading months 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 A1 in the Appendix demonstrates how net risk-adjusted 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 net Sharpe ratio of the CRD portfolio drops by roughly a quarter to 0.9.

Figure 4 depicts the scalability of systematic corporate bond strategies under the MMI transaction cost. 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 4 shows that the capacity of reversal strategies with no turnover constraints is relatively

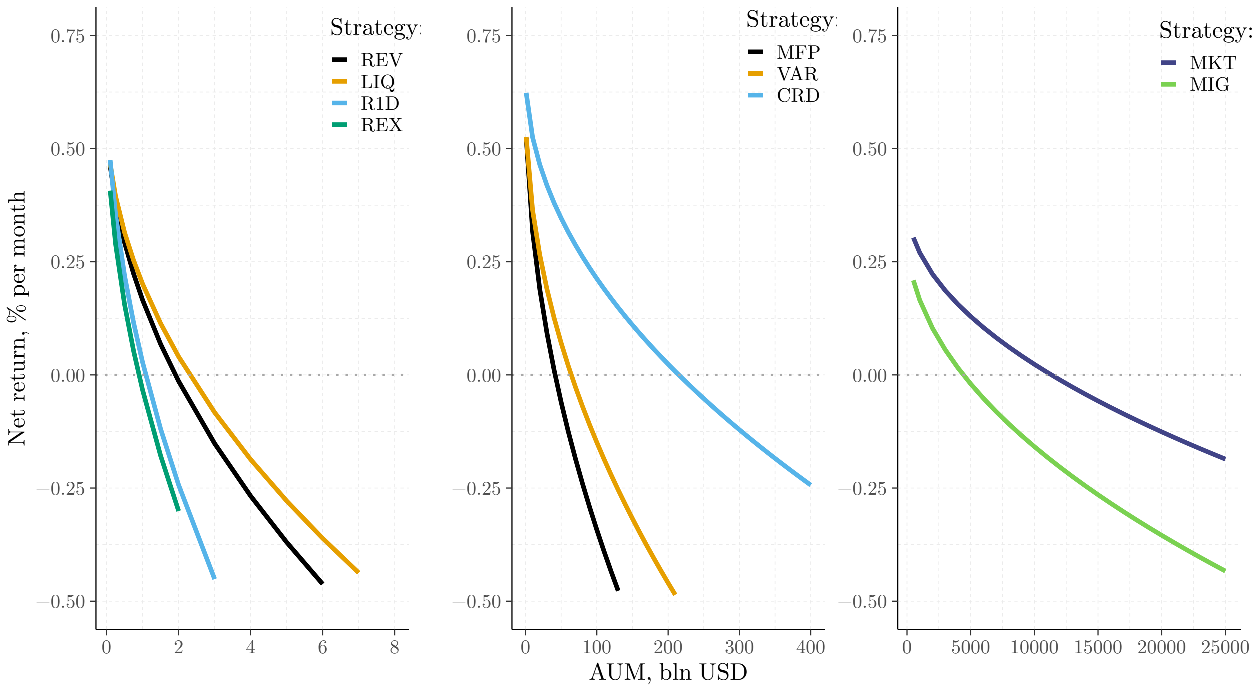


Figure 4: **Net systematic corporate bond return under MMI T-cost and varying fund size.** The x-axis is the AUM, in $ bn. The y-axis is the average net-of-cost portfolio return. There are no turnover constraints imposed on the systematic strategies on this plot. The underlying trading cost is in equation (2) and varies across bonds and months. The sample period is Jan 2010–Dec 2022.

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 that the funds trade and rebalance identically and at the same time.[25] VAR and CRD strategies are considerably more scalable, with capacity extending to $65 and $215 bn, respectively. The capacity of market strategies is at around $4.4-$11.3tr (MIG and MKT, the latter being higher), which is above the total notional amount of bonds in respective portfolios. The difference between capacity constraints under the MMI and the V-shaped cost assumptions (reported explicitly in the next section) is negligibly small because only the MMI component of the V-shaped function generates a price impact that grows with trade size and hence implies a capacity limit of a strategy.

[25]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.

# 4 Implementation constraints and capacity

In this section, we make theoretical portfolios more realistic by imposing practically-motivated bond selection and rebalancing criteria. We describe such implementation constraints in the first part of the section. In the second part, we solve for the capacity limit of constrained strategies.

## 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 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 $100k) 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 outweigh 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).

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 $100m 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.Since bond portfolios in this paper are not equally weighted, 50% of the 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. 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 single outsized transaction does not make the bond liquid. Here, we restrict our portfolios to bonds traded for at

least five business days in the previous month. A fund manager can easily implement such selection criteria by observing real-time TRACE reports.

The mechanics of rebalancing restrictions are 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 the target of 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. The target portfolios change for 'sampling' and 'selection on past trading activity'. 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.

Table 8 presents key portfolio performance characteristics by sequentially adding implementation constraints to our benchmark $500m AUM systematic funds. Part B of Table 8 restricts trade size to institutional (the unrestricted performance is in Part A). No retail-sized rebalancing means that the smallest new holdings are not making it into the portfolio. Therefore, the portfolios most affected by this constraint (in terms of holdings) are the ones that originally had many such small positions: MKT and MIG. For instance, the average number of bond holdings in the broad market portfolio (MKT) drops from 8,000 to approximately 3,000 after the restriction on retail-sized rebalancing. The turnover of market portfolios also drops, but it has only a marginal impact on the performance

| | MKT | MIG | CRD | VAR | LIQ | MFP | REV | R1D | REX |
|---|---|---|---|---|---|---|---|---|---|
| (A) Unrestricted portfolios | | | | | | | | | |
| Avg. turnover, % month | 1.52 | 1.83 | 13.15 | 9.79 | 43.44 | 20.74 | 75.00 | 72.39 | 73.69 |
| Mean MMI illiquidity, b.p. | 46.48 | 45.32 | 46.87 | 64.09 | 78.09 | 62.86 | 56.61 | 63.53 | 62.42 |
| Gross mean return, % month | 0.38 | 0.32 | 0.68 | 0.61 | 0.62 | 0.63 | 0.64 | 0.72 | 0.65 |
| Net mean return, % month | 0.37 | 0.30 | 0.59 | 0.54 | 0.33 | 0.48 | 0.25 | 0.33 | 0.26 |
| Gross Sharpe (annualized) | 0.76 | 0.59 | 1.36 | 0.73 | 0.98 | 1.01 | 0.86 | 0.78 | 0.69 |
| Net Sharpe (annualized) | 0.73 | 0.56 | 1.18 | 0.65 | 0.49 | 0.74 | 0.28 | 0.32 | 0.23 |
| Avg. no. bonds | 7847 | 5157 | 1336 | 968 | 1522 | 2998 | 1535 | 768 | 764 |
| of them, not traded, % | 26 | 15 | 30 | 9 | 24 | 7 | 17 | 38 | 33 |
| (B) Inst. trades only | | | | | | | | | |
| Avg. turnover, % month | 1.40 | 1.52 | 9.74 | 8.62 | 40.86 | 10.12 | 69.93 | 71.57 | 72.94 |
| Mean MMI illiquidity, b.p. | 42.78 | 43.67 | 46.98 | 64.39 | 78.24 | 62.97 | 57.05 | 63.59 | 62.48 |
| Gross mean return, % month | 0.39 | 0.32 | 0.67 | 0.62 | 0.62 | 0.60 | 0.63 | 0.72 | 0.65 |
| Net mean return, % month | 0.38 | 0.32 | 0.62 | 0.57 | 0.36 | 0.53 | 0.28 | 0.34 | 0.26 |
| Gross Sharpe (annualized) | 0.76 | 0.61 | 1.36 | 0.75 | 0.98 | 1.02 | 0.88 | 0.79 | 0.69 |
| Net Sharpe (annualized) | 0.75 | 0.60 | 1.24 | 0.68 | 0.53 | 0.90 | 0.35 | 0.33 | 0.24 |
| Avg. no. bonds | 2985 | 2818 | 1329 | 980 | 1493 | 3288 | 1630 | 769 | 770 |
| of them, not traded, % | 44 | 13 | 33 | 11 | 26 | 25 | 23 | 27 | 24 |
| (C) As in B, and partial rebalancing | | | | | | | | | |
| Avg. turnover, % month | 1.39 | 1.53 | 5.95 | 6.57 | 22.25 | 10.51 | 28.28 | 28.54 | 28.65 |
| Mean MMI illiquidity, b.p. | 42.80 | 43.66 | 46.48 | 63.90 | 73.76 | 62.21 | 56.66 | 63.35 | 61.16 |
| Gross mean return, % month | 0.39 | 0.32 | 0.67 | 0.59 | 0.57 | 0.62 | 0.57 | 0.66 | 0.60 |
| Net mean return, % month | 0.38 | 0.32 | 0.64 | 0.56 | 0.45 | 0.56 | 0.46 | 0.54 | 0.48 |
| Gross Sharpe (annualized) | 0.76 | 0.61 | 1.32 | 0.71 | 0.93 | 1.00 | 0.87 | 0.85 | 0.75 |
| Net Sharpe (annualized) | 0.75 | 0.60 | 1.26 | 0.66 | 0.72 | 0.89 | 0.70 | 0.68 | 0.59 |
| Avg. no. bonds | 2985 | 2793 | 1178 | 851 | 924 | 2248 | 776 | 437 | 436 |
| of them, not traded, % | 44 | 13 | 37 | 14 | 45 | 34 | 43 | 49 | 43 |
| (D) As in C, and sampling | | | | | | | | | |
| Avg. turnover, % month | 1.39 | 1.60 | 7.26 | 7.06 | 22.90 | 11.15 | 28.72 | 28.64 | 28.74 |
| Mean MMI illiquidity, b.p. | 41.93 | 40.13 | 42.74 | 60.60 | 72.31 | 60.83 | 53.31 | 60.79 | 56.94 |
| Gross mean return, % month | 0.38 | 0.31 | 0.63 | 0.56 | 0.58 | 0.63 | 0.56 | 0.61 | 0.59 |
| Net mean return, % month | 0.37 | 0.30 | 0.60 | 0.52 | 0.47 | 0.57 | 0.46 | 0.48 | 0.46 |
| Gross Sharpe (annualized) | 0.72 | 0.57 | 1.27 | 0.64 | 0.86 | 0.95 | 0.83 | 0.74 | 0.71 |
| Net Sharpe (annualized) | 0.71 | 0.55 | 1.20 | 0.60 | 0.67 | 0.85 | 0.66 | 0.57 | 0.54 |
| Avg. no. bonds | 2953 | 2604 | 617 | 446 | 554 | 1269 | 477 | 257 | 256 |
| of them, not traded, % | 11 | 4 | 37 | 7 | 24 | 24 | 26 | 25 | 21 |
| (E) As in D, and most actively traded bonds | | | | | | | | | |
| Avg. turnover, % month | 1.38 | 1.61 | 4.97 | 5.49 | 20.22 | 8.47 | 23.92 | 22.65 | 24.50 |
| Mean MMI illiquidity, b.p. | 42.09 | 40.17 | 42.76 | 62.37 | 69.61 | 60.77 | 51.89 | 58.05 | 54.97 |
| Gross mean return, % month | 0.38 | 0.31 | 0.65 | 0.56 | 0.54 | 0.61 | 0.54 | 0.63 | 0.60 |
| Net mean return, % month | 0.38 | 0.30 | 0.63 | 0.53 | 0.44 | 0.56 | 0.46 | 0.52 | 0.49 |
| Gross Sharpe (annualized) | 0.73 | 0.57 | 1.28 | 0.70 | 0.84 | 0.95 | 0.84 | 0.82 | 0.77 |
| Net Sharpe (annualized) | 0.72 | 0.55 | 1.24 | 0.66 | 0.67 | 0.87 | 0.69 | 0.67 | 0.62 |
| Avg. no. bonds | 2952 | 2551 | 649 | 587 | 667 | 1468 | 561 | 310 | 298 |
| of them, not traded, % | 12 | 5 | 40 | 12 | 23 | 23 | 22 | 22 | 20 |

Table 8: **Performance of systematic strategies under turnover constraints and the V-shaped T-cost.** The fund size is $500m. The strategies are as in Table 2. Part A of the table contains previously reported performance characteristics from Table 7. Part B prohibits rebalancing trades smaller than $100k 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. The sample is Jan 2010–Dec 2022. An analogous table but for the MMI cost is Table A3 in the Appendix.

since MKT and MIG portfolios 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 0.74 to 0.9 amid a two-times drop in turnover. Portfolios with high unrestricted turnover and relatively few holdings (like R1D and REX) 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 8, 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 case, 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 by up to two-thirds to levels between 20 and 30% per month.[26] Importantly, even the gross performance of reversal and liquidity portfolios does not deteriorate much with turnover reduction – the reversal signal is diluted only to a limited extent. Net-of-cost Sharpe ratios increase for all reversal and liquidity strategies in Part C of Table 8 relative to Part B. The impact of partial rebalancing on CRD and VAR portfolios is moderate. For the MFP portfolio, partial rebalancing increases 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 little effect on market portfolios on top of the no-retail-

[26] 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.

trades constraint. This is because, for a market portfolio of $500m 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 8, 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. Also, it considerably reduces the fraction of non-traded bonds in portfolios. However, having fewer holdings while keeping fund size fixed means having more institutional-sized turnover, price impact, and lower net returns. As a result, net Sharpe ratios of all portfolios are smaller in Part D of Table 8 than in Part C. Comparing sampled and constrained portfolios with original unrestricted portfolios (Part A), one finds that ex-cost risk-adjusted performance gets worse for both market portfolios and the VAR strategy, but improves for all other portfolios, in particular, the higher-turnover ones (LIQ, REV, R1D, and REX).

In Part E of Table 8, target portfolios of Part D are further restricted to only include bonds that were actively traded in the past. One consequence of this additional restriction is a further drop in turnover in all considered portfolios (except the MIG). This is likely due to individual corporate bonds' persistent trading frequencies. The set of bonds traded more than five business days a month does not change much from one month to another. For instance, the turnover of CRD and VAR portfolios is now around 5%, which is lower than the average reported monthly turnover of corporate bond mutual funds in the CRSP Mutual Funds dataset (Table 6). When the benefits of lower turnover outweigh the dilution of the original signal, net returns remain unchanged or increase (all strategies except LIQ and MFP). As a result, net Sharpe ratios remain unchanged or increase relative to part D. Given these results, we consider portfolios in Part E of Table 8 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 yet as equity trading costs. 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.

According to Li et al. (2023) and Meli and Todorova (2023), portfolio trading has recently grown as a percentage of trading volume and the percentage of the corporate bond universe eligible for portfolio trading. Portfolio trading refers to bond dealers bidding for a basket of bonds as part of one trade that involves many individual bonds at once. The trade is executed in an all-or-none fashion and can put multiple dealers in competition to price the entire basket. In future research, the impact of portfolio trading could be incorporated into systematic corporate bond strategy transaction cost and capacity estimates. Li et al. (2023) show that portfolio trading can increase or decrease bond transaction costs depending on market conditions, which means that the impact on capacity constraints is likely not to be straightforward but rather state-dependent.

## 4.2 Capacity

This section has only considered constrained portfolios of a fixed size of $500m so far. We now turn to discuss the capacity limits of constrained systematic bond strategies. Capacity limits arise because relative transaction costs may increase in trade size, like in equation (2) or, for the largest trade sizes, in equation (3).

To estimate the capacity, we vary the size of a hypothetical bond fund and evaluate transaction costs and returns. For a given strategy, the capacity limit is the size of the fund at which the average monthly net return in 2010–2022 drops to zero. We only consider MMI and V-shaped T-cost functions here because the downward-sloping EHP T-cost yields an infinite capacity. 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.

| | MKT | MIG | CRD | VAR | LIQ | MFP | REV | R1D | REX |
|---|---|---|---|---|---|---|---|---|---|
| (A) Unrestricted turnover | 11343 | 4425 | 215 | 64 | 2.3 | 42 | 1.9 | 1.1 | 0.9 |
| (B) Inst. trades only | 11343 | 4425 | 215 | 64 | 2.3 | 42 | 1.9 | 1.1 | 0.9 |
| (C) As B, and partial rebalancing | 11010 | 4474 | 576 | 93 | 5.4 | 96 | 8.8 | 5.5 | 4.9 |
| (D) As C, and sampling | 8981 | 3848 | 235 | 52 | 3.7 | 64 | 6.5 | 3.6 | 3.7 |
| (E) As D, and most actively traded bonds | 11332 | 4280 | 493 | 100 | 4.6 | 113 | 9.8 | 6.7 | 5.5 |

(a) **MMI cost**

| | MKT | MIG | CRD | VAR | LIQ | MFP | REV | R1D | REX |
|---|---|---|---|---|---|---|---|---|---|
| (A) Unrestricted turnover | 11389 | 4456 | 219 | 67 | 5.2 | 51 | 4.6 | 2.7 | 2.4 |
| (B) Inst. trades only | 11389 | 4456 | 219 | 67 | 5.2 | 51 | 4.6 | 2.7 | 2.4 |
| (C) As B, and partial rebalancing | 11010 | 4475 | 576 | 93 | 7.5 | 96 | 9.9 | 6.1 | 5.6 |
| (D) As C, and sampling | 8981 | 3848 | 235 | 52 | 5.1 | 64 | 7.2 | 3.9 | 4.0 |
| (E) As D, and most actively traded bonds | 11332 | 4280 | 493 | 100 | 6.0 | 113 | 10.3 | 6.9 | 5.7 |

(b) **V-shaped cost**

Table 9: **The capacity of systematic strategies ($ bn) under different T-cost models**. The MMI model is equation (2). The V-shaped model is equation (3). The constraints correspond to those in Table 8. The sample period is Jan 2010 – Dec 2022.

Table 9 reports capacity estimates obtained by solving numerically for a single-fund AUM that sets the ex-cost returns of the respective strategies to zero. Panel (a) presents the results for the MMI transaction cost model, and Panel (b) uses the V-shaped model.[27] The first row of Panel (a) reports capacity limits for unrestricted portfolios plotted previously in Figure 4.

[27] Table A4 in the Appendix presents capacity limits for the MMI in the case of a 5% truncation of the right tails of monthly MMI distributions. Such capacity limits are roughly half of those in Table 9.

Reversal and illiquidity strategies (LIQ, REV, R1D, and REX) see their capacity growing thanks to implementation constraints. The unrestricted capacity is \$0.9–5.2b (depending on the strategy and the T-cost model) while the most constrained case (line E) increase it to \$4.6–10.3b. Partial rebalancing and past trading activity restrictions help to increase the capacity higher. The capacity is higher under the V-shaped cost for a given strategy and turnover constraint, thanks to a less steep price impact in large trade sizes.

Default, credit, and multi-factor strategies (VAR, CRD, and MFP) also see the capacity grow two to three thanks to implementation constraints. As for reversal portfolios, partial rebalancing (line C) is the constraint that strongly boosts capacity. Importantly, sampling (line D) reduces 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) recovers what sampling reduces. It pushes the capacity even higher than in a pure partial rebalancing case for VAR and MFP strategies but not for the CRD. The capacity limits for these strategies range from \$100b (VAR) to almost \$600b (CRD). There is virtually no difference between the MMI and V-shaped costs at such capacity levels. The largest trades, which are priced almost identically in two models, are pivotal for the capacity.

The Market portfolio strategy capacity is relatively insensitive to implementation constraints and the choice of the T-cost model. The unrestricted capacity of about \$4.5tr for the MIG and \$11tr for the MKT remains stable in lines A to C. This is because market portfolios are very broadly diversified and have a low turnover already in the unrestricted case. Line D (sampling) shows again the detrimental impact of sampling on capacity: 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. As before, the additional restriction on past trading activity (line E) allows for recovery of the part of capacity lost due to sampling. Bonds that traded actively in the past tend to remain actively traded and hence are more MMI-liquid, which contains the price impact.

Overall, the capacity estimates in Table 9 suggest that there is still considerable room for growth in systematic corporate bond investment. Even reversal strategies can withstand several $b 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 drawdown or credit risk can generate positive net-of-cost returns for sizes up to several hundreds of billion of assets under management. Our multi-factor portfolios does 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 price impact increasing in trade size. As the size of the bond fund increases, the price impact part of transaction costs drives net return down to zero. High-turnover strategies that exploit reversal and illiquidity signals reach capacities up to $10 bn. Low-turnover strategies targeting credit risk premia have capacities up to $600 bn. These capacity limits are achieved under restrictions on portfolio rebalancing. A broad market portfolio has a capacity several times higher than the market size in our sample, 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.

## References


Ardia, David, Emanuele Guidotti, and Tim Alexander Kroencke, 2022, Efficient estimation of bid-ask spreads from open, high, low, and close prices, Working Paper, available at https://dx.doi.org/10.2139/ssrn.3892335.

Asquith, Paul, Thom Covert, and Parag Pathak, 2013, The effects of mandatory transparency in financial market design: Evidence from the corporate bond market, NBER Working Papers 19417, National Bureau of Economic Research, Inc.

Bali, Turan G., Amit Goyal, Dashan Huang, Fuwei Jiang, and Quan Wen, 2022, Predicting corporate bond returns: Merton meets machine learning, Working Paper, available at https://dx.doi.org/10.2139/ssrn.3686164.

Bao, Jack, Jun Pan, and Jiang Wang, 2011, The illiquidity of corporate bonds, *The Journal of Finance* 66, 911–946.

Bartram, Söhnke M., Mark Grinblatt, and Yoshio Nozawa, 2023, Book-to-market, mispricing, and the cross-section of corporate bond returns, Working Paper, available at https://ssrn.com/abstract=3510630.

Ben Dor, Arik, Lev Dynkin, Jay Hyman, Patrick Houweling, Erik van Leeuwen, and Olaf Penninga, 2007, DTS (Duration Times Spread), *The Journal of Portfolio Management* 33, 77–100.

Berk, Jonathan B., and Richard C. Green, 2004, Mutual fund flows and performance in rational markets, *Journal of Political Economy* 112, 1269–1295.

Bonelli, Maxime, Augustin Landier, Guillaume Simon, and David Thesmar, 2019, The capacity of trading strategies, Working Paper, available at https://dx.doi.org/10.2139/ssrn.2585399.

Cabrol, Axel, Wolfgang Drobetz, Tizian Otto, and Tatjana Xenia Puhan, 2023, Predicting corporate bond illiquidity via machine learning, Working Paper, available at https://ssrn.com/abstract=4489504.

Chordia, Tarun, Amit Goyal, Yoshio Nozawa, Avanidhar Subrahmanyam, and Qing Tong, 2017, Are capital market anomalies common to equity and corporate bond markets? an empirical investigation, *Journal of Financial and Quantitative Analysis* 52, 1301–1342.

DeMiguel, Victor, Alberto Martín-Utrera, Francisco J Nogales, and Raman Uppal, 2020, A Transaction-Cost Perspective on the Multitude of Firm Characteristics, *The Review of Financial Studies* 33, 2180–2222.

Dick-Nielsen, Jens, Peter Feldhütter, Lasse Heje Pedersen, and Christian Stolborg, 2023, Corporate bond factors: Replication failures and a new framework, Working Paper, available at https://papers.ssrn.com/abstract=4586652.

Dickerson, Alexander, Christian Julliard, and Philippe Mueller, 2023a, The corporate bond factor zoo, Working Paper, available at https://ssrn.com/abstract=4589786.

Dickerson, Alexander, Philippe Mueller, and Cesare Robotti, 2023b, Priced risk in corporate bonds, *Journal of Financial Economics* 150, 103707.

Dickerson, Alexander, Cesare Robotti, and Giulio Rossetti, 2023c, Return-based anomalies in corporate bonds: Are they there?, Working Paper, available at https://ssrn.com/abstract=4575879.

Diep, Peter, Lukasz Pomorski, and Scott Anthony Richardson, 2022, Sustainable systematic credit, *The Journal of Fixed Income* 32, 61–90.

Edwards, Amy K., Lawrence E. Harris, and Michael S. Piwowar, 2007, Corporate bond market transaction costs and transparency, *The Journal of Finance* 62, 1421–1451.

Feldhütter, Peter, 2012, The Same Bond at Different Prices: Identifying Search Frictions and Selling Pressures, *The Review of Financial Studies* 25, 1155–1206.

Frazzini, Andrea, Ronen Israel, and Tobias J. Moskowitz, 2015, Trading costs of asset pricing anomalies, Research Paper no. 14-05, Chicago Booth Research Paper Series.

Gârleanu, Nicolae, and Lasse Heje Pedersen, 2013, Dynamic trading with predictable returns and transaction costs, *The Journal of Finance* 68, 2309–2340.

Green, Richard C., Burton Hollifield, and Norman Schürhoff, 2007, Financial intermediation and the costs of trading in an opaque market, *The Review of Financial Studies* 20, 275–314.

Guo, Xin, Charles-Albert Lehalle, and Renyuan Xu, 2022, Transaction cost analytics for corporate bonds, *Quantitative Finance* 22, 1295–1319.

Harris, Lawrence, 2015, Transaction costs, trade throughs, and riskless principal trading in corporate bond markets, Working Paper, available at https://dx.doi.org/10.2139/ssrn.2661801.

Houweling, Patrick, and Jeroen van Zundert, 2017, Factor investing in the corporate bond market, *Financial Analysts Journal* 73, 100–115.

Israel, Ronen, Diogo Palhares, and Scott Richardson, 2018, Common factors in corporate bond returns, *Journal of Investment Management* 16, 17–46.

Joenväärä, Juha, Robert Kosowski, and Pekka Tolonen, 2019, The effect of investment constraints on hedge fund investor returns, *Journal of Financial and Quantitative Analysis* 54, 1539–1571.

Kargar, Mahyar, Benjamin Lester, David Lindsay, Shuo Liu, Pierre-Olivier Weill, and Diego Zúñiga, 2021, Corporate Bond Liquidity during the COVID-19 Crisis, *The Review of Financial Studies* 34, 5352–5401.

Kyle, Albert S., and Anna A. Obizhaeva, 2016, Market microstructure invariance: Empirical hypotheses, *Econometrica* 84, 1345–1404.

Kyle, Albert S., and Anna A. Obizhaeva, 2020, Trading liquidity and funding liquidity in fixed income markets: Implications of market microstructure invariance, Working Paper no. 0271, New Economic School (NES) Working Paper Series.

Li, Jessica, Maureen O'Hara, Andreas Rapp, and Xing Zhou, 2023, Bond market illiquidity: Is portfolio trading the solution?, Working Paper, available at https://ssrn.com/abstract=4495516.

Meli, Jeffrey, and Zornitsa Todorova, 2023, Portfolio trading in corporate bond markets, Working Paper, available at https://ssrn.com/abstract=4295453.

Novy-Marx, Robert, and Mihail Velikov, 2015, A Taxonomy of Anomalies and Their Trading Costs, *The Review of Financial Studies* 29, 104–147.

Patton, Andrew J., and Brian M. Weller, 2020, What you see is not what you get: The costs of trading market anomalies, *Journal of Financial Economics* 137, 515–549.

Pintér, Gábor, Chaojun Wang, and Junyuan Zou, 2024, Size discount and size penalty: trading costs in bond markets, *The Review of Financial Studies (forthcoming)* .

Reichenbacher, Michael, and Philipp Schuster, 2022, Size-adapted bond liquidity measures and their asset pricing implications, *Journal of Financial Economics* 146, 425–443.

Schestag, Raphael, Philipp Schuster, and Marliese Uhrig-Homburg, 2016, Measuring liquidity in bond markets, *The Review of Financial Studies* 29, 1170–1219.

van Binsbergen, Jules H., Yoshio Nozawa, and Michael Schwert, 2023, Duration-Based Valuation of Corporate Bonds, Working Paper, available at https://dx.doi.org/10.2139/ssrn.3914422.

Yan, Zhen, 2020, Returns to scale among corporate bond mutual funds, Working Paper, available at https://ssrn.com/abstract=3339511.

# Appendix A Recovering 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.

Assuming the square-root functional form of the T-cost function, equity portfolio transitions imply the following parametrization of the cost function under the MMI [28]:

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

Above, $\sigma_{it}$ 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). The cost function 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 1m shares. We 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 14.16 b.p., of which 2.08 b.p. is half of the bid-ask spread, and 12.08 b.p. is the price impact.

[28]This is formula 38 in Kyle and Obizhaeva (2016). Kyle and Obizhaeva (2020) apply a linear MMI T-cost function to fixed-income markets. We are able to replicate their linear MMI T-cost starting from formula 37 in Kyle and Obizhaeva (2016) and applying the procedure similar to the one presented below. However, we are not aware of adaptions of the square-root MMI cost function to corporate bonds in the literature.

To use the MMI cost function for corporate bonds, one must first re-scale it appropriately. Here is our approach:

$$\begin{aligned}
C_{it}^{\%,\text{sqrt}}(Q) &= \frac{\sigma_{it}}{0.02}\left(\frac{2.08}{10^4}\left[\frac{W_{it}}{(0.02)(40)(10^6)}\right]^{-\frac{1}{3}} + \frac{12.08}{10^4}\left[\frac{Q}{(0.01)V_{it}}\right]^{\frac{1}{2}}\right) = \\
&= \underbrace{\left[\sigma_{it}W_{it}^{-\frac{1}{3}}Ci^2\right]}_{\equiv\frac{1}{L_{it}}}\left(\frac{1}{0.02}\frac{1}{Ci^2}\frac{2.08}{10^4}\alpha^{\frac{1}{3}} + \frac{1}{0.02}\frac{1}{Ci^2}\frac{12.08}{10^4}W_{it}^{\frac{1}{3}}\frac{1}{\sqrt{0.01}}\left[\frac{P_{it}Q}{P_{it}V_{it}}\right]^{\frac{1}{2}}\right) = \\
&= \frac{1}{L_{it}}\left(\frac{1}{0.02}\frac{1}{Ci^2}\frac{2.08}{10^4}\alpha^{\frac{1}{3}} + \frac{1}{0.02}\frac{1}{Ci^2}\frac{12.08}{10^4}\frac{1}{\sqrt{0.01}}\underbrace{\frac{W_{it}^{\frac{1}{3}}}{\sqrt{P_{it}V_{it}}}}_{\sqrt{\sigma_{it}W_{it}^{-\frac{1}{3}}}}\sqrt{P_{it}Q}\right) = \\
&= \frac{1}{L_{it}}\left(\underbrace{\frac{1}{0.02}\frac{1}{Ci^2}\frac{2.08}{10^4}\alpha^{\frac{1}{3}}}_{\kappa} + \underbrace{\frac{1}{0.02}\frac{1}{Ci^{\frac{3}{2}}}\frac{12.08}{10^4}\frac{1}{\sqrt{0.01}}}_{\lambda}\frac{1}{\sqrt{CL_{it}}}\sqrt{P_{it}Q}\right) \Rightarrow \\
C_{it}^{\%,\text{sqrt}}(X) &= \frac{1}{L_{it}}\left(\kappa + \lambda\frac{1}{\sqrt{CL_{it}}}X\right),
\end{aligned}$$

where $C$ and $i^2$ are invariant parameters evaluated 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,[29] and $C \approx \$2000$ is the cost of executing an average-sized bet. In the derivation above, we used the definition of the MMI illiquidity $\frac{1}{L_{it}} \equiv \sigma_{it}W_{it}^{-\frac{1}{3}}Ci^2$ (formula 15 in Kyle and Obizhaeva, 2016) and the definition of the dollar size of daily risk transfer $W_{it} \equiv \sigma_{it}P_{it}V_{it}$ that yields $\sigma_{it}W_{it}^{-\frac{1}{3}} = \frac{W_{it}^{\frac{2}{3}}}{P_{it}V_{it}}$. By direct calculation, $\kappa \approx 0.04883$ and $\lambda \approx 0.30721$. 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.

[29] Based on Kyle and Obizhaeva (2016), $i^{-2} = \exp\left(-5.71 + \frac{2}{3}\ln\left(40 \times 10^6 \times 0.02\right) + \frac{2.53}{2}\right) \approx 0.009886^{-1}$.

## Appendix B EHP transaction cost

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):

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

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 $t$.[30] Two latter factors represent bond-specific carry and systematic return components. $\eta_{ts}$ is a mean-zero error term with variance $\sigma^2_{ts}$ that equals to:

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

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.

[30] For the same-day transactions, we set both the day-count factor and the market factor to zero.

We regularize individual-bond transaction cost functions

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

within rating-maturity-size buckets. We consider two credit rating bins (investment-grade and high-yield), three maturity bins (the breakpoints are 3 and 7 years to maturity) and three size bins (the breakpoints are \$450m and \$900m outstanding amount) that yield 18 rating-maturity-size 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-size bucket. If a cost for a given trade size is negative, it is replaced with a zero.

# Appendix C  Additional Figures and Tables (Internet Appendix)

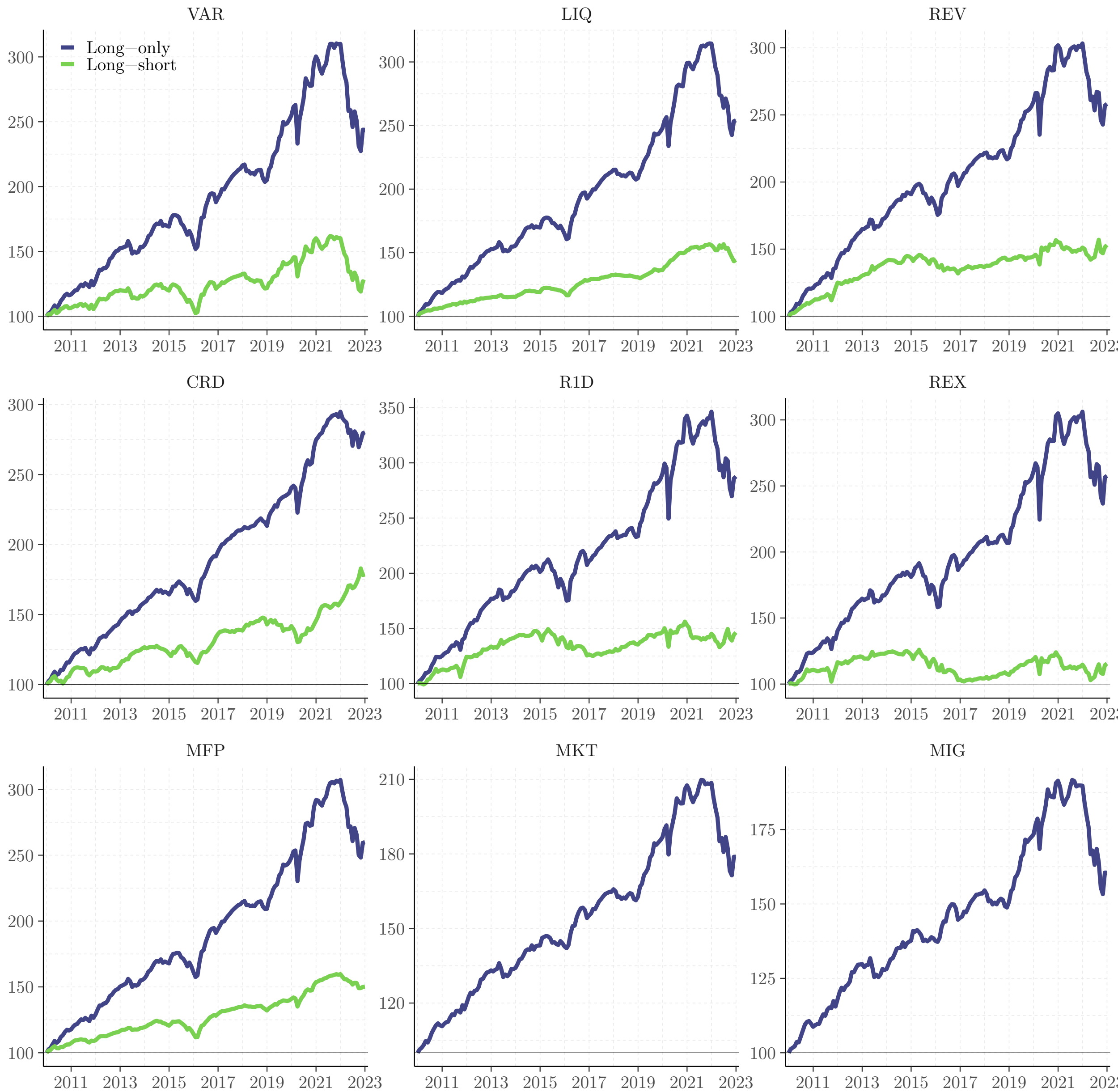


Figure A1: **Cumulative performance of long-only and long-short strategies before TC adjustment.** Portfolios are worth 100 at inception, which is end-Dec 2009.

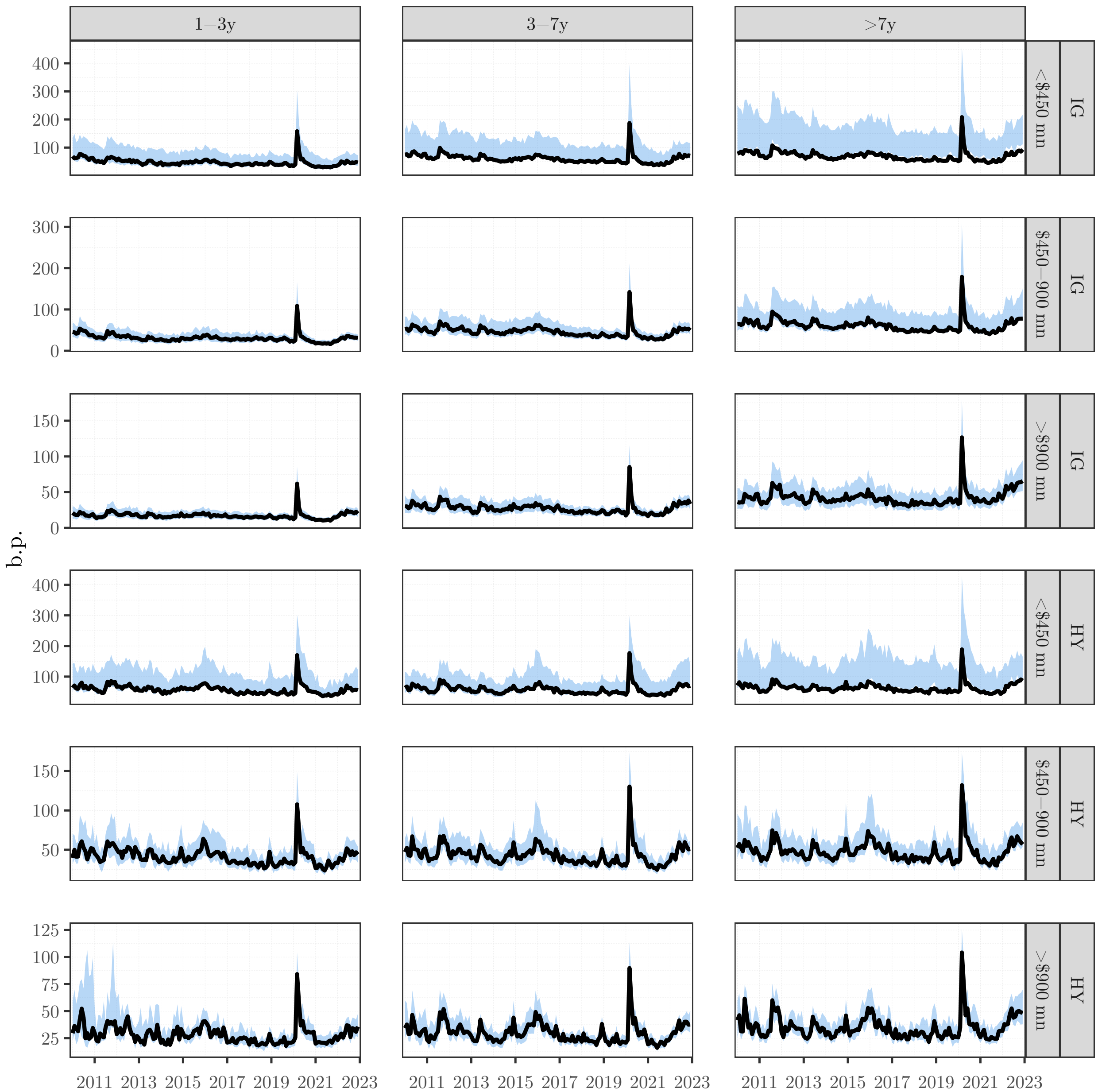


Figure A2: **MMI illiquidity: inter-quartile range (IQR) of the untruncated metric and the median truncated one**. The shaded areas are within-month IQR of the untruncated MMI illiquidity. The solid lines are within-month medians of the MMI illiquidity truncated at 25% separately each month. The columns are different maturity categories, and the rows are rating and size categories (same as in Figure 3). The sample period is Jan 2010 – Dec 2022.

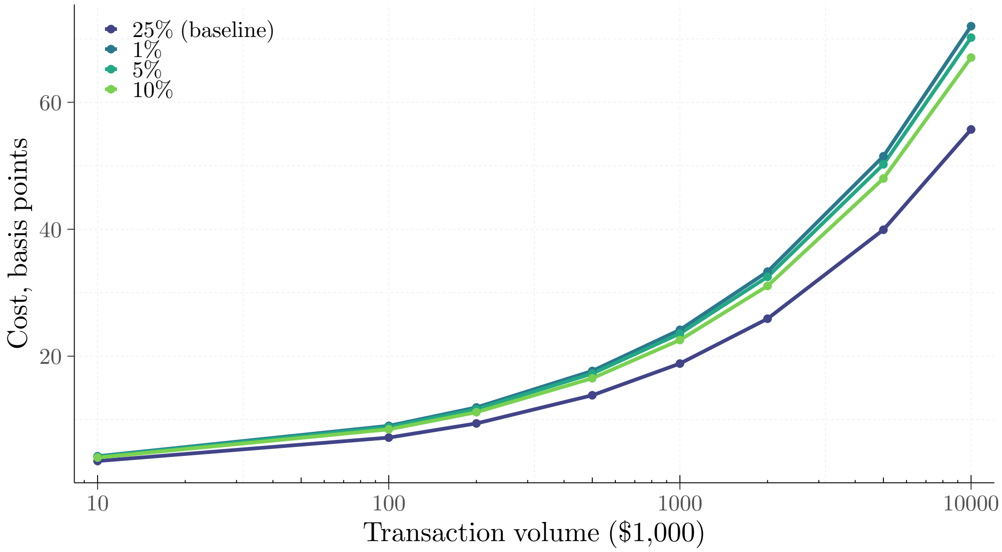


Figure A3: **MMI T-cost under different truncation levels of the MMI illiquidity.** Different lines correspond to different truncation levels. 25% is the baseline case considered in the paper. The functions presented in this figure are volume-weighted averages of individual bond estimates.

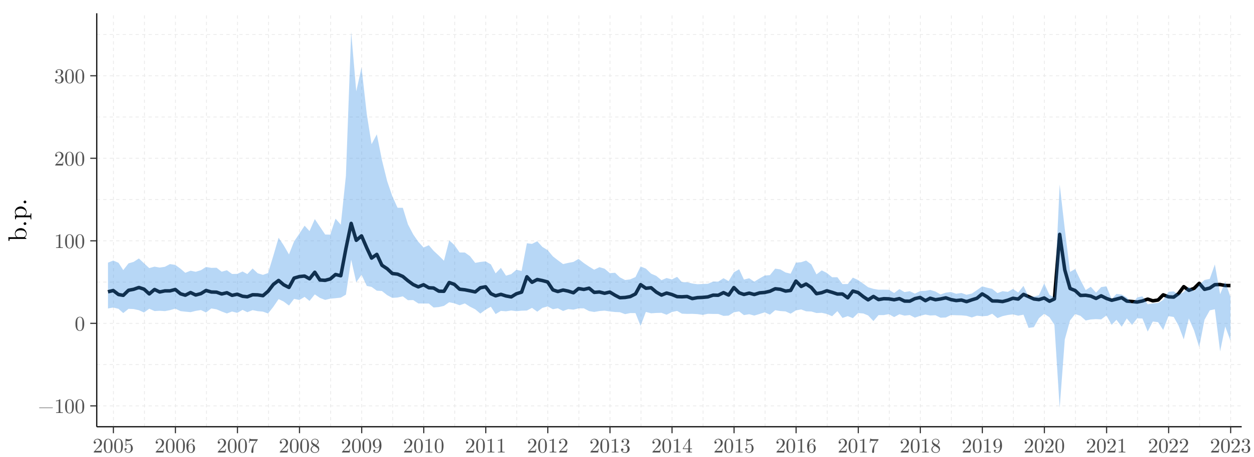


Figure A4: **Inter-quartile range of Bao et al. (2011) illiquidity and the MMI illiquidity**. MMI illiquidity (solid line) is the illiquidity measure of Kyle and Obizhaeva (2016), volume-weighted within each month. The shaded area is a within-month inter-quartile range of a signed square root of an absolute value of the illiquidity measure of Bao et al. (2011). Negative observations in the shaded area mean that the covariance of daily prices was positive for those bonds and months. The time-series correlation between the solid line (MMI) and the central tendency of the shaded area (median BPW) is 0.85 here.

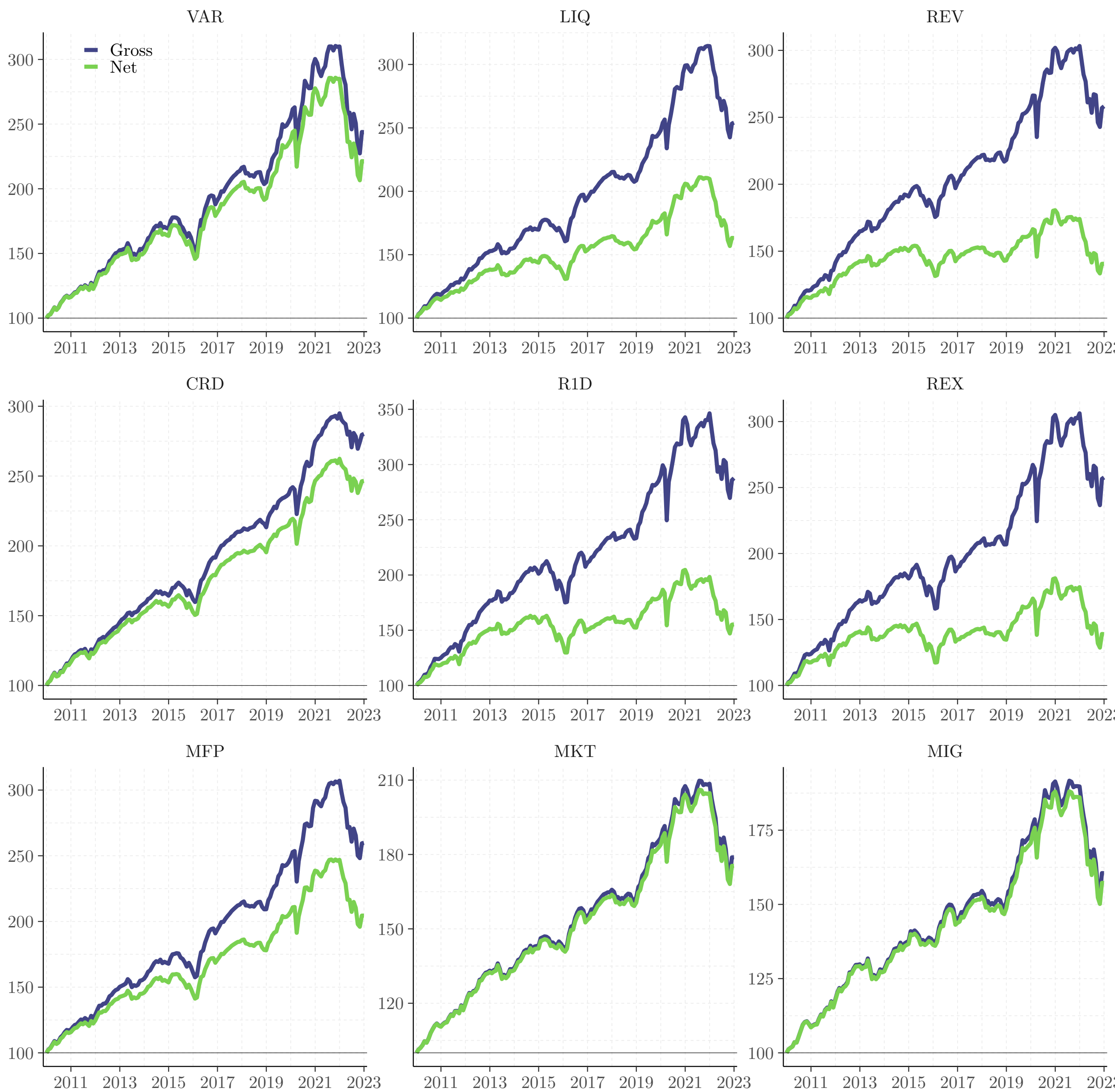


Figure A5: **Cumulative performance of long-only strategies before and after TC adjustment** for a fixed fund size of $500m AUM. Portfolios are worth 100 at inception, which is Dec 2009. The trading costs are V-shaped.

| | MKT | MIG | CRD | VAR | LIQ | MFP | REV | R1D | REX |
|---|---|---|---|---|---|---|---|---|---|
| | | | | With imputed returns | | | | | |
| Mean return, % month | 0.38 | 0.32 | 0.68 | 0.61 | 0.62 | 0.63 | 0.64 | 0.72 | 0.65 |
| St. dev., % month | 1.50 | 1.55 | 1.57 | 2.62 | 1.99 | 1.99 | 2.35 | 2.98 | 3.01 |
| Sharpe (annualized) | 0.76 | 0.59 | 1.36 | 0.73 | 0.98 | 1.01 | 0.86 | 0.78 | 0.69 |
| | | | | Only observed returns | | | | | |
| Mean return, % month | 0.36 | 0.31 | 0.64 | 0.59 | 0.59 | 0.61 | 0.72 | 0.82 | 0.72 |
| St. dev., % month | 1.63 | 1.61 | 2.10 | 2.75 | 2.39 | 2.32 | 2.55 | 3.26 | 3.23 |
| Sharpe (annualized) | 0.66 | 0.55 | 0.97 | 0.68 | 0.77 | 0.82 | 0.90 | 0.81 | 0.72 |

(a) Before trading cost adjustment

| | MKT | MIG | CRD | VAR | LIQ | MFP | REV | R1D | REX |
|---|---|---|---|---|---|---|---|---|---|
| | | | | With imputed returns | | | | | |
| Mean return (% month) | 0.38 | 0.31 | 0.64 | 0.55 | 0.31 | 0.55 | 0.29 | 0.22 | 0.16 |
| St. dev. (% month) | 1.50 | 1.55 | 1.57 | 2.61 | 1.96 | 1.98 | 2.33 | 2.96 | 2.99 |
| Sharpe (annualized) | 0.76 | 0.58 | 1.28 | 0.66 | 0.46 | 0.87 | 0.35 | 0.19 | 0.12 |
| | | | | Only observed returns | | | | | |
| Mean return (% month) | 0.36 | 0.30 | 0.61 | 0.53 | 0.28 | 0.53 | 0.37 | 0.31 | 0.22 |
| St. dev. (% month) | 1.63 | 1.61 | 2.09 | 2.74 | 2.36 | 2.32 | 2.53 | 3.24 | 3.22 |
| Sharpe (annualized) | 0.65 | 0.54 | 0.91 | 0.61 | 0.33 | 0.71 | 0.44 | 0.28 | 0.19 |

(b) After trading cost adjustment

Table A1: **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 MMI-implied cost. The AUM is $500m, and the sample period is from Jan 2010 to Dec 2022.

| | Dependent variable: $1/L_{it}$, b.p. | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Intercept | 49.45*** | | | | 50.58*** | | | |
| | (1.59) | | | | (1.60) | | | |
| Size ($ mln) | −0.01*** | −0.01*** | −0.01*** | −0.01*** | −0.01*** | −0.01*** | −0.01*** | −0.01*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Maturity (years) | 1.02*** | 1.01*** | 1.03*** | 1.01*** | 1.01*** | 1.02*** | 1.07*** | 1.05*** |
| | (0.03) | (0.03) | (0.03) | (0.03) | (0.04) | (0.04) | (0.03) | (0.03) |
| Rating (1 to 21) | 0.55*** | 1.02*** | 0.43*** | 0.95*** | 0.13 | 0.25 | 0.49*** | 0.98*** |
| | (0.09) | (0.27) | (0.07) | (0.13) | (0.10) | (0.20) | (0.08) | (0.12) |
| Size × Pre-GFC | | | | | 0.001 | −0.0001 | −0.004*** | −0.003*** |
| | | | | | (0.001) | (0.001) | (0.001) | (0.001) |
| Size × GFC | | | | | 0.0004 | −0.001 | −0.01*** | −0.01*** |
| | | | | | (0.001) | (0.001) | (0.002) | (0.002) |
| Maturity × Pre-GFC | | | | | −0.28*** | −0.42*** | −0.46*** | −0.50*** |
| | | | | | (0.07) | (0.06) | (0.05) | (0.05) |
| Maturity × GFC | | | | | 0.80*** | 0.73*** | 0.09 | 0.07 |
| | | | | | (0.16) | (0.15) | (0.09) | (0.08) |
| Rating × Pre-GFC | | | | | 0.26** | 0.21 | −0.58*** | −0.46*** |
| | | | | | (0.13) | (0.15) | (0.11) | (0.13) |
| Rating × GFC | | | | | 3.49*** | 3.37*** | 0.46* | 0.54** |
| | | | | | (0.48) | (0.49) | (0.27) | (0.26) |
| Issuer FE | NO | YES | NO | YES | NO | YES | NO | YES |
| Year-month FE | NO | NO | YES | YES | NO | NO | YES | YES |
| Observations | 845,307 | 845,307 | 845,307 | 845,307 | 845,307 | 845,307 | 845,307 | 845,307 |
| Adjusted $R^2$ | 0.19 | 0.26 | 0.48 | 0.53 | 0.29 | 0.35 | 0.49 | 0.54 |
| *Note:* | *p<0.1; **p<0.05; ***p<0.01 | | | | | | | |

Table A2: **MMI illiquidity and bond characteristics.** Pre-GFC (dummy) is Oct 2004 to May 2008, and GFC (dummy) is Jun 2008 to Dec 2009. The standard errors are double-clustered in time and issuer.

| | MKT | MIG | CRD | VAR | LIQ | MFP | REV | R1D | REX |
|---|---|---|---|---|---|---|---|---|---|
| (A) Unrestricted portfolios | | | | | | | | | |
| Avg. turnover, % month | 1.52 | 1.83 | 13.15 | 9.79 | 43.44 | 20.74 | 75.00 | 72.39 | 73.69 |
| Mean MMI illiquidity, b.p. | 46.48 | 45.32 | 46.87 | 64.09 | 78.09 | 62.86 | 56.61 | 63.53 | 62.42 |
| Gross mean return, % month | 0.38 | 0.32 | 0.68 | 0.61 | 0.62 | 0.63 | 0.64 | 0.72 | 0.65 |
| Net mean return, % month | 0.38 | 0.31 | 0.64 | 0.55 | 0.31 | 0.55 | 0.29 | 0.22 | 0.16 |
| Gross Sharpe (annualized) | 0.76 | 0.59 | 1.36 | 0.73 | 0.98 | 1.01 | 0.86 | 0.78 | 0.69 |
| Net Sharpe (annualized) | 0.76 | 0.58 | 1.28 | 0.66 | 0.46 | 0.87 | 0.35 | 0.19 | 0.12 |
| Avg. no. bonds | 7847 | 5157 | 1336 | 968 | 1522 | 2998 | 1535 | 768 | 764 |
| of them, not traded, % | 26 | 15 | 30 | 9 | 24 | 7 | 17 | 38 | 33 |
| (B) Inst. trades only | | | | | | | | | |
| Avg. turnover, % month | 1.40 | 1.52 | 9.74 | 8.62 | 40.86 | 10.12 | 69.93 | 71.57 | 72.94 |
| Mean MMI illiquidity, b.p. | 42.78 | 43.67 | 46.98 | 64.39 | 78.24 | 62.97 | 57.05 | 63.59 | 62.48 |
| Gross mean return, % month | 0.39 | 0.32 | 0.67 | 0.62 | 0.62 | 0.60 | 0.63 | 0.72 | 0.65 |
| Net mean return, % month | 0.38 | 0.32 | 0.64 | 0.56 | 0.32 | 0.55 | 0.31 | 0.22 | 0.16 |
| Gross Sharpe (annualized) | 0.76 | 0.61 | 1.36 | 0.75 | 0.98 | 1.02 | 0.88 | 0.79 | 0.69 |
| Net Sharpe (annualized) | 0.75 | 0.60 | 1.29 | 0.67 | 0.48 | 0.94 | 0.39 | 0.20 | 0.12 |
| Avg. no. bonds | 2985 | 2818 | 1329 | 980 | 1493 | 3288 | 1630 | 769 | 770 |
| of them, not traded, % | 44 | 13 | 33 | 11 | 26 | 25 | 23 | 27 | 24 |
| (C) As in B, and partial rebalancing | | | | | | | | | |
| Avg. turnover, % month | 1.39 | 1.53 | 5.95 | 6.57 | 22.25 | 10.51 | 28.28 | 28.54 | 28.65 |
| Mean MMI illiquidity, b.p. | 42.80 | 43.66 | 46.48 | 63.90 | 73.76 | 62.21 | 56.66 | 63.35 | 61.16 |
| Gross mean return, % month | 0.39 | 0.32 | 0.67 | 0.59 | 0.57 | 0.62 | 0.57 | 0.66 | 0.60 |
| Net mean return, % month | 0.38 | 0.32 | 0.64 | 0.54 | 0.38 | 0.57 | 0.42 | 0.45 | 0.40 |
| Gross Sharpe (annualized) | 0.76 | 0.61 | 1.32 | 0.71 | 0.93 | 1.00 | 0.87 | 0.85 | 0.75 |
| Net Sharpe (annualized) | 0.76 | 0.60 | 1.28 | 0.65 | 0.60 | 0.91 | 0.63 | 0.56 | 0.48 |
| Avg. no. bonds | 2985 | 2793 | 1178 | 851 | 924 | 2248 | 776 | 437 | 436 |
| of them, not traded, % | 44 | 13 | 37 | 14 | 45 | 34 | 43 | 49 | 43 |
| (D) As in C, and sampling | | | | | | | | | |
| Avg. turnover, % month | 1.39 | 1.60 | 7.26 | 7.06 | 22.90 | 11.15 | 28.72 | 28.64 | 28.74 |
| Mean MMI illiquidity, b.p. | 41.93 | 40.13 | 42.74 | 60.60 | 72.31 | 60.83 | 53.31 | 60.79 | 56.94 |
| Gross mean return, % month | 0.38 | 0.31 | 0.63 | 0.56 | 0.58 | 0.63 | 0.56 | 0.61 | 0.59 |
| Net mean return, % month | 0.37 | 0.30 | 0.60 | 0.50 | 0.36 | 0.57 | 0.40 | 0.38 | 0.37 |
| Gross Sharpe (annualized) | 0.72 | 0.57 | 1.27 | 0.64 | 0.86 | 0.95 | 0.83 | 0.74 | 0.71 |
| Net Sharpe (annualized) | 0.71 | 0.56 | 1.20 | 0.57 | 0.50 | 0.85 | 0.56 | 0.43 | 0.41 |
| Avg. no. bonds | 2953 | 2604 | 617 | 446 | 554 | 1269 | 477 | 257 | 256 |
| of them, not traded, % | 11 | 4 | 37 | 7 | 24 | 24 | 26 | 25 | 21 |
| (E) As in D, and most actively traded bonds | | | | | | | | | |
| Avg. turnover, % month | 1.38 | 1.61 | 4.97 | 5.49 | 20.22 | 8.47 | 23.92 | 22.65 | 24.50 |
| Mean MMI illiquidity, b.p. | 42.09 | 40.17 | 42.76 | 62.37 | 69.61 | 60.77 | 51.89 | 58.05 | 54.97 |
| Gross mean return, % month | 0.38 | 0.31 | 0.65 | 0.56 | 0.54 | 0.61 | 0.54 | 0.63 | 0.60 |
| Net mean return, % month | 0.38 | 0.31 | 0.63 | 0.51 | 0.35 | 0.56 | 0.41 | 0.45 | 0.41 |
| Gross Sharpe (annualized) | 0.73 | 0.57 | 1.28 | 0.70 | 0.84 | 0.95 | 0.84 | 0.82 | 0.77 |
| Net Sharpe (annualized) | 0.73 | 0.56 | 1.23 | 0.64 | 0.52 | 0.87 | 0.62 | 0.57 | 0.51 |
| Avg. no. bonds | 2952 | 2551 | 649 | 587 | 667 | 1468 | 561 | 310 | 298 |
| of them, not traded, % | 12 | 5 | 40 | 12 | 23 | 23 | 22 | 22 | 20 |

Table A3: **Performance of systematic strategies under turnover constraints and the MMI T-cost.** This table is analogous to Table 8 of the main paper; the only difference is the underlying transaction cost model.

| | MKT | MIG | CRD | VAR | LIQ | MFP | REV | R1D | REX |
|---|---|---|---|---|---|---|---|---|---|
| (A) Unrestricted turnover | 2298 | 1333 | 84 | 19 | 0.5 | 11 | 0.6 | 0.3 | 0.3 |
| (B) Inst. trades only | 2298 | 1333 | 84 | 19 | 0.6 | 11 | 0.6 | 0.3 | 0.3 |
| (C) As B, and partial rebalancing | 2470 | 1420 | 278 | 34 | 1.9 | 33 | 4.5 | 2.8 | 2.8 |
| (D) As C, and sampling | 4197 | 2132 | 122 | 21 | 1.4 | 22 | 3.5 | 2.0 | 2.2 |
| (E) As D, and most actively traded bonds | 5135 | 2404 | 273 | 42 | 1.8 | 42 | 5.8 | 3.9 | 3.4 |

Table A4: **Capacity of systematic strategies ($ bn) under 5%-truncated MMI cost**. The sample period is Jan 2010 – Dec 2022.