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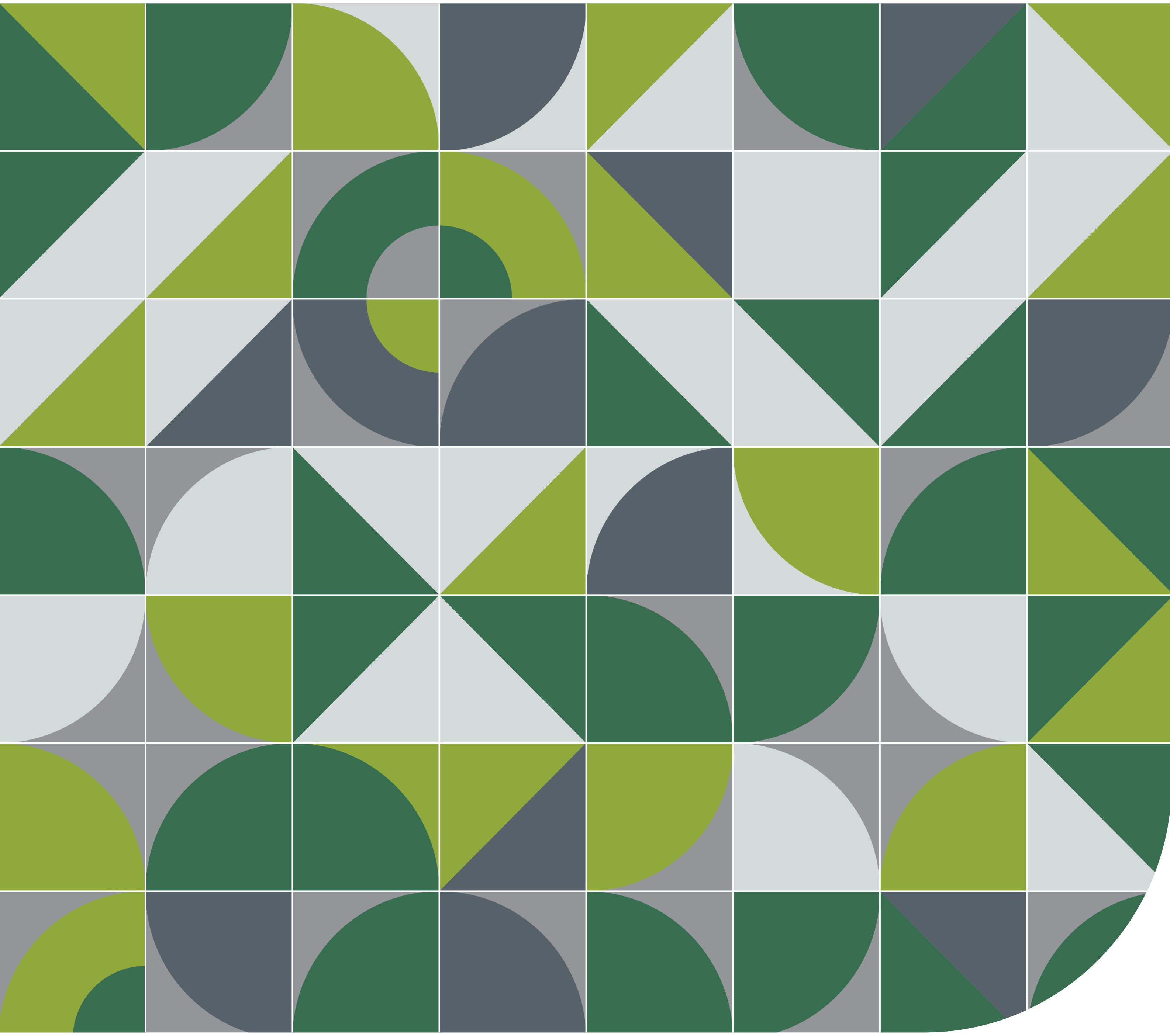

Incorporating pre-trade bond liquidity data into corporate bond management

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Summary

The identification of liquidity is a key factor for successful corporate bond management. We show how the incorporation of pre-trade liquidity data into the portfolio construction process provides more precise estimates of tradability, tradable volumes, and transaction costs. It also increases relative portfolio performance.

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About Quoniam

Quoniam is a pioneer in quantitative asset management. Our goal is to create client-oriented investment solutions with a reliable alpha for institutional investors based on scientific findings and modern technology. As a partner-led company with more than 120 employees in Frankfurt and London, we manage approximately 21 billion euros in equity, fixed income, and multi-asset strategies. Our success is rooted in the efficient processing of the increasing amount of capital market data and information and employing this data to facilitate reliable investment decisions. We operate independently and seek innovative solutions. Simultaneously, our entrepreneurial freedom is grounded in a solid financial foundation owing to our affiliation with Union Investment Group. We passionately strive to create value for our clients and to make positive contributions to society. We are committed to the Principles for Responsible Investment and aim to globally promote sustainable investment.

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Introduction

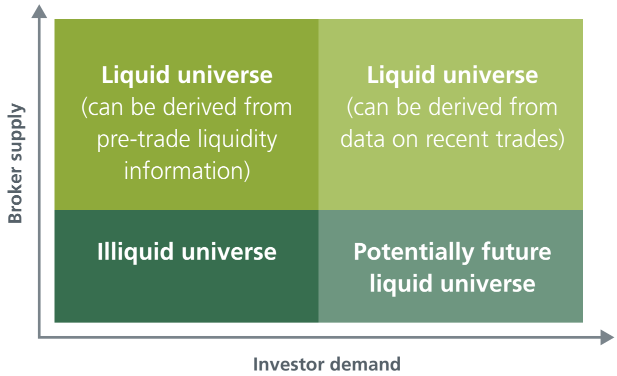
This study analyses the value of liquidity information in the management of corporate bond portfolios and how pre-trade information can help obtain better liquidity, tradability, and transaction cost estimates. Navigating liquidity in the corporate bond market is a challenge for credit managers. Contrary to the equity market, most trading in bonds does not take place on regulated exchanges but in over-the-counter (OTC) markets, where buyers of a bond need to find a willing seller and no publicly available limit order book exists. Therefore, investors must identify the existing liquidity in corporate bonds and leapfrog other investors when trading on liquidity.

Although many stocks trade every day, only 23 USD bonds out of a universe of more than 47,000 bonds in TRACE traded on more than 240 days in 2023, whereas almost half of the universe of bonds (47%) traded no more than once during the entire year. The problem of low liquidity is exacerbated by regulatory changes requiring dealers to add more capital to their portfolios, resulting in smaller bankbooks and lower dealer inventory.

The way asset managers deal with scarce liquidity and incorporate it into their portfolio construction process is highly relevant to the overall success of corporate bond investments. Performance will be higher, the broader the universe that an asset manager can buy and sell, and the level of diversification will increase with a larger universe. One way to use liquidity information is to examine past trades and derive liquidity estimates from past trading activities. The availability of forward-looking pre-trade information in the form of broker interest in buying and selling has increased in recent years, allowing for additional types of data to be considered.

The use of backward-looking post-trade data only for liquidity management has several drawbacks, which make pre-trade data a promising addition. Firstly, there is still no consolidated tape for corporate bond trades in euro available in the market. Secondly, while this consolidated tape exists for USD trades in the TRACE database, information on executed trades only identifies bonds in which both supply and demand are sufficiently large to cause trading activity. The types of bonds with different liquidity characteristics are shown in Figure 1.

Figure 1: Liquidity segments in the corporate bond universe



Source: Quoniam Asset Management GmbH

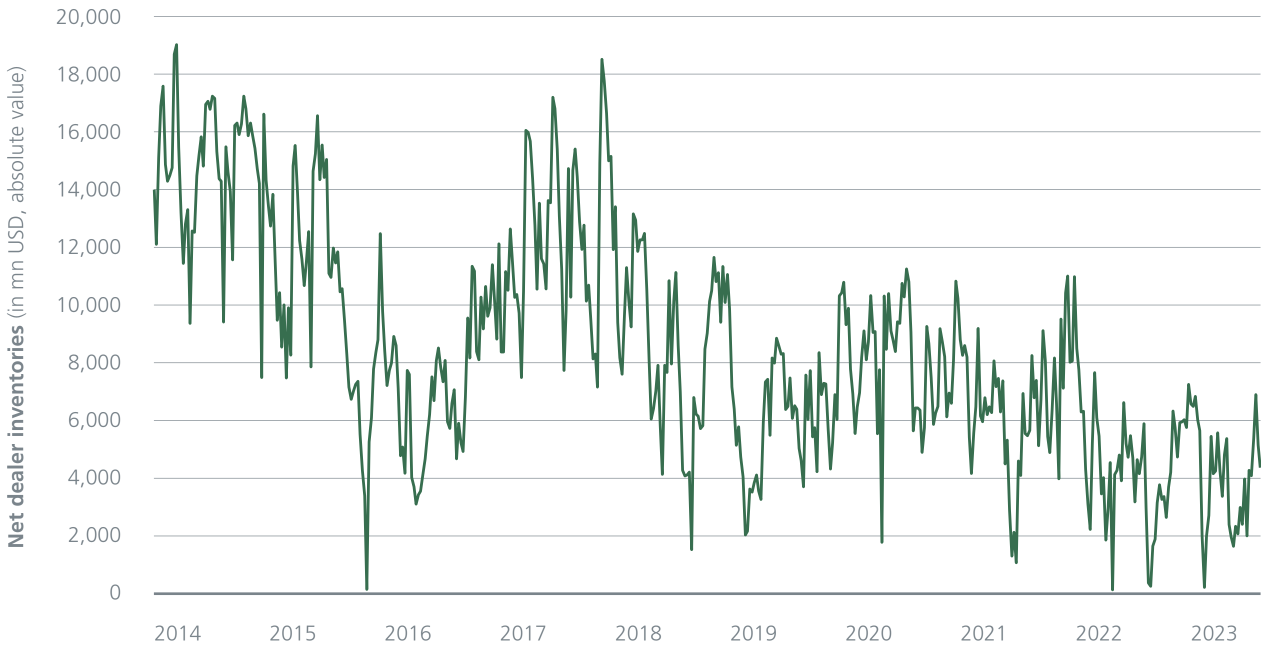
The liquid part, with considerable trade activity, is relatively limited, and most investors incorporate these bonds into their opportunity set. Therefore, the performance potential of the bonds in this group is limited. If investors want to extend the investable universe, bonds in the upper-left square with considerable broker axes but limited investor interest (e.g., due to low analyst coverage) look particularly interesting. If asset managers can identify these bonds from pre-trade information, the liquid universe can be meaningfully extended, and performance potential will increase.

This study uses sell-side pre-trade information to analyse its effect on the construction process of corporate bond portfolios. In the next section, we cover liquidity in the corporate bond market in greater detail. Subsequently, we describe the pre-data we use and show their impact on identifying liquidity, tradability, transaction costs, and performance before concluding the paper.

Liquidity in corporate bond markets

Liquidity in the corporate bond market is systematically different from that in the equity markets. The OTC market structure is less transparent and increases the search costs for liquidity, whereas broker-dealers act as intermediaries on behalf of buy-side clients or trade in their own books. Regulatory changes after the financial crisis of 2008 and 2009 considerably tightened dealer books because they must be covered with additional equity. The effect of decreasing dealer holdings over time is massive and can be seen in Figure 2.

Figure 2: Net dealer inventories

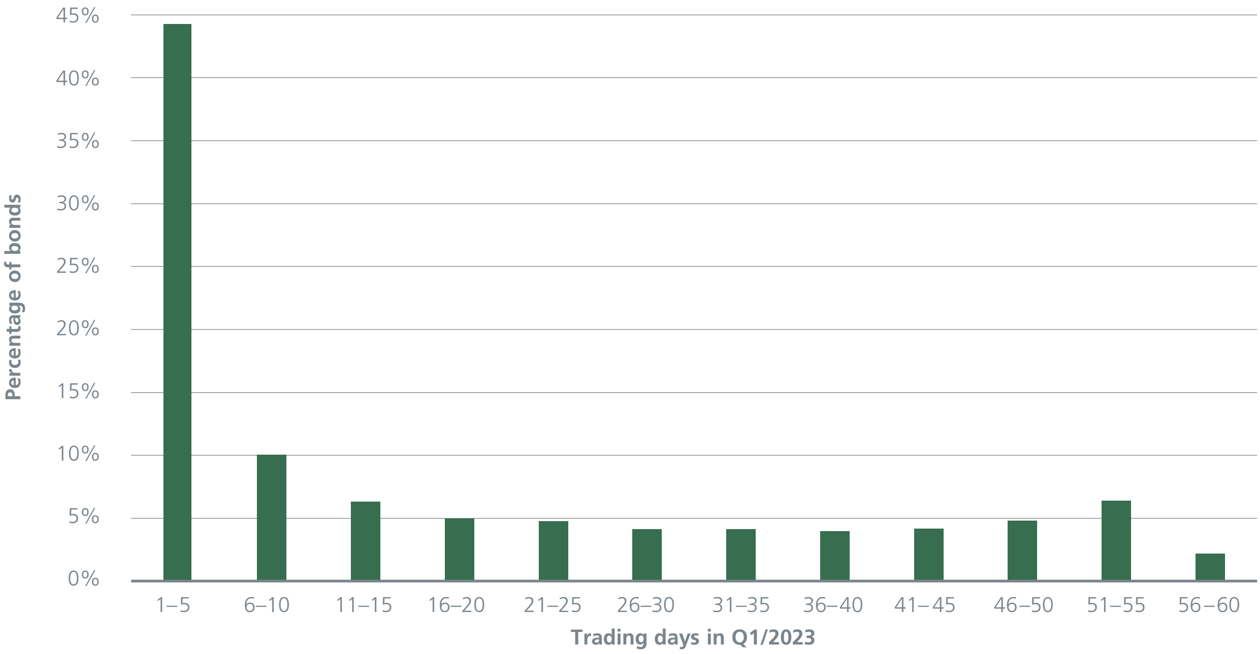


The graph shows the absolute value of net US dealer inventories for IG corporate bonds. Source: Federal Reserve, Quoniam Asset Management GmbH

The weekly statistics provided by the Federal Reserve show a clear downward trend in the size of dealer books. The average weekly inventory in 2014 was 14.8 bn USD, this number decreased to 12.5 bn in 2017, USD 8 billion in 2020, and 3.8 bn in 2023 (first half). Investors who contacted their bond dealers in 2023 found a quarter of the liquidity available ten years ago.

With fewer dealer books, matching buyers with sellers has become increasingly challenging. While most of the volume in Figure 2 can be considered liquidity for trading, investors may not be interested in trading the bonds the dealers want to trade or may be willing to trade on the same side as the dealer. In these cases, no trade occurred. Indeed, the consolidated corporate bond tape TRACE in the US shows that most bonds in the market trade infrequently. Figure 3 shows the distribution of bonds with respect to the number of days they were traded over time.

Figure 3: Number of trading days per bond in the US IG corporate bond market



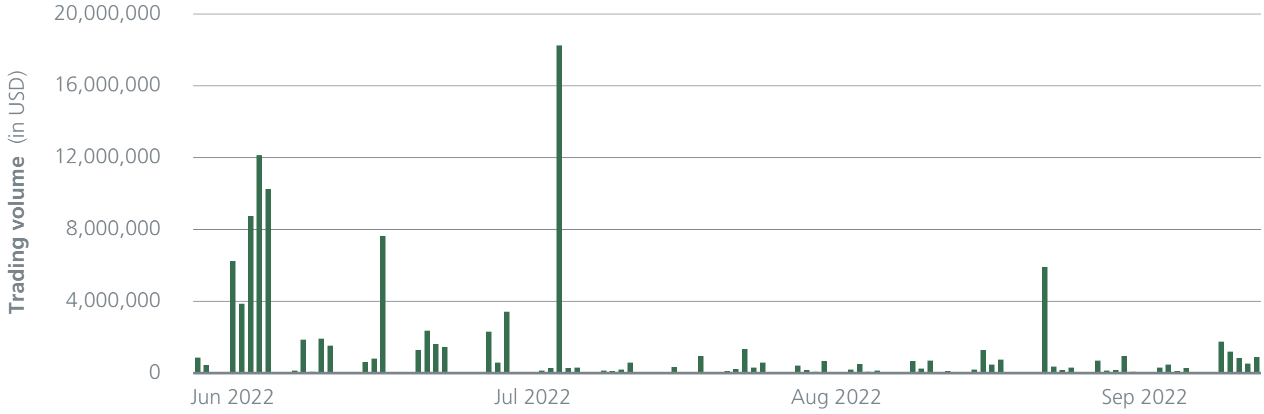
Source: TRACE, Quoniam Asset Management GmbH

The data show trades recorded in the first quarter of 2023. Of the approximately 28,600 bonds in which trade took place, 12,662 bonds (44.3 %) traded for no more than five days in the quarter. The number of bonds traded in less than half of the days in Q1 2023 was 21,779 or 74.4%. These numbers clarify that most bonds trade infrequently and that using post-trade data will probably qualify most of the investable universe in USD corporate bonds as illiquid.

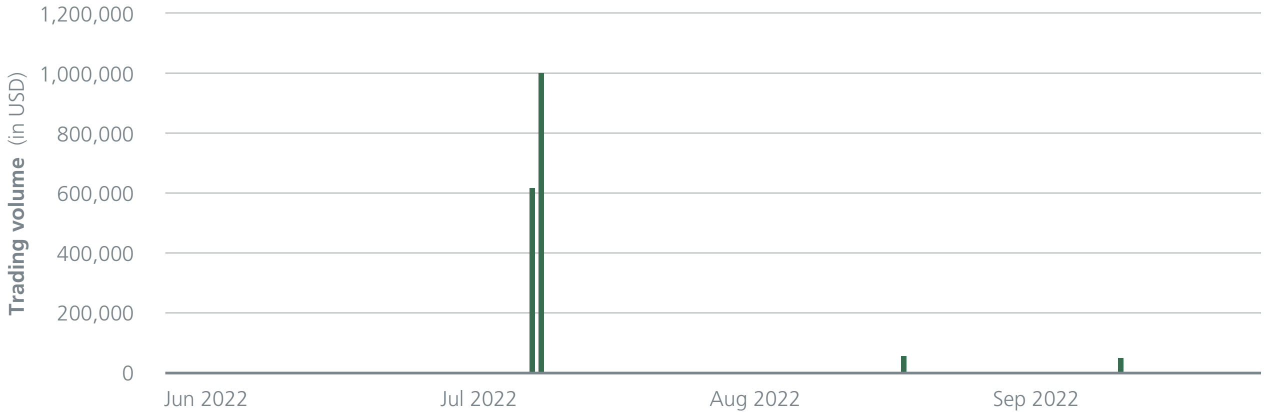
Another point to consider is the time-varying nature of the liquidity in individual bonds. While Figure 3 shows that some bonds trade almost daily, others trade less frequently and their liquidity is strongly clustered over time. Figure 4 shows examples of two such bonds.

Figure 4: Time-varying trading activity in ABT 3.75% 11/30/26 and AEP 4% 12/01/46

Abbott Laboratories 3.75% 11/30/2026



AEP Transmission 4% 12/01/2046



Source: Finra, Quoniam Asset Management GmbH

The first example illustrates the relatively liquid bonds in Abbot Laboratories: 3.75% 11/30/26. Over June and the first half of July 2022, on average, more than 2.8 million nominal was traded daily in the bond. For the following months, the average drops to below 350,000 USD nominal per day. Liquidity varied dramatically throughout this period.

In the second example, the AEP Transmission 4% 12/01/46 bond did not trade at all until mid-July. However, as can be seen from Figure 4, this does not mean that trading in a specific bond is not possible. On two consecutive days, an overall nominal amount of 1.6 million USD was executed. However, for the rest of the displayed period, only two retail-size transactions were reported in TRACE. Thus, investors who find this bond attractive from a valuation perspective may have been discouraged from attempting to buy it, given its very low liquidity in the market.

While the problem of limited, time-varying, and less transparent liquidity in corporate bonds is obvious, the question remains as to how to deal with it during the construction process of corporate bond portfolios. As post-trade information does not seem sufficient to capture most of the potentially liquid universe, as shown in Figure 1, the use of pre-trade data on broker interest to buy and sell can help identify pockets of liquidity that are not visible in post-trade data. We demonstrate the benefits of using these data in the portfolio construction process and help discover tradable bonds that seem illiquid using only post-trade data.

Data

We use post-trade data from the Trade Reporting And Compliance Engine (TRACE) which is governed by the Financial Industry Regulatory Authority (FINRA). TRACE aggregates data on trade in USD-denominated fixed-income instruments, such as corporate bonds, agency debt, and mortgage securities, with trade histories available since 2009. There is a regulatory requirement to report trades in TRACE-eligible bonds to FINRA within 15 min of the conclusion of the trade. These reports must include the side of the trade (buy or sell), price, volume, timestamp, and type of buyer or seller (e.g., whether a broker or buyside firm trades on that side of the trade). Access to these data is available to the public for a fee. However, precautionary measures are taken to protect brokers and investors, for example, by capping the reported volume of corporate bonds at 5 million USD, even if the actual trade size is larger.

Pre-trade information is obtained from the Neptune Network data provider[1]. The Neptune database connects more than 30 large bond brokers and aggregates real-time runs and axes using various fixed-income instruments. The data include bid and offer volumes and the prices/spreads at which these sell-side firms signal interest in trading a certain bond. These can be retrieved from large databases and incorporated into portfolio construction, order management, and execution management systems. The usefulness of this information depends on the topicality of the data and the commitment of various brokers to execute trades at the indicative volumes close to the indicative spread levels.

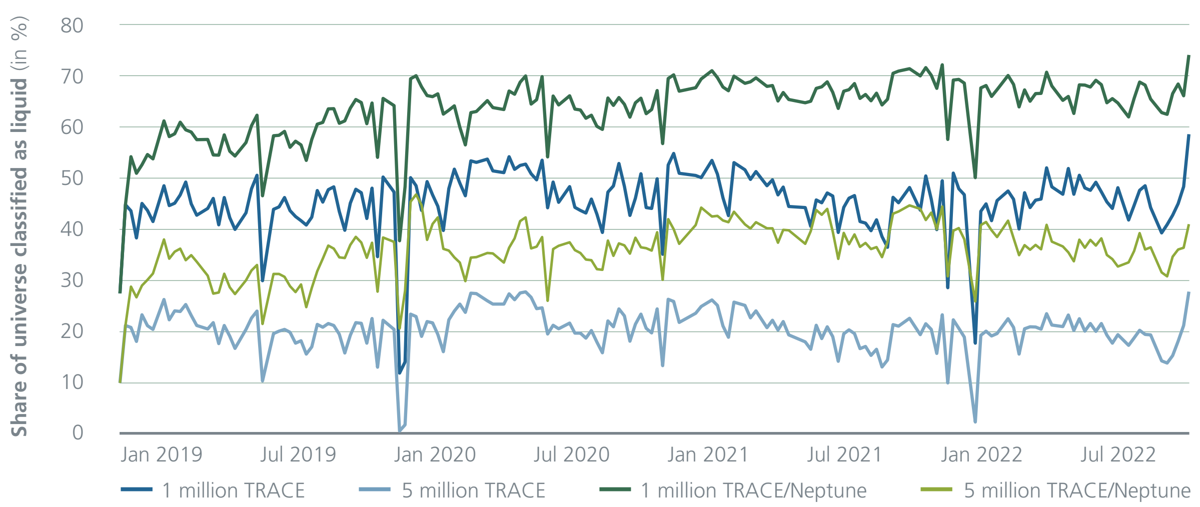
We examine data for USD investment grade (IG) credit from 2019 to 2022. In our analysis, we exclude dealer-to-dealer trade and focus on dealer-investor trade. On average, we see approximately nine trades per asset per week in TRACE, with 48.3% bought and 51.7% sold by investors. In Neptune, 7,372 bonds were included during this period, with a daily median of 2,934; in TRACE, the total number was 24,915 with a daily median of 12,145.

To distinguish between liquid and illiquid bonds, we must define a threshold for the trading volume above which a bond is considered liquid. We used two definitions to ensure the robustness of the results. In the first definition, we consider all bonds with a trading volume of USD 1 million in TRACE in a particular week to be liquid. Second, a stricter definition requires the trading of USD 5 million in nominal value in a bond in a certain week to be considered liquid.

When we use TRACE information to forecast liquidity for a week, we use the aggregate volume of the previous week as our predictor. As pre-trade data becomes stale faster, we take a liquidity snapshot every Friday using the maximum nominal amount offered or bid in a particular bond on that day. This information is used to forecast the following week's liquidity. The following figure shows which part of the universe is classified as liquid using the liquidity definitions above.

[1] There are other providers of pre-trade data in the market. This study does not aim to compare various pre-trade data providers, but to focus on one to demonstrate the value of this type of data.

Figure 5: Share of the universe classified as liquid

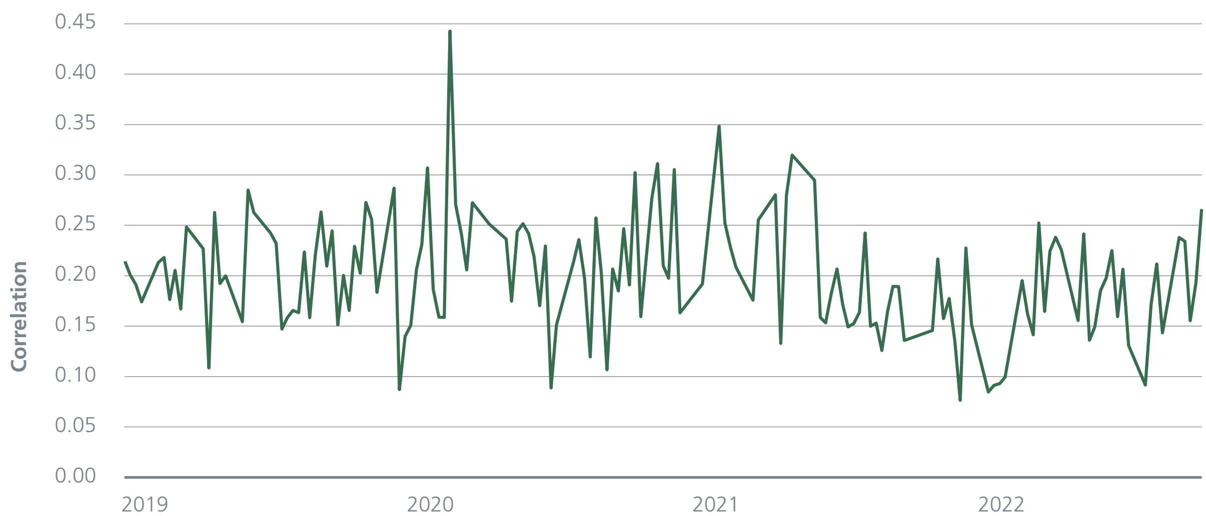


Source: Finra, Neptune Networks, Quoniam Asset Management GmbH

The weekly liquidity estimates suggest that the introduction of pre-trade data significantly increased the share of the universe classified as liquid. If one uses a one-million par value threshold to distinguish between liquid and illiquid bonds, the inclusion of pre-trade data increases the average share of the universe defined as liquid from 46.5% to 64.1% from January 01/2019 to 09/2022. If a more conservative 5 million threshold is used, the share of the universe classified as liquid jumps from 22.2% to 37.4%. In both cases, considerably more bonds are classified as liquids than when using post-trade data alone.

An inspection of the correlation between the volume indicators derived from pre-trade and TRACE's post-trade in the same week reveals that the correlation is low which leaves much additional information in the pre-trade data that can potentially help improve the liquidity estimate of the universe.

Figure 6: Correlation between individual bond trading volume estimates in Neptune and TRACE



Source: Finra, Neptune Networks, Quoniam Asset Management GmbH

Tradability

We analyse the tradability estimates from post-trade TRACE data and compare the results in terms of reliability with blended post-trade and pre-trade data. Specifically, we answer the question of whether the addition of pre-trade information improves tradability forecasts and lowers forecast errors. We define tradability as an indicator that equals one if the bond is estimated to be liquid and zero if it is estimated to be illiquid.

We find that the share that is classified as illiquid but trades as liquid in the market decreases if we combine pre-trade and post-trade data compared with a forecast based on the previous week's TRACE volume alone. Moreover, the share of bonds correctly classified as liquids increased significantly with the inclusion of pre-trade data.

To evaluate the forecast quality of various tradability definitions, we use the following matrix to determine the errors in tradability forecasts and compare them across universes:

Figure 7: Error matrix

Bond classified as illiquid	Shoud be reduced using pre-trade information	Either correctly classified or lack of demand
Bond classified as liquid	Correctly classified liquid universe	Either bond wrongly classified or lack of demand
	Bond does trade	**Bond does not trade**

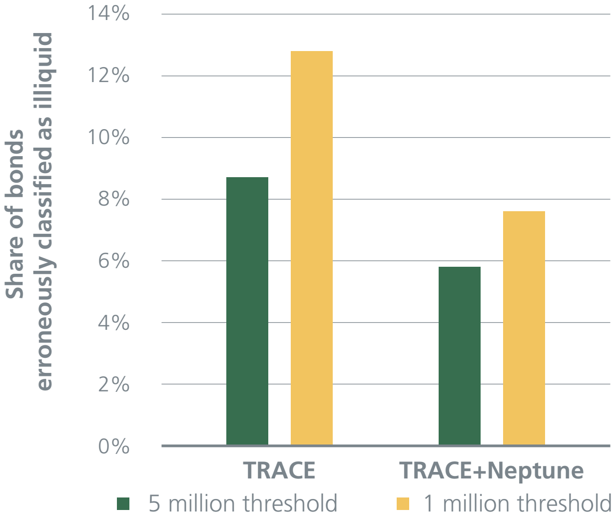
Source: Quoniam Asset Management GmbH

We calculate whether a bond is classified as tradable in a certain week and then observe whether it trades in the following week using the liquidity definitions above. We were particularly interested in the squares on the left side of the matrix. If pre-trade data add useful information to the process of identifying tradability in the market, the share of bonds correctly classified as tradable should increase, and the forecast error in the upper left square of the matrix should decrease. This error captures bonds that are classified as not tradable but traded.

The right-hand side of the matrix, which contains bonds that did not trade in a particular week, is more difficult to interpret. The fact that a bond does not trade does not necessarily mean that it is not tradable. It may have been possible to trade it in meaningful amounts, but the lack of investor demand or supply prevented trade. Therefore, we focus on the left-hand side, where the fact that the trade took place shows that the bond was tradable.

The following graph shows the percentage of bonds erroneously classified as illiquid for both liquidity definitions for the use of post-trade data only and the incorporation of pre-trade data.

Figure 8: Share of bonds erroneously classified as illiquid

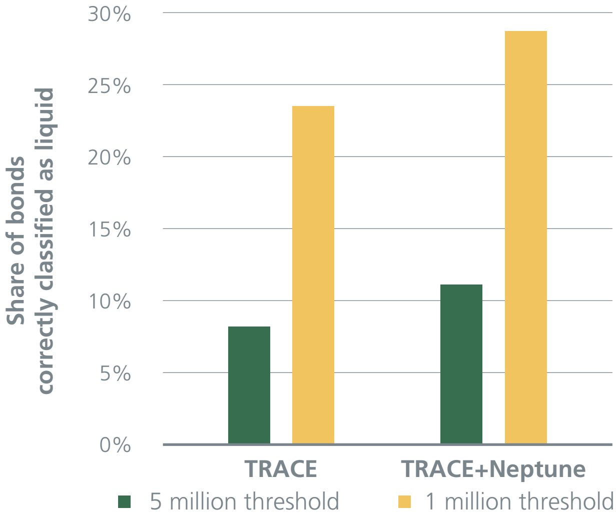


Source: Finra, Neptune Networks, Quoniam Asset Management GmbH

The inclusion of pre-trade data significantly decreases the share of bonds erroneously classified as untradable. For a liquidity threshold of 5 million par value, the share of these bonds decreases from 8.7% to 5.8%, whereas for a one million par value, the figure falls from 12.8% to 7.6%.

These numbers show that pre-trade data help identify tradable bonds traded less frequently in the market. Similarly, the share of bonds correctly classified as tradable is also higher for the dataset that includes pre-trade data.

Figure 9: Share of bonds correctly classified as tradable



Source: Finra, Neptune Networks, Quoniam Asset Management GmbH

Using the 5 million USD liquidity threshold, the share of bonds classified as tradable that traded in the following week increased from 8.2%, using only post-trade TRACE data, to 11.1%, incorporating pre-trade information. If the threshold is lowered to one million USD, the share of bonds correctly classified as tradable increases from 23.5% to 28.7%. Therefore, for both thresholds, the number of bonds classified as tradable increases significantly. This provides a larger range from which to choose when constructing corporate bond portfolios.

To further analyse the additional contribution of pre-trade data to our tradability indicator, we estimate the following regression equation using a standard logit model:

$$I_{T}=\beta_0 + \beta_{Tr}\log(V_{Tr}) + \beta_{Ne}\log(V_{Ne}) + \sum_{i=1}^{3}\beta_i X_i + \varepsilon$$

I_T is an indicator variable that is 1, if the bond's trading volume was above the pre-defined threshold in the following week, and 0 otherwise; V_{Tr} is the realised trading volume on TRACE in the week before, V_{Ne} is the indicative trading volume in Neptune on the Friday before, X_i are control variables and β and ε are the regression coefficients and the error term, respectively.

We used the log of the volume to account for outliers in this variable. As control variables, we use the bond spread and the bond's amount outstanding, duration, and age. We use a logit model to estimate the above equation because the dependent variable is a binary indicator. Moreover, we estimated this equation using both a one million USD par value threshold and a five million USD threshold.

If the trading volumes in TRACE and Neptune, respectively, help explain the realised trading volume in the following week, we expect the coefficients β_{Tr} and β_{Ne} to be positive and significant. The former represents the liquid part of the universe (the upper-right sector in Figure 1), while the latter represents the upper-left sector. Thus, the regression provides a quantitative estimate of the individual contributions of the two data sources to tradability. The results are summarised in Table 1.

Table 1: Logistic regression results
Panel A: 5 million USD par value threshold

Variable	Regression coefficient	t-value
Log (Volume TRACE)	0.18	401.1
Log (Volume Neptune)	0.05	229.1

Panel B: 1 million USD par value threshold

Variable	Regression coefficient	t-value
Log (Volume TRACE)	0.16	605.6
Log (Volume Neptune)	0.04	235.8

Source: FINRA, Neptune Networks, Quoniam Asset Management GmbH

As can be seen, both the previous week's volume in TRACE and Neptune help explain the bonds' realised trading volume in the subsequent week. Both coefficients are positive and highly significant. The results hold for both the liquidity thresholds defined above and indicate that the addition of pre-trade information significantly increases the precision of a tradability indicator.

The coefficient of the TRACE volume was four times larger than that of the pre-trade volume. This is partly driven by the fact that bonds with higher TRACE volumes tend to be more liquid, trade more frequently, and have a higher volume. Therefore, we run the same logit regression again, but replace the (log) volumes of TRACE and Neptune with an indicator of whether the respective bond is estimated as liquid according to our two definitions. In this version of the regression, on the left-hand side, there is an indicator that it is one if the bonds traded as liquid in a certain week and zero otherwise; on the right-hand side, there are two indicators that equal one if the bond was flagged as liquid on TRACE and Neptune, respectively, in the previous week plus the control variables, as defined above. Therefore, the difference in the traded volumes between the bonds that are liquid in TRACE and those in Neptune is explicitly removed from the equation.

The regression coefficients of TRACE and Neptune are 2.3 (2.5) and 1.5 (1.4), respectively, for the 5 million USD (1 million USD) threshold. Both coefficients remained statistically highly significant. These numbers were much closer to each other, indicating the importance of Neptune volumes in determining a precise tradability estimate.

Liquidity

Next, we analyse whether pre-trade information helps forecast not only tradability but also traded volume. Specifically, we want to know whether the volume of a bond bought (sold) in a particular week is a function of the TRACE buy (sell) volume or the Neptune buy (sell) axes of the previous week. This helps us understand the relative importance of pre-trade and post-trade data in estimating available liquidity.

We find that both post-trade and pre-trade volumes are positively correlated with trading volumes in the following week. For the previous week's TRACE volume, sells have a larger effect on determining the next week's buy volume than buys. The same holds true for buys that determine the next week's sell volume, indicating some mean reversion in the direction of trading activity. However, this effect is not present for pre-trade volumes, indicating that the direction of trade interest in pre-trade data has a strong impact on realised trade.

To investigate liquidity estimation, we focus only on the liquid part of the universe. We analyse bonds traded above our liquidity threshold definitions in a certain week and calculate whether the previous week's volume influences the traded volume. We split the universe into buy and sell volumes because we have this information for both post-trade and pre-trade data.

We want to analyse the following questions:

- What are the dynamics of the buy and sell axes when forecasting subsequent buy and sales?
- What is the relative contribution of pre-trade information to information sourced from TRACE?

First, we estimate the following regression equation:

$$\log(V^B_{Tr,t+1}) = \beta_0 + \beta^B_{TR}\log(V^B_{TR,t}) + \beta^S_{TR}\log(V^S_{TR,t}) + \beta^B_{Ne}\log(V^B_{Ne,t}) + \beta^S_{Ne}\log(V^S_{Ne,t}) + \sum_{i=1}^{4}\beta_i X_i + \varepsilon,$$

where we regress the (log) buy volume from TRACE in week T+1 on the (log) buy and sell volumes from both TRACE and Neptune in the previous week. We again add the bond spread, outstanding amount, duration, and age to control for the different liquidity levels per bond.

Table 2: Regression results for buy trading volumes

	5 million USD threshold – buy volume		1 million USD threshold – buy volume	
Independent variables	Regression coefficent	t-value	Regression coefficent	t-value
TRACE Volume Buy	0.185	6.7	0.195	10.7
TRACE Volume Sell	0.625	23.2	0.850	101.4
Neptune Volume Buy	0.370	13.8	0.086	63.7
Neptune Volume Sell	0.053	2.0	0.024	18.0

Source: Finra, Neptune Networks, Quoniam Asset Management GmbH

The results are presented in Table 2, several results stand out. Firstly, TRACE's buy volume is positive and significant, but the coefficient of TRACE's sell volume is three and a half times larger and highly significant. These results indicate two things: persistent liquidity effects due to the higher trading volume of bonds that had already traded more frequently in the previous week and a weekly mean reversion in the direction of trades. The more a bond is sold in the previous week, the higher the buy volume in the following week.

Interestingly, the results differed for the pre-trade volumes. The volume indicator for Neptune is positive and highly significant for both definitions of the liquidity threshold. The greater the buy volume indicated in Neptune in the previous week, the greater the buy volume realised in the following week. This indicates that the pre-trade information helps explain subsequent market activities.

Moreover, indicative pre-trade buy volumes have a seven times larger effect on subsequent buys than sell volumes for the same bond. The difference between the two coefficients is highly significant, indicating that, contrary to TRACE volumes, buy indications help explain subsequent buys better than sell volumes. Sell volumes are only borderline significant, potentially capturing the fact that more liquid bonds are traded more frequently on both sides.

We now repeat the analysis using the following week's sell volume on the left-hand side as the dependent variable. The results of the regression of TRACE's sell volume on the previous week's buy and sell volumes for TRACE and Neptune are presented in Table 3.

Table 3: Regression results for sell trading volumes

	5 million USD threshold – buy volume		1 million USD threshold – buy volume	
Independent variables	Regression coefficent	t-value	Regression coefficent	t-value
TRACE Volume Buy	0.567	21.1	0.744	41.6
TRACE Volume Sell	0.194	7.0	0.229	12.4
Neptune Volume Buy	0.181	6.9	0.198	11.3
Neptune Volume Sell	0.159	6.1	0.215	12.5

Source: Finra, Neptune Networks, Quoniam Asset Management GmbH

The results for sales volumes confirm the mean-reverting properties of the trade time series weekly. Although all the coefficients are positive, the sales volume coefficient for TRACE is three times smaller than the buy volume coefficient.

Similar to the buy regression, for sells, the indicative pre-trade sell volume coefficient is significantly positive, indicating that the sell liquidity in Neptune the week before is positively correlated with actual sells in the following week. Again, the pre-trade volume for the buy volume is also significantly positive, indicating some liquidity effect of bonds in the universe. Contrary to the buy regression, however, for the sell regression, the coefficient of pre-trade buy volume is roughly the same as the coefficient of pre-trade sell volume, indicating some asymmetry in the coverage of buys and sells

One reason for this asymmetry is that investors are usually more flexible when buying bonds than when selling. An investor intending to buy a certain bond in a company may switch to a different issue in the same company if the originally planned purchase is too expensive or impossible. However, if an investor wants to divest a certain bond, he has no choice but to find a willing buyer. Switching to a different bond for sale is not a viable alternative unless investors hold several bonds with the same issuer.

Overall, the results strongly confirm the usefulness of incorporating pre-trade data into market liquidity estimations.

Transaction costs

The next aspect that we want to shed light on is the estimation of transaction costs. In addition to estimating which bonds can be traded and at which size, asset managers must also have a realistic estimate of the costs associated with buying and selling a bond. If the potential tightening potential of the bond (which is uncertain and lies in the future) cannot compensate for the cost of buying the bond (which is certain and immediate), the trade harms performance and should be avoided.

We find that the transaction costs are very persistent. Bonds with high transaction costs in the previous week continue to incur high transaction costs in the following week. When we sort the transaction cost deciles by pre-trade volume, we observe a decrease in transaction costs with increasing volume. This effect is particularly visible for high-cost bonds.

In this section, we analyse whether the incorporation of pre-trade data helps calibrate transaction costs to more realistic levels. Measuring the transaction costs is difficult when only TRACE data are available. From the recorded trade prices in a bond during the day, it is difficult to assess the deviation from the prevailing mid-price, because this price changes constantly with moving rates and spread markets. Therefore, we compare investor trades with dealer-to-dealer trades and calculate the difference between these prices as the cost (to mid-price) of an individual transaction. To prevent market moves from biasing this estimate, we consider only trades that occurred within one minute of a dealer-to-dealer transaction. None of the other transactions were considered in the analysis.

We first examined the relationship between the realised transaction costs taken from TRACE and the Neptune volume in the previous week. Transaction costs are defined as the difference between the bid (ask) price for selling (buying) and the mid-price of the bid/ask spread. The hypothesis is that all else being equal, a higher indicative pre-trade volume leads to lower transaction costs for both buying and selling.

To achieve this, we focus on bonds traded over two consecutive weeks. We split these bonds into ten portfolios of equal size by transaction costs in TRACE during the first week. Portfolio 0 consists of 10% of bonds with the lowest transaction costs in the previous week, and portfolio 9 consists of the 10% bonds with the highest transaction costs.

Each of these ten portfolios is again split into ten subportfolios according to the Neptune volume. Portfolio 0 consists of all bonds without pre-trade volume, whereas portfolios 1 to 9 are sorted in ascending order with respect to the indicative pre-trade volume[2]. Portfolio (9, 9), for example, consists of the highest Neptune volume bonds of the highest TRACE transaction cost bonds in week 1. We calculate the average transaction costs for each portfolio in week 2.

[2] That means that portfolios 1 to 9 have the same size while portfolio 0 deviates.

Figure 10: Heatmap of realised transaction costs depending on Neptune volume

Panel A: Transaction costs for buys (in bp)

	No Neptune volume	1 Lowest Neptune volume	2	3	4	5	6	7	8	9 Highest Neptune volume
Lowest TRACE Costs 0	18	16	17	18	17	16	17	16	17	17
1	15	12	13	14	13	14	14	13	13	13
2	13	11	11	11	11	11	10	10	10	11
3	14	12	12	12	12	12	11	11	11	12
4	16	13	13	13	13	13	13	14	13	14
5	17	15	15	15	15	15	16	16	16	16
6	19	18	18	18	17	18	17	19	18	19
7	24	22	22	21	22	21	22	22	22	22
8	33	32	32	32	31	31	30	30	30	29
Highest TRACE costs 9	53	57	56	57	57	58	55	53	54	50

Panel B: Transaction costs for sells in bp

	No Neptune volume	1 Lowest Neptune volume	2	3	4	5	6	7	8	9 Highest Neptune volume
Lowest TRACE Costs 0	15	12	13	12	13	12	12	12	11	13
1	13	11	10	12	11	10	9.8	10	9.5	11
2	12	9	9.7	9.6	9	8.3	8.7	9.1	8.9	9
3	13	9.4	9.9	9.9	9.8	9.1	9.2	8.9	8.8	9.6
4	14	12	11	11	11	10	10	9.7	9.6	10
5	14	11	12	12	12	11	11	11	11	11
6	15	14	13	13	12	13	13	12	12	12
Highest TRACE costs 7	18	16	16	16	16	15	15	14	14	14
8	23	20	20	20	19	20	19	19	19	17
9	33	29	29	28	31	29	28	27	24	20

Source: Finra, Neptune Networks, Quoniam Asset Management GmbH

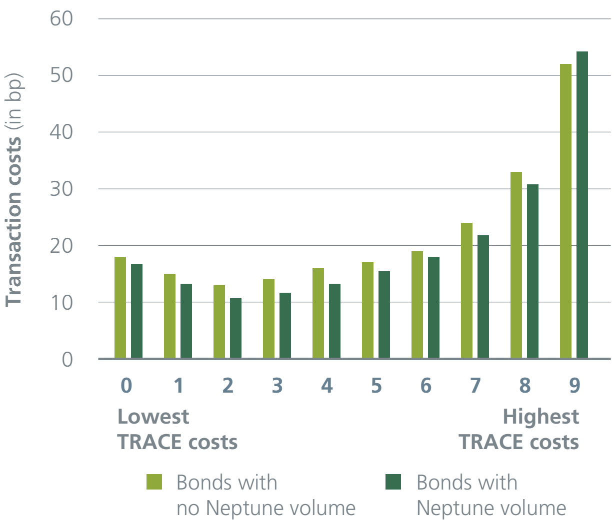
Figure 10 shows the average transaction costs (in basis points) for all 100 portfolios. This study yielded several observations. Firstly, bonds without indicative pre-trade volume have on average higher transaction costs (22.2 bp for buys and 17 bp for sells) relative to the bond with indicative pre-trade volume (20.7 bp for buys and 13.7bp for sells). However, this difference may be owing to the different liquidity characteristics of the two bond groups. Moreover, the generally higher transaction costs of the purchases reflect the period under consideration.

Secondly, bonds with higher pre-trade volumes in week 1 tend to have lower transaction costs in week 2. For bonds with the lowest pre-trade volume, the average week 2 transaction costs are 20.8 bp for buys and 14.3 bp for sells, whereas for the bonds with the highest pre-trade volumes these numbers drop to 20.3 bp for buys and 12.7 bp for sells, respectively.

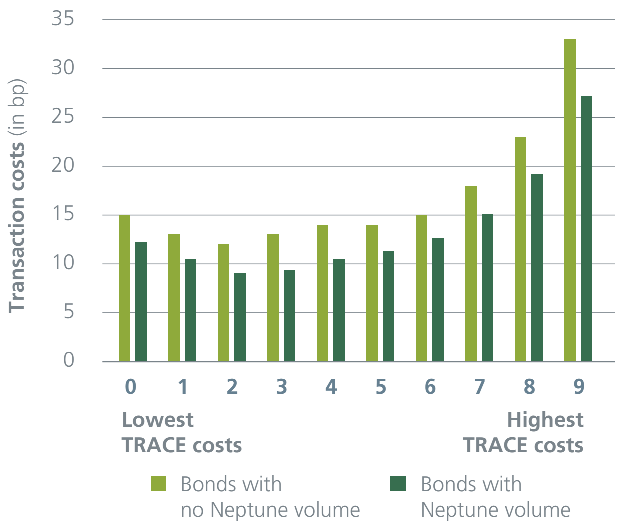
Thirdly, the reduction in realised transaction costs for high pre-trade volume bonds is particularly pronounced for bonds that tend to have higher average transaction costs. For the last two rows, TRACE portfolios 8 and 9, which cover the bonds with the highest transaction costs, the average costs decrease from 33 bp to 29 bp for portfolio 8 and from 53 bp to 50 bp for portfolio 9 on the buy side when one moves from Neptune portfolios 1 to 9. For the sell side, Portfolio 8 transaction costs drop from 23 bp to 17 bp, and for Portfolio 9, from 33 bp to 20 bp with increasing pre-trade volume. Therefore, pre-trade data on volume can help reduce transaction costs particularly for the most expensive names.

In the next graph, we analyse whether the TRACE transaction costs differ depending on the pre-trade indication of broker interest. By classifying bonds according to TRACE transaction costs, we compared bonds with relatively similar cost characteristics.

Figure 11: Transaction costs of bonds with and without indicative pre-trade volume
Panel A: Buy transaction costs



Panel B: Sell transaction costs



Source: Finra, Neptune Networks, Quoniam Asset Management GmbH

Figure 11 shows the difference in the transaction costs of bonds with and without pre-trade volume per TRACE transaction-cost decile from the previous week. For buys, nine out of ten deciles show a decrease in transaction costs that equals, on average, ten percent. A slight increase in the realised transaction cost is recorded only for the highest TRACE transaction cost decile. These results are even more pronounced for selling transaction costs. Here, all deciles see a decrease in the average transaction costs of bonds with pre-trade volumes relative to those without. The average reduction in transaction costs is 20%.

The results clearly show that with more indicative pre-trade interest, realised transaction costs show an improvement, particularly for more expensive and less liquid issues.

Performance

Finally , we examined the performance impact of incorporating pre-trade data into the portfolio construction process. We want to understand how and why the average alpha potential of a USD IG corporate bond portfolio changes if the liquid universe is extended from a TRACE-only definition to a definition of liquid bonds using both post-trade and pre-trade data as sources of liquidity. We again use two different thresholds of USD 1 million and USD 5 million to determine whether a bond is liquid.

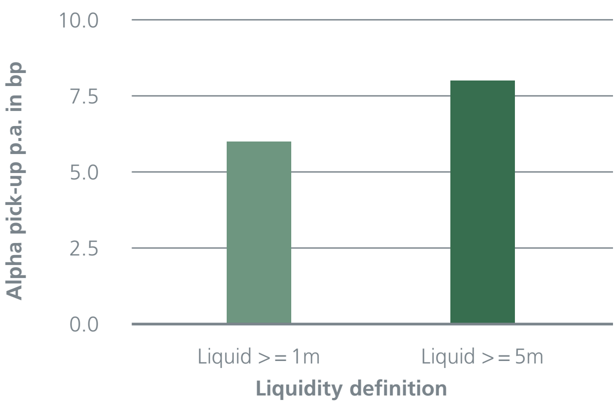
We find that a factor portfolio constructed from an investable universe built on both pre- and post-trade data outperforms a portfolio containing only post-trade information by six to eight basis points p.a., depending on the selected liquidity threshold. This performance increase is proportional to an increase in factor exposure in the portfolios.

To identify the performance impact of an extension of the liquid universe using pre-trade information, we use a systematic factor signal to construct a portfolio that loads this signal by combining systematic factors such as carry, momentum, and value. We compare the following two portfolios: Portfolio A is selected from all bonds classified as liquid using TRACE data only, and Portfolio B selects bonds from a universe defined as liquid using both post-trade and pre-trade data. Therefore, portfolio B has a larger pool of bonds from which to choose. We compare both portfolios using the same credit benchmark, which includes liquid and illiquid bonds.

We calculate backtests to optimise the expected returns of portfolios A and B at the end of each month using the same risk characteristics for both portfolios. The portfolios are identical in duration, DTS positions, average ratings, monthly turnover, and credit spread. The period we investigated ranged from January 2019 to September 2022, for which pre-trade data were available.

The alpha differences between the two portfolios are displayed in Figure 12 for both liquidity definitions.

Figure 12: Alpha pick-up with incorporated pre-trade data



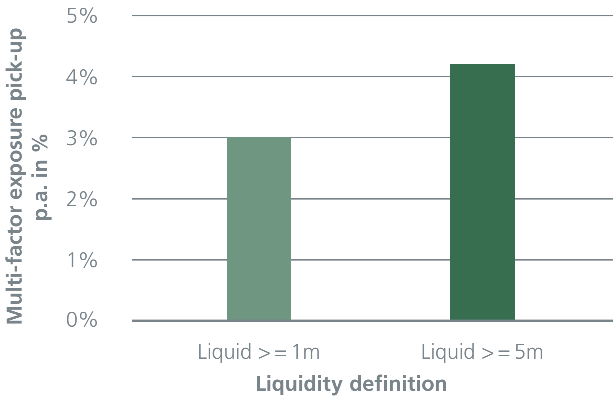
Source: Quoniam Asset Management GmbH

As can be seen, the average annualised alpha increases once the liquid universe is enlarged with the incorporation of pre-date data. For a liquidity definition of one million USD, the alpha potential of a factor portfolio increases by six basis points per annum, and for a stricter definition of liquidity of five million USD, the value-added of pre-trade data increases by eight basis points per year.

The results show that extending the investable universe by incorporating forward-looking information affects asset managers' performance. For a quantitative factor strategy, the impact on the performance can be calculated with reasonable precision. As all other risk characteristics of the portfolios are held constant, the performance difference can be explained by the larger pool of available bonds owing to the larger liquid universe.

The availability of a larger pool of investable bonds increases not only investment opportunities but also opportunities to translate into higher realised alphas. What drives the systematically higher returns? The next graph compares the differences in the factor exposures of portfolios A and B for the two definitions of liquidity.

Figure 13: Multi-factor exposure pick-up with incorporated pre-trade data



Source: Quoniam Asset Management GmbH

As shown in this figure, a larger pool of bonds allows for higher exposure to the factor signal by choosing from a larger pool of liquid bonds indicating a higher alpha potential for the portfolio. Again, the effect is larger for a more restrictive definition of liquidity and is proportionate to the impact of alpha. We conclude that the factor strategies that work best in large universes can profit from more precise information on the liquidity of the underlying bond universe. Although all actively managed portfolios should profit from an extension of the investable universe, we can quantify the impact of performance for a factor portfolio.

Conclusion

This study analyses the incorporation of pre-trade data into the portfolio-management process by determining which bonds are tradable, at which size, at which cost, and to which performance effect. For example, we use the pre-trade bid and ask axes from Neptune and incorporate these data into the liquidity determination process.

This study focuses on US IG credit because of its transparency owing to the availability of consolidated tape. The lack of such information in Euro IG credit makes a rigorous investigation difficult, as one would need to rely on incomplete data from different sources. We hope that the efforts to create a consolidated tape in Europe will finally bear fruit so that we will get more transparency in this market segment as well.

We find that pre-trade data significantly increases the part of the universe that is correctly classified as tradable, adds predictive power to the traded volume, and helps lower the estimation error for transaction costs. A backtest with different liquid universes, including and excluding pre-trade data, to determine the liquid universe yields annual performance differences of up to eight basis points.

Information is the key to success, particularly in an opaque OTC market such as the corporate bond market. By incorporating pre-trade data into the investment process, value can be added to corporate bond portfolios. Because systematic strategies profit the most from liquid trading, properly addressing the challenges of identifying liquidity is a decisive feature of quantitative factor strategies.

Further reading

White papers

- Distinguishing factor strategies in corporate bonds and equities
- Diversifying credit portfolios with factor investing

See also

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Imprint

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