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Bond liquidity and dealer inventories: Insights from US and European regulatory data

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Abstract

Most corporate bond research on liquidity and dealer inventories is based on the USD-denominated bonds transactions in the US reported to TRACE. Some of these bonds, however, are also traded in Europe, and those trades are not subject to the TRACE reporting requirements. Leveraging our access to both TRACE and ZEN, the UK's trade reporting system which is not publicly available, we find an overlap of about 30,000 bonds that are traded both in the US and in Europe. This paper examines how using the CUSIP-level information from TRACE and ZEN affects the computation of bond liquidity metrics, dealer inventories, and the relationship between the two. We find that in the combined dataset, the weekly volume traded and number of trades are significantly higher than in TRACE: e.g., the average unconditional number of trades in investment-grade (high-yield) bonds is 17% (20%) higher and the average unconditional volume traded is 15% (17%) higher when we incorporate the information from ZEN. We find a strong positive relationship between inventories and liquidity, as proxied by the trading activity metrics (i.e., number of trades, zero trading days, or par value traded) in TRACE data, and this result carries over to the combined dataset. When measuring bond liquidity with the Amihud ratio, we find strong relationships in both TRACE and ZEN but of opposite signs: greater (lagged) inventories result in higher liquidity in the US but lower liquidity in Europe. The two effects offset each other and significance disappears in the combined dataset. We conclude that (i) neither of the individual datasets paints a complete picture of the effects of dealer inventories on bond market liquidity, (ii) the measures based on the combined dataset appear more precise in describing the market characteristics, and (iii) data sharing across transaction reporting databases would allow a variety of stakeholders to gain a more accurate understanding of the liquidity and dealer inventories in global bond markets.

Keywords: Bond liquidity, dealer inventories, regulatory cooperation, TRACE, ZEN.

JEL classification: G10, G12, G23.

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1 Executive summary

Purpose of the paper

This research is motivated by two simple empirical observations. First, broker-dealers can—and do—trade globally across multiple jurisdictions. Second, the financial data compiled by each jurisdiction's financial regulator is generally limited to transactions occurring within that particular jurisdiction.[1] Thus, the inherent incompleteness of each individual dataset may prevent regulators, as well as academic researchers, from seeing the full picture of integrated financial markets. This paper highlights this issue and attempts to help alleviate it by leveraging the authors' access to datasets from two jurisdictions—TRACE for the US and ZEN for the UK.[2]

In the present paper we illustrate the benefits of international cooperation and data sharing between regulators using as an example a study of liquidity metrics and dealer inventories in the corporate bond market. The paper represents the first research collaboration between the staff of the Securities and Exchange Commission and the Financial Conduct Authority. We hope that by highlighting the benefits of such collaboration, we will encourage further collaborative work between the staff of our respective agencies and other global regulators.

The paper achieves its goal in two steps. First, we compute summary statistics on bond liquidity measures based on TRACE, ZEN, and TRACE and ZEN combined. Second, we construct dealer inventories and study how bond liquidity is related to inventories while controlling for various bond and issuer characteristics as well as macroeconomic variables that may affect the credit market. The existing literature on corporate bond liquidity is predominantly based on TRACE, as this dataset covers trades made in the US, the largest corporate bond market. In addition, there are widely available public versions of TRACE. There is no publicly available version of ZEN, the UK reporting system. Our main contribution lies in demonstrating, as a proof-of-concept, how using data from other jurisdictions (in this case the UK) to supplement TRACE can materially impact empirical results in this area of study.

In the present paper, we focus on the corporate bond market for three main reasons. First, it is a key source of capital for businesses and an important savings vehicle for households. Second, the corporate bond market is largely a dealer-intermediated market and there is evidence that dealer inventories have declined from pre-crisis levels. However, this does not appear to have led to a decline in a range of traditional corporate bond liquidity metrics. These conflicting results on liquidity have led to a lively debate in the academic literature and among practitioners on the state of liquidity in the corporate bond market following the financial crisis and subsequent

[1] Within the European Union (EU), of which the UK is a member during the period we analyze, transaction reports are pooled across member countries in a process coordinated by the European Securities and Markets Authority (ESMA). National Competent Authorities (NCAs) submit all transaction reports received in their jurisdiction to ESMA. For the securities for which a NCA is the lead authority it receives from ESMA transaction reports from all NCAs in the EU. This is how the FCA's ZEN dataset that we use in this paper was constructed.

[2] Although we are currently unable to fully combine the two datasets at the transaction level (due to legal constraints pertaining to shared MiFID data ownership), we present statistics and results from the individual datasets and on a "virtually" combined dataset based on daily aggregate measures.

regulatory reforms. We believe that improving data quality, which can be achieved through regulatory cooperation, will play a key role in resolving the debate and, more importantly, contributing to measures to improve liquidity. However, the approach we take in this study is just one of many lines of inquiry to pursue. Lastly, due to the low frequency with which most corporate bonds trade, this market provides a unique setting where we can draw meaningful inference from aggregate metrics that can be computed without fully sharing the underlying data across jurisdictions.

Key findings

We examine the liquidity of USD-denominated corporate bonds that trade in both the US and Europe using a range of metrics on a weekly basis for the period August 1, 2011 to December 31, 2016. Further, we explore how these metrics are related to dealer inventories over the sample period. We perform this analysis three times: once for each of the reporting datasets to which each agency has access (regulatory TRACE in the US and ZEN in the UK) and then by replicating the analysis using aggregate information from both datasets. The aggregated information allows us to show what the analysis would produce, had it been possible to create a combined dataset. To our knowledge, this is the first paper that uses such granular data across jurisdictions.

- On liquidity metrics, we find that the US bond market is characterized by greater liquidity relative to the European bond market in the USD-denominated bonds as judged by measures of market activity: the number of trades, par value traded, and number of zero trading days. Using the combined dataset, we observe higher liquidity in the integrated market relative to either one of the two jurisdictions separately. For example, we find that in the combined dataset, the weekly volume traded and number of trades are significantly higher than in TRACE: e.g., the average unconditional number of trades in investment-grade (high-yield) bonds is 17% (20%) higher and the average unconditional volume traded is 15% (17%) higher when we incorporate the information from ZEN. Looking at measures of transaction cost, we find a mixed picture. We find a lower price impact (Amihud measure) in the European data than in the US, and the Amihud measure based on the combined dataset is between that based on TRACE and on ZEN. Conversely, based on roundtrip costs for institutional investors, we find transaction costs are lower in the US relative to Europe, with the combined dataset again in-between. Overall, we find that combining the data from the two jurisdictions materially impacts the quantifiable liquidity metrics and allows for a more precise calculation.
- On dealer inventories, we find that dealers pursue various strategies with respect to inventory management. For the majority of dealers in our sample, net changes in nominal inventory are dominated by either the US or the European side of the market. However, for a subset of dealers, net changes across markets are much more balanced.

- On the relationship between bond liquidity and dealer inventories, we find a strong positive relationship between inventories and liquidity, as proxied by the trading activity metrics (i.e., number of trades, zero trading days and par value traded), in TRACE data. No such relationship exists in ZEN for these metrics, and the TRACE-based results carry over to the combined dataset. When measuring bond liquidity with the Amihud metric, we find strong relationships in both TRACE and ZEN but with opposite signs. Greater inventories result in higher liquidity in the US but lower liquidity in Europe. The two effects offset each other and significance disappears in the combined dataset. For our composite measure of liquidity, we find a negative relationship between liquidity and inventory in ZEN but none in TRACE, and the relationship in the combined dataset is dominated by the ZEN results.
- The meaningful differences in results between the virtually combined dataset and either of the two individual sets (i.e., TRACE or ZEN) point to potential benefits of data sharing for a variety of stakeholders interested in capital markets, such as market participants, regulators, and academics.

2 Regulatory and market environment

Research cooperation

Regulators routinely collaborate and share data on an ad-hoc basis when conducting supervisory and enforcement work. However, at present there are a number of legal and data protection restrictions on sharing regulatory reporting datasets across jurisdictions. Access to such datasets is crucial when researching the way modern capital markets operate. Capital markets and their key participants are integrated across jurisdictions, whereas regulatory datasets usually are not. Any single dataset will only capture part of the activity in a market. Therefore, by using multiple datasets one can reduce the risk of drawing biases and spurious conclusions. It is exceedingly difficult for any single agency to measure the extent of this bias without exchanging some information with its counterparts in other jurisdictions. The problem is not ameliorated for academics or private sector data providers, as they usually work with anonymized or less complete versions of the datasets available to regulatory authorities and, to our knowledge, not with data from multiple jurisdictions.

Market setting

In writing this paper, we rely on unique characteristics of the corporate bond market. In the corporate bond market, the vast majority of trades are made over the counter and are dealer intermediated (Dick-Nielsen and Rossi (2019); Bessembinder, Jacobsen, Maxwell and Venkataraman (2018)). However, any individual bond trades infrequently. Goldstein and Hotchkiss (2020) find that in their sample the median bond in TRACE trades on average less than once a week. The low trading frequency and the importance of dealers as counterparty in most trades make this a setting where having complete data across markets can be of particular importance.

To get a sense for the reporting requirements, data coverage as well as our rationale for analyzing jointly TRACE and ZEN, consider the following stylized chain of transactions: (i) a US client sells a bond to a FINRA-member broker-dealer, (ii) the FINRA-member broker-dealer sells this bond to its UK non-member affiliate, and (iii) the UK non-member affiliate sells the bond to the UK client. The first of these three transactions will be reported to TRACE only, the second transaction (i.e., the affiliate trade) will appear in both TRACE and ZEN, and the third transaction will be reported to ZEN only.[3] Thus, one of the important institutional details is that the dealer comprises a US entity that is a registered FINRA member subsidiary and a UK non-member subsidiary. All the transactions by the US FINRA member subsidiary of the dealer would be reflected in TRACE regardless of counterparty, while the UK affiliate would report to ZEN.

The information presented in either of the datasets, therefore, is incomplete with respect to the number of transactions, par traded, and pricing. As a result, trading metrics in a given bond can be distorted when a dealer trades across jurisdictions and not all of the transactions are reflected in any one reporting system. Likewise, dealer inventories that can be constructed from such limited information may be inaccurate, especially when a dealer does not centralize inventory management and thus does not have offsetting trades with its local affiliates. Put differently, true values for liquidity metrics and dealer inventories would be unobservable to either jurisdiction unless regulators make arrangements to share their datasets.

3 Data

In this study we use data on corporate bonds from both the Regulatory version of TRACE, which records trades reported in the United States, and from ZEN, which records trades reported in the United Kingdom.[4] Brief descriptions of each dataset follow.

Reporting in TRACE

TRACE requires reporting of trades in TRACE-eligible securities where a FINRA member is counterparty or helps intermediate the transaction. As TRACE requires reporting only for USD-denominated bonds, our analysis is limited to such bonds. Primary market (issuance) and repo transactions are excluded from reporting. Trades in the TRACE dataset are publicly

[3] In every aspect of our methodology we rely on TRACE and ZEN reporting requirements as well as the presumption that reported data conforms to the (legally binding) reporting requirements.

[4] High-yield bonds comprise 81% of our sample. High-yield and investment-grade bonds can in general have different trading characteristics. As Table 3 below shows, however, in our sample these two types of bonds exhibit very similar liquidity attributes. Additionally, in all our regressions we control for credit rating.

disseminated with some restrictions.[5] As a result, the majority of published academic research is based on the TRACE dataset.

Given that this is the best publicly available dataset, some authors may fail to appreciate the important reporting and institutional details that underpin the data collected for the TRACE dataset. Perhaps unsurprisingly, many authors consistently assert that TRACE captures all trading in the relevant bonds to a very large extent. For example, Feldhütter (2012) states that "TRACE covers all trades in the secondary over-the-counter market for corporate bonds and accounts for more than 99% of the total secondary trading volume in corporate bonds" (p. 1165). This is true in a specific case—for trades involving a FINRA member (and only for USD-denominated bonds), as TRACE reporting obligations apply to specific legal entities that are FINRA members. If a broker-dealer trades through a different legal entity, for example a branch or a subsidiary outside the US, this trade will not necessarily be captured in TRACE.

Reporting in ZEN

ZEN was the UK transaction reporting system administered by the FCA at the time our research was conducted. ZEN replaced the previous reporting system (SABRE II) in August 2011, which determines the start of period we study in this paper. The obligation to report to ZEN is imposed on a very wide range of counterparties.[6] Reportable instruments are not limited by currency, rather, in the case of corporate bonds they are limited to those admitted to trading on a regulated or prescribed market. In terms of information content, reporting requirements in ZEN are broadly similar to those in TRACE. As there is no public version of ZEN, this dataset is rarely used in academic publications.

Affiliate trades and liquidity metrics across datasets

Affiliate trades are trades that occur between different legal entities within a given firm. They do not constitute true trading activity. When calculating liquidity metrics in the virtually combined TRACE and ZEN dataset, we avoid double counting of affiliate trades by removing these transactions from ZEN and counting them in TRACE only. Whereas it is not possible to reliably identify affiliate trades in TRACE prior to the introduction of the affiliate flag in November 2015, it is possible to do so in ZEN for our entire sample (since August 2011). Therefore, all of the affiliate trades show up in our TRACE volume as we decided to not exclude them for a fraction of the sample for consistency over time and comparability with the previous

[5] There are several public versions of the TRACE dataset. In addition to the basic version (no dealer identifiers and masked volumes with cut-offs at \$1m and \$5m), there is an enhanced version (no dealer identifiers and unmasked volume) and an enhanced version with anonymized dealer identities. The enhanced versions are available with an 18-month delay and at varying expense.

[6] During our period of interest, the obligation to report to ZEN was imposed on investment firms (both EEA and third country), their branches, along with those of credit institutions in the UK, and on managers of investment and pension funds.

TRACE studies. All affiliate trades are deleted from ZEN when calculating liquidity metrics. This has the effect of overestimating the liquidity in TRACE and underestimating it in ZEN.

Having addressed how we deal with double-counting of affiliate trades in our paper, it is worth mentioning another possible source of double counting. If the FINRA member legal entity of a broker dealer directly trades with a UK client, this trade can potentially appear in both TRACE and ZEN. Although this scenario is theoretically possible, we believe that it is very unlikely.[7] Unfortunately, without combining the raw data (which we are legally not authorized to do at this stage) there is no way for us to check how many of such transactions, if any, occur and show up in both TRACE and ZEN.

Therefore, it can be said that our liquidity metric analysis across both markets adopts a US perspective and can be viewed as a very conservative assessment of ZEN's contribution to the information contained in TRACE.[8] This makes it relevant to existing work, because almost all previous US corporate bond research has been done on the publicly available versions of TRACE. Broadly speaking, our paper underscores the inherent incompleteness of the data collected and maintained by any individual jurisdiction and, therefore, points to potential benefits of regulatory data sharing in research and policymaking.

Data cleaning and sample construction

Both TRACE and ZEN data have been cleaned by applying the standard filters used in the literature (e.g., Dick-Nielsen (2009, 2014)). In particular, we remove cancellations, reversals, and corrected transactions. We also remove duplicate trade reports for dealer-to-dealer transactions. To deal with the issue of erroneous price entries, for TRACE we apply a filter similar to the median and reversal filter in Edwards et al. (2007).[9] With the same objective, in ZEN we discard trades with periodic prices less than 1% of par value and more than 1000% of par value.

In calculating liquidity metrics, we exclude retail-sized trades of less than $100,000 in par value in line with prior studies (e.g., Dick-Nielsen et al. (2012)). As documented by Feldhütter (2012), these trades have a much wider dispersion in price and therefore have a disproportional impact in calculating Amihud (which is exactly what we observe in our sample) thereby leading to a reduction in the representativeness of trading costs of institutional investors.[10]

[7] Conditional on such a trade actually occurring, it would have to be a client with MiFID reporting obligations for this trade to show up in ZEN (in addition to TRACE). The likelihood of such a trade is low because the UK client would have to choose to trade with a FINRA-member legal entity of the broker-dealer instead of a local affiliate of this broker-dealer. It would be unusual for a client to not trade with a local desk that it normally trades with, particularly in light of the clearance and settlement issues (e.g., difficult to clear with the US desk without involving the local affiliate). Unless the client stands to somehow benefit from the trade being disseminated in TRACE, it is not clear why the client would not engage the UK affiliate. That said, we cannot rule out such transactions and the possibility that they can be reflected in ZEN in addition to TRACE.

[8] We use the phrase "conservative assessment" because we filter out from ZEN all non-customer transactions.

[9] Each price is compared with five previous and five subsequent transactions by averaging these neighboring prices and requiring that the price in question be within 50% of this average. Trades with prices outside of this range are removed from the dataset.

[10] The exclusion of the retail-sized trades constitutes a caveat that should be kept in mind when drawing policy implications based on the results reported in our paper.

To get information on control variables, we supplement our dataset with bond characteristics from the TRACE masterfile as well as bond and issuer characteristics from Mergent Fixed Income Securities Database (FISD). Merging the transactions data with FISD reduces our full sample from 32,470 overlapping CUSIPs (i.e., CUSIPs that are traded both in the US and Europe) to 20,608 bonds. Finally, we remove from our sample 168 perpetual bonds, as these unique bonds would not allow us to include some of the controls frequently used in the literature (e.g., time to maturity). Our final sample consists of 20,440 bonds.

Issuer summary

The 20,440 bonds in our final sample have 5,115 distinct issuers. Table 1 presents a summary of the various issuer characteristics at both issuer (Panel A) and CUSIP (Panel B) levels. Our sample is dominated by US firms, which account for 71% of issuers and 76% of bonds. This is not surprising in light of the fact that TRACE contains only USD-denominated bond transactions. Eleven percent of CUSIPs are associated with European issuers, and the remaining 13% originate in the rest of the world. More than half of our issuer sample (57%) are industrial firms and these account for 52% of the bonds. The second most represented industry group is finance (29% of the issuers), followed by utility companies (7%) and government (4%).

Table 1: Issuer Characteristics

A. By Issuer

	U.S. Issuer				European Issuer			
	Yes		No		Yes		No	
Total	3,641	71.20%	1,475	28.80%	534	10.40%	4,582	89.60%

	Industry Group											
	Industrial		Finance		Utility		Government		Miscellaneous		Not Available	
Total	2,904	56.80%	1,479	28.90%	390	7.60%	189	3.70%	153	3.00%	1	0.00%

B. By CUSIP

	U.S. Issuer				European Issuer			
	Yes		No		Yes		No	
Inv. Grade	3,218	15.70%	704	3.40%	312	1.50%	3,610	17.70%
High Yield	12,408	60.70%	4,113	20.10%	1,889	9.20%	14,632	71.60%
Total	15,626	76.40%	4,817	23.60%	2,201	10.80%	18,242	89.20%

	Industry Group											
	Industrial		Finance		Utility		Government		Miscellaneous		Not Available	
Inv. Grade	1,548	7.60%	1,107	5.40%	357	1.70%	890	4.40%	20	0.10%	–	0.00%
High Yield	9,174	44.90%	5,400	26.40%	1,388	6.80%	238	1.20%	320	1.60%	1	0.00%
Total	10,722	52.40%	6,507	31.80%	1,745	8.50%	1,128	5.50%	340	1.70%	1	0.00%

Bond summary

We focus on USD-denominated corporate bonds that traded between August 2011 and December 2016, and match bonds by CUSIP across TRACE and ZEN. We find that, in the reference period, out of c. 100,000 corporate bonds that traded in the US and out of c. 60,000 USD-denominated bonds that traded in Europe, 32,470 bonds had at least one trade in both datasets. This figure shows significant integration between markets as it represents approximately one third of corporate bonds traded in the US and more than half of USD-denominated bonds that traded in Europe during the period we examine.[11] After excluding perpetual bonds and requiring that bonds have data for the controls we use in Mergent FISD, our final sample consists of 20,440 bonds.

Table 2 presents a summary of the various characteristics of the bonds in our sample. High-yield bonds comprise 81% of our sample. About a quarter of the sample are privately placed bonds traded under Rule 144A. Globally issued securities—i.e., those that are issued simultaneously in two or more jurisdictions—account for 23%.[12] Less than 1% of bonds in the sample are asset-backed securities. Finally, in our regressions below we also control for credit rating, thereby addressing the unusual IG/HY split in our sample, and for bond features such as being putable and convertible.

Table 2: Bond Characteristics

	Rating		Rule 144A				Global Issue					
			Yes		No		Yes		No		Not Available	
Inv. Grade	3,924	19.20%	425	2.10%	3,497	17.10%	1,417	6.90%	2,473	12.10%	32	0.20%
High yield	16,516	80.80%	5,219	25.50%	11,302	55.30%	4,432	21.70%	11,844	57.90%	245	1.20%
Total	20,440	100%	5,644	27.60%	14,799	72.40%	5,849	28.60%	14,317	70.00%	277	1.40%

	Credit Enhancement						Asset Backed					
	Yes		No		Not Available		Yes		No		Not Available	
Inv. Grade	636	3.10%	3,255	15.90%	31	0.20%	44	0.20%	3,844	18.80%	34	0.20%
High Yield	3,989	19.50%	12,287	60.10%	245	1.20%	65	0.30%	16,172	79.10%	284	1.40%
Total	4,625	22.60%	15,542	76.00%	276	1.40%	109	0.50%	20,016	97.90%	318	1.60%

	Putable						Convertible					
	Yes		No		Not Available		Yes		No		Not Available	
Inv. Grade	62	0.30%	3,823	18.70%	37	0.20%	35	0.20%	3,853	18.80%	34	0.20%
High Yield	210	1.00%	16,027	78.40%	284	1.40%	906	4.40%	15,332	75.00%	283	1.40%
Total	272	1.30%	19,850	97.10%	321	1.60%	941	4.60%	19,185	93.80%	317	1.60%

[11] The majority of USD-denominated bonds which had trades in ZEN, but not in TRACE, during our reference period were bonds of government, quasi-government, or supranational issuers, for which reporting in TRACE is not required.

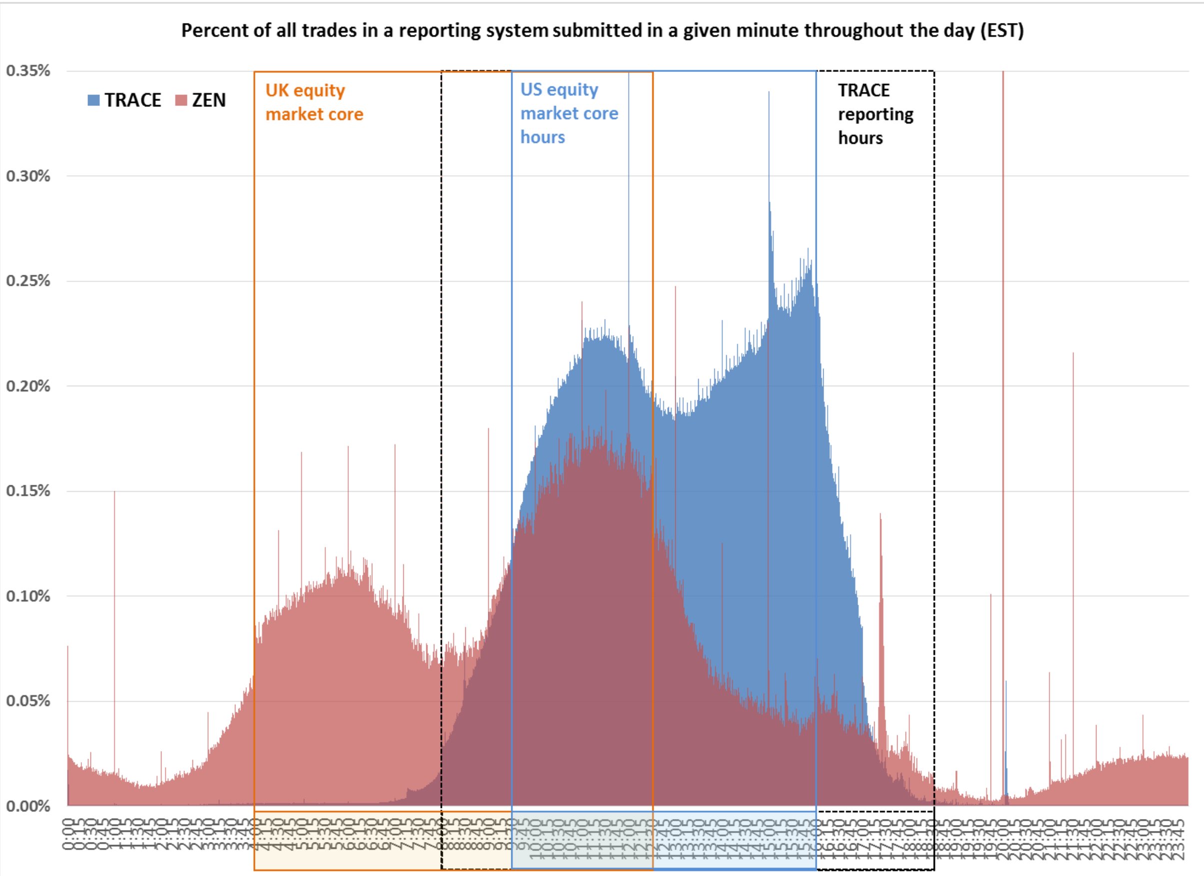
[12] Globally issued bonds are characterized by relatively low transaction costs (Edwards et al. (2007)).

Trade time chart

It is informative to highlight the extent to which bond trading across the two markets is contemporaneous over the course of a typical trading day. Given that the vast majority of trades in corporate bonds are carried out over-the-counter, i.e., directly between counterparties as opposed to through trading venues, trading is theoretically possible 24 hours a day. However, the availability of counterparties and the search costs incurred will vary over the business day in both the US and Europe.

Because individual bonds trade so infrequently, the baseline probability of a trade happening in a given minute on a given day is very low. To present a clear picture, we have aggregated the information for all bonds and all trading days in our sample. Figure 1 presents the percentage of all trades in a reporting system (calculated separately for TRACE and ZEN) submitted in a given minute throughout the day. This illustrates the probability of a trade happening in a given minute in the average day in our sample, conditional on a trade happening at all. The data for ZEN is presented in red and is superimposed on the data for TRACE presented in blue.[13] The chart is presented in Eastern Standard Time and adjusted for the time difference with Greenwich Mean Time and daylight savings.

Figure 1: Time Distribution of Trades in TRACE and ZEN



We can see from the chart that in both the UK and the US markets, bond trading is

[13] The area where the series for ZEN and TRACE overlap appears as a darker red in the ZEN series.

concentrated during the respective equity market core hours. For the UK market, trades are most frequent during the time both the UK and the US equity markets are open. For the US market, trades are most frequent in the hour prior to the close of US equity markets and during the time both the UK and the US equity markets are open. Overall trading in the US market is more compressed in time during the course of the average day relative to the UK market.

Prices within certain bands of volume of corporate bond trades submitted during TRACE reporting hours (8AM to 6:30PM EST) are generally made public. While it is hard to disentangle the effects of TRACE reporting hours from US equity market core hours, it does not appear that the probability of trading in either the US or the UK market is strongly affected by TRACE reporting hours.

4 Liquidity measures

We compute a range of liquidity metrics widely used in the academic literature and in previous regulatory work: weekly number of trades, zero trading days, par volume traded, turnover ratio, Amihud ratio, and Imputed Roundtrip Costs (IRC) (Aquilina and Suntheim (2016), Friewald, Jankowitsch and Subrahmanyam (2012), Dick-Nielsen et al. (2012)). To compute the Amihud ratio and the IRC, we follow the methodology in Dick-Nielsen et al. (2012). As in Aquilina and Suntheim (2016), we find that the Amihud is very sensitive to outliers, so we winsorize it at the 1% level. We compute all metrics weekly for the bonds that have at least one trade in TRACE or in ZEN in the period from August 2011 to December 2016. We then combine the underlying aggregate information for each metric by day and CUSIP, and compute the metrics to represent the virtual combined dataset.

Similar to Goldstein and Hotchkiss (2020), and to a lesser extent to Edwards, Harris and Piwowar (2007), we use all bonds in our cleaned sample, as opposed to focusing on the most liquid subset of bonds. This choice per se does not limit the number of liquidity metrics we can compute. This is because we are already constrained to computing metrics that do not require precise sequencing of trades within the day by the need to approximate a combined dataset. For example, we cannot compute the Bao, Pan and Wang (2011) price reversal measure or the Roll (1984) measure, as computing those measures for the combined dataset requires sequencing trades in time, which cannot be done without sharing the data contained in the individual trade observations.

Table 3 presents the distribution of the weekly values of the liquidity metrics in our sample in the respective datasets for high-yield (Panel A) and investment-grade (Panel B) bonds. These are weekly averages aggregated across CUSIPs. Conditional versions of the number of trades and volume traded are computed based on CUSIP-weeks in which there was at least one trade. The number of trades is widely reported in previous work and is an important metric in a setting where so few trades occur. Focusing on the high-yield bonds (Panel A), the mean (median) number of trades for an average week across all bonds in TRACE is 8.8 (5.3).[14] These are

[14]For reference, Goldstein and Hotchkiss (2020) find that the median bond in their TRACE sample has 0.6 institutional-sized trades in a month.

higher than the mean (median) based on ZEN, which is 2.9 (2.2). Thus, based on this liquidity metric, the US bond market is characterized by higher liquidity relative to Europe. Expectedly, the combined dataset produces a greater mean (median) number of trades—10.2(6)—than either TRACE or ZEN.

A similar picture emerges when one uses par value traded as a measure of liquidity: TRACE shows the median of \$9.9m vis-à-vis the median of \$2.9m in ZEN. The corresponding value in the combined dataset is \$10.9m. As expected, the values for the unconditional number of trades and volume traded are lower than their conditional counterparts. Another conventional liquidity metric and a measure of market activity is the number of days with zero trades. Based on TRACE, an average CUSIP in an average week does not trade for five days. This number jumps to six when one uses ZEN, indicating once again that the European bond market is less liquid than then US market.[15]

Interestingly, the Amihud measure paints a different picture in both high-yield (Panel A) and investment-grade (Panel B) bonds. Focusing on high-yield bonds, according to TRACE, the median price impact is 53.1bps per \$1m par traded, whereas ZEN-based calculations produce a median price impact of 11.9bps per \$1m par traded. The median Amihud measure across the USD denominated bonds in our sample suggests that in the US bond market is less liquid and that the price impact in the US is about five times higher than in Europe. If we look at the mean Amihud measure across bond the price impact in the US is 84.6bps which is more than twice that of 34.4bps in Europe.

Finally, the metrics for the daily round trip costs for institutional investors are much closer aligned across the two markets than the Amihud measures. The mean (median) roundtrip cost is 20.2bps (13.9bps) if computed using TRACE and 30.2bps (18.5bps) if computed using ZEN. The distribution of roundtrip costs based on the combined dataset is close to that based on TRACE.

Overall, Amihud, our key measure of price impact shows a picture of relative liquidity contrary to that based on the simpler metrics of activity such as number of trades, volume traded, and zero trade days. This finding may be explained by the section effects that determine the composition of our sample, as we focus only on USD denominated bonds that trade both in the US and Europe. The majority of activity by number of trades and volume is in the US and it may be that trades are more likely to be made away from the US when more favorable prices can be secured by the dealers.

The distributions of liquidity metrics for investment grade bonds in Panel B are similar to those for high-yield bonds, hence we omit a detailed discussion of those results.

The results reported above underscore the importance of examining various proxies for liquidity and to match them with the research objective (e.g., measuring market activity vs. measuring costs of transacting).[16] Still, as shown above in the case of Amihud and roundtrip costs, both of

[15] Dick-Nielsen et al. (2012) find that the number of zero trading days is priced in bond yields. In their TRACE sample the median bond does not trade on 60.7% of days in a given quarter.

[16] Our results for the two types of liquidity metrics—i.e., market activity and costs of transacting—can be construed as mapping out the liquidity price-quantity combinations, which, in turn, are the outcome of the interactions between liquidity supply and liquidity demand. We leave the questions about the identification of

Table 3: Liquidity Metrics

A. High-Yield Bonds

	TRACE				ZEN				Combined			
	Q1	Mean	Median	Q3	Q1	Mean	Median	Q3	Q1	Mean	Median	Q3
Number of Trades (conditional)	3.2	8.8	5.3	10.4	1.7	2.9	2.2	3.1	3.6	10.2	6	11.9
Number of Trades (unconditional)	1.3	6.6	3.3	8	0.1	1.3	0.4	1.3	1.5	7.9	3.8	9.3
Volume Traded (conditional, millions par)	5.4	17.7	9.9	19.7	1.5	5.4	2.9	5.2	5.9	19.9	10.9	22.1
Volume Traded (unconditional, millions par)	2.2	12.7	5.8	14.2	0.1	2	0.5	1.8	2.5	14.8	6.6	16.6
Number of Days Zero Trades	4.3	5.3	5.6	6.4	6.3	6.5	6.8	6.9	4.3	5.2	5.5	6.3
Amihud (bps per million)	28	84.6	53.1	93.7	1.1	34.4	11.9	34.3	28	81.2	52.8	94.7
Round Trip Cost (bps)	8	20.2	13.9	22.7	8.2	30.2	18.5	33.8	7.8	20.1	13.6	22.3

B. Investment-Grade Bonds

	TRACE				ZEN				Combined			
	Q1	Mean	Median	Q3	Q1	Mean	Median	Q3	Q1	Mean	Median	Q3
Number of Trades (conditional)	2.6	8	4.1	8.6	1.5	2.8	2	2.7	2.9	9.2	4.6	9.7
Number of Trades (unconditional)	0.7	6.4	2.3	7.4	0	1.1	0.1	0.8	0.9	7.5	2.7	8.3
Volume Traded (conditional, millions par)	3.8	24.1	7.9	22.1	1.5	11	3.1	7.4	4.2	27.6	9	25.5
Volume Traded (unconditional, millions par)	1.2	17.8	4.1	14.2	0	2.6	0.3	1.6	1.5	20.4	5	17
Number of Days Zero Trades	4.4	5.4	5.9	6.6	6.6	6.6	6.9	7	4.3	5.3	5.8	6.6
Amihud (bps per million)	18.5	94.8	54.5	111.4	0	28.8	4.3	20.6	18	88.9	53.1	109.9
Round Trip Cost (bps)	5.1	19.5	11.9	24.2	6	36.8	14.3	29.9	5.1	19.8	11.6	23.9

which measure an impact of a trade on the cost of trading, even within the same objective the alternative liquidity metrics can produce opposite results. In light of this realization, we proceed to construct a composite measure of liquidity that would reflect the information embedded in each of the individual liquidity metrics.

We follow Dick-Nielsen et al. (2012) and Aquilina and Suntheim (2016) in constructing a composite liquidity measure and carry out a Principal Component Analysis (PCA) on the following metrics: number of trades, zero trading days, turnover, Amihud, standard deviation of Amihud, roundtrip cost, and standard deviation of roundtrip cost. The results of the PCA for TRACE, ZEN, and combined datasets are reported in Appendix B. We find that the variance decomposition in the first principal component in TRACE is very similar to the previous work (e.g., Dick-Nielsen et al. (2012)). Namely, four liquidity measures, including Amihud, its standard deviation, roundtrip costs and its standard deviation, load up approximately evenly, while the rest of the metrics are rendered inconsequential. This allows us to construct a composite measure of liquidity by weighting these four metrics equally, which is in line with Dick-Nielsen et al. (2012) and Aquilina and Suntheim (2016).

In the PCA of the ZEN data only, Amihud, roundtrip cost, and the standard deviation of roundtrip cost span the first component. Although the standard deviation of Amihud drops out, for the ZEN data we use the same equal weights and the same four liquidity metrics as we did for TRACE in order to make our measures comparable across datasets. Finally, in the combined datasets the contributions of the Amihud, roundtrip cost, and their standard deviations are more equal than in ZEN, with the standard deviation of Amihud still contributing less than what we found in the TRACE data. Once again we apply the 25% weight to each of these four metrics to construct the composite measure.

5 Dealer inventory

Nominal net inventory

We calculate daily changes in inventory for each CUSIP by MPID as the identifier in TRACE and by FRN/BIC in ZEN. As any firm, and in particular dealers, can have multiple reporting identifiers in each dataset, we aggregate inventories to the firm level using the TRACE master file and FCA register as the principal sources to identify firms.

When calculating inventories, we use only principal trades with counterparties external to the firm (we exclude trades with affiliates and internal account trades). We do this as we are interested in the net capital committed by a given dealer firm as a whole. However, there is no reliable way to identify or match individual internal trades across our entire reference period in the TRACE dataset.[17] Therefore, it is possible that some affiliate trades in TRACE remain in the data we use for the analysis.

bond liquidity supply and demand to that promising strand of the literature.

[17]The TRACE affiliate trade flag was only introduced in November 2015. In ZEN a similar flag exists for the entirety of our reference period.

In our reference period of August 2011 to December 2016, we identify 320 firms that traded the bonds in our sample in TRACE and 535 firms in ZEN. In the present paper, we focus on bank dealers, and consequently we filter out non-bank firms (the majority of which are fund managers) and interdealer brokers. We then manually match firms using names and corporate structures across the two datasets. We are left with 51 bank dealers matched across datasets. This group of matched dealers accounts for 40% of par volume in TRACE, 88% of par volume in ZEN, and 47% of par volume in the combined data. The top ten matched dealers collectively account for 36%, 78%, and 43% of par volume in TRACE, ZEN, and the combined data, respectively.

The mean weekly nominal change in inventory for the group of 51 dealers for all CUSIPs in the period is −\$25,075 million in TRACE, −\$300 million in ZEN and −\$26,256 million in the combined data. On aggregate, it is not surprising that dealers are net sellers over the period, similar to results in Aquilina and Suntheim (2016) for bonds traded in the UK. Dealers buy bonds at issuance (both TRACE and ZEN exclude such primary transactions) and then sell them on to other investors.

Since we do not have access to data on primary, repo, and credit derivatives transactions, no conclusion can be drawn based on our dataset on the aggregate change in the risk exposure of dealers or the capital committed by dealers over the period. We note that Bessembinder et al. (2018) find that the capital committed by dealers has decreased relative to the pre-crisis period and that the role of corporate bond dealers has changed, as they trade less on a principal basis and more in a search-and-match brokerage role.

Based on the trades that we do observe, the dealers in our sample pursue very different inventory management strategies across markets, as the illustrative examples in Figure 2, based on anonymized dealers in our dataset, show. For the majority of dealers over the period, net nominal changes in inventory are dominated by either the US (like Dealer A) or Europe (like Dealer B) side of the market. However, for a subset of dealers (like Dealer C), net nominal changes across markets cancel each other out.

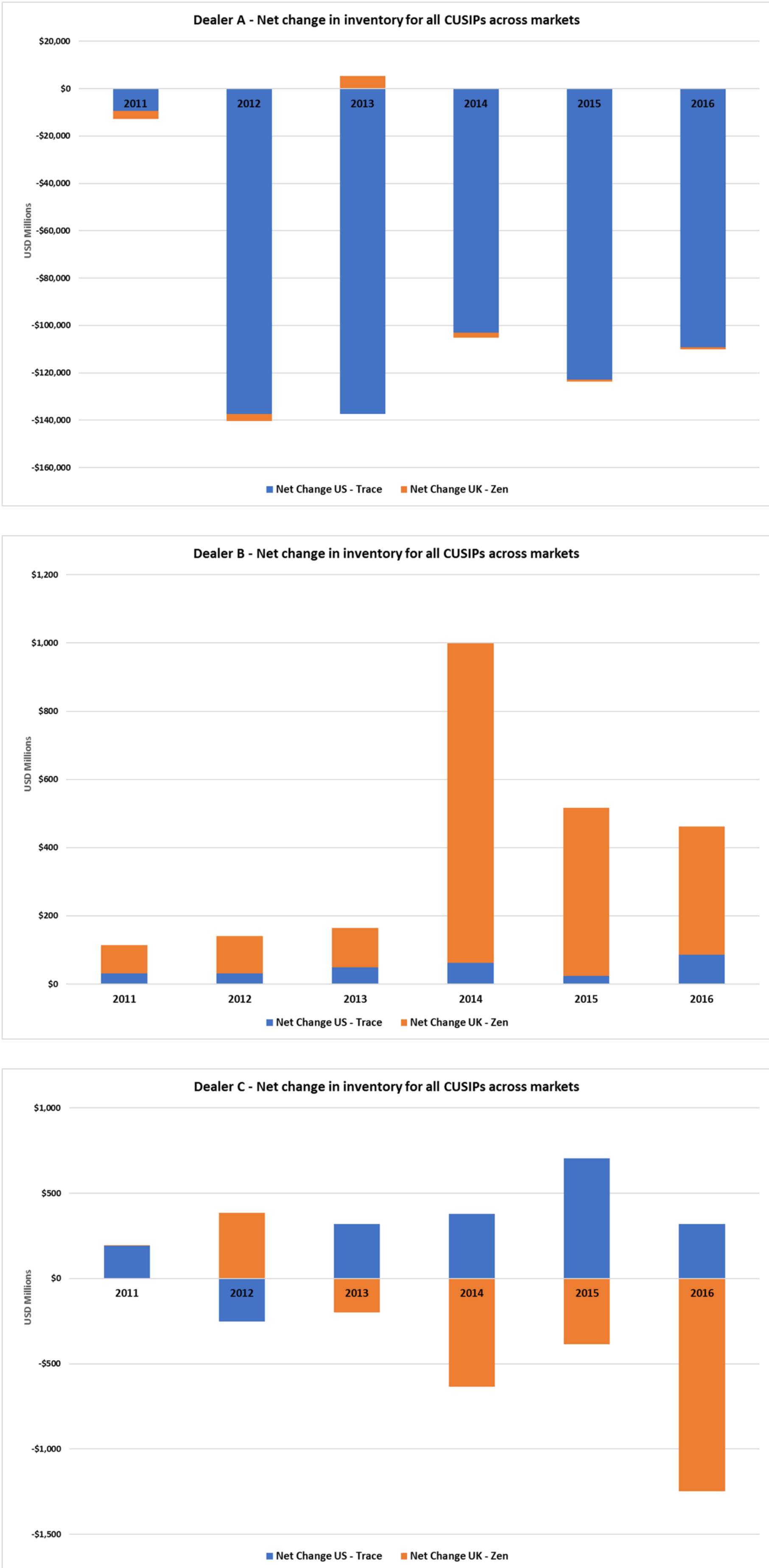
Standardized net inventory

As discussed, changes that we observe in the nominal inventory of dealers in each bond are not very informative, as we do not have data on primary, repo, and credit derivative transactions. Without access to data on primary transactions, we cannot estimate the initial inventory in a bond, and therefore cannot calculate the nominal risk exposure of a given dealer. To overcome this obstacle, we do not rely directly on nominal inventory, but instead construct a standardized dealer inventory measure.

To construct standardized aggregate dealer inventory in a given CUSIP in a given week, we follow the methodology of Friewald and Nagler (2016), described in Appendix A. As with the liquidity metrics, we calculate the inventory separately for TRACE, ZEN, and the combined aggregated data.

This methodology has three key advantages for our set-up. First, it provides a metric

Figure 2: Net Changes in Dealer Inventories



independent from the starting inventory by construction. Since we do not observe primary market transactions, this is of key importance. Second, it allows for time variation in both a dealer's target inventory and risk tolerance by estimating conditional means and standard deviations using a rolling time window. Third, it allows us to aggregate dealer positioning across dealers in a given CUSIP.

Following Friewald and Nagler (2016), we compute the standardized aggregate dealer inventory weekly, using a 52-week (one-year) rolling window for the reference period for the within-dealer standardization. Similarly, for the aggregation across dealers, a dealer is considered to provide liquidity in a bond if they have made at least one trade in a rolling 52-week window.

6 Methodology

To estimate the relationship between bond liquidity and dealer inventories, we use our panel of weekly observations between August 2011 and December 2016 for 20,440 CUSIPs. For each of the liquidity metrics as a dependent variable and each dataset (i.e., TRACE, ZEN, and TRACE and ZEN combined), we run pooled OLS regressions with standard errors clustered by issuer.[18] Our main explanatory variable is one week lagged (standardized) inventory. We use a broad set of controls that are commonly used in the corporate bond literature (e.g., Edwards et al. (2007), Dick-Nielsen et al. (2012), Friewald et al. (2012), Dick-Nielsen and Rossi (2019), Friewald and Nagler (2016), Schestag et al. (2016), and Goldstein and Hotchkiss (2020)), including the following bond and issuer characteristics: offering amount, amount outstanding, age, time to maturity, coupon rate, rating at issuance (high-yield vs. investment grade), and dummy variables for Rule 144A, asset-backed security, convertible, putable, covenants, credit enhancement, global offer, issuer domicile (US vs. Europe vs. rest of the world), and industry dummies for finance and utility. We also control for various macroeconomic variables that can affect the credit market, including credit spread, TED spread, term spread, and the level and slope of the swap curve (see, e.g, Dick-Nielsen et al. (2012), Dick-Nielsen and Rossi (2019)). Finally, we include in the regression year dummy variables to control for any unobserved time effects.

7 Results

Tables C1 through C6 of Appendix C present the regression results, respectively, for the number of trades, zero trading days, par value traded, roundtrip costs, Amihud, and the composite measure of liquidity. The regressions for each of the metrics are run on our three datasets—TRACE, ZEN, and TRACE and ZEN combined. As described in the methodology section, these are pooled OLS regressions with standard errors clustered at the issuer level.

[18] Clustering the standard errors by issuer is in line with the literature (e.g., Dick-Nielsen and Rossi (2019)) and produces conservative estimates. Clustering at a lower level, i.e., by CUSIP (e.g., Di Maggio et al. (2017)), results in smaller standard errors and hence greater significance of the coefficients. The results with CUSIP clustering are not reported for brevity.

Table 4 summarizes our main results by compiling the impact of the lagged inventory variable on liquidity and its statistical significance from all 18 regressions (six liquidity metrics regressions each run on three datasets).

Table 4: Summary of Regression Results: Impact of Dealer Inventories on Liquidity as Measured by Dependent Variable

Note: Asterisks denote the following significance levels: *** 1%, ** 5%, and *10%.

Dependent Variable	TRACE	ZEN	Combined
Number of Trades	Positive ***	Negative	Positive ***
Zero Trading Days	Positive ***	Positive	Positive ***
Par Value Traded	Positive ***	Positive	Positive ***
Round-Trip Cost	Negative	Negative	Negative *
Amihud $1M	Positive ***	Negative ***	Positive
Composite Measure	Positive	Negative **	Negative **

In the number-of-trades regressions (Table C1 and the first row of Table 4) we observe a statistically strong, positive relationship (at the 1% significance level) between bond liquidity and dealer inventory in TRACE. In contrast, there is no significant relationship between the two variables in ZEN. The results for the combined dataset are dominated by TRACE and show a high significance of the coefficient on the inventory.

The same pattern emerges when one attempts to explain the variation in zero trading days (Table C2 and the second row of Table 4) and the variation in par value traded (Table C3 and the third row of Table 4). The results based on TRACE point to the great explanatory power of inventories with respect to these liquidity metrics, while no discernable relationship exists in the ZEN data. The results based on TRACE once again carry over to the combined dataset and point to a high significance of the inventory coefficient.

We have not explored the underlying mechanism in the positive relationship between bond liquidity and dealer inventory we identify and leave that for future work. One possible mechanism for such a link is that when the average deviation from target inventory across dealers is high, dealers increase their counterparty search intensity in addition to changes in quotes. This, in turn, endogenously reduces the counterparty search cost of all market participants and results in additional trading activity. This can be modeled in Duffie, Garleanu and Pedersen's (2005) OTC setting with multiple dealers and can be potentially tested with empirical data.

In contrast to the results obtained for the three measures of market activity (i.e., number of trades, zero trading days and par value traded), the roundtrip cost regressions indicate the absence of the relationship between liquidity and inventories in both TRACE and ZEN (Table C4 and the fourth row of Table 4). There is a negative relationship of marginal significance (at the 10% level) of this coefficient in the combined dataset.

Perhaps the most striking results pertain to the Amihud measure of liquidity (Table C5 and the fifth row of Table 4). There is a strong relationship between bond liquidity and dealer inventory in both TRACE and ZEN, but with opposite signs of the coefficient. In the TRACE data, a higher lagged inventory translates into a lower current price impact and hence greater liquidity. The opposite is the case in the ZEN data: an increase in an inventory over an average week is associated with a greater price impact (i.e., lower liquidity). Interestingly, these effects offset each other in the combined dataset and the significance disappears.

Finally, when studying the composite measure of liquidity (Table C6 and the sixth row of Table 4), we find a negative relationship between liquidity and lagged inventories in this metric in ZEN significant at the 5% level but no relationship in TRACE. Now the combined dataset is dominated by ZEN and the relationship retains its sign and significance.

These results confirm our prior that each jurisdiction's data might not paint a complete picture, and that the results based on individual datasets can differ, sometimes dramatically. We also find that the potential benefits of regulatory cooperation increase with the complexity of the liquidity metric and, more generally, with the degree of data point leverage. For the three liquidity metrics which reflect the market activity (i.e., number of trades, zero trading days and par value traded), there seems to be no discernable benefit for the US of supplementing TRACE with ZEN as the inference based on TRACE carries over to the combined dataset. From the UK perspective it is important to supplement ZEN with TRACE for these measures of market activity. That is likely because the comparatively low activity levels in the CUSIPs under consideration do not allow identifying the true relationship in the UK data and therefore the results change drastically when one moves from ZEN to the combined dataset (see our liquidity summary statistics presented in Table 3).

In contrast, for the measures of liquidity that reflect the costs of trading as opposed to the level of market activity (such as the Amihud metric), the results based on the combined dataset are quite different from what can be gleaned from either of the individual datasets. Arguably, these more complex measures that reflect trading costs are more informative for market participants and thus may be of greater interest for regulators and academics. We hope to demonstrate with our results that sharing data across jurisdictions could be important in accurately assessing the economic relationship between dealer inventory and corporate bond liquidity. Understanding this relationship is essential for evaluating liquidity in the OTC markets, particularly in relatively thinly-traded instruments such as bonds. In bond markets dealers supply liquidity by both intermediating customer trades and by trading on a principal basis (i.e., from their own account). We believe this is also the case in other areas of research and policymaking related to integrated capital markets.

We would also like to note an interesting secondary result on relative liquidity of European and other issuers in our sample relative to US issuers. Table 5 summarizes the dummy variable coefficients for European and Other Non-US issuers from all 18 regressions. As delineated above, higher (lower) values of number of trades and par value traded are indicative of higher (lower) liquidity. Thus, in the regressions with these metrics as proxies for liquidity, a positive (negative) coefficient on the dummy variable for European or Other Non-US issuer would suggest greater bond liquidity, ceteris paribus, for bonds issued by firms in those locations relative to the liquidity of bonds issued by US firms. Conversely, higher (lower) values of zero trading days, roundtrip cost, Amihud, and the composite measure reflect lower (higher) liquidity. Accordingly, in the regressions where these metrics are dependent variables, a positive (negative) coefficient on the dummy variable for European or other non-US issuer would indicate lower (higher) bond liquidity for bonds issued by firms in that domicile relative to liquidity associated with US CUSIPs.

Table 5: Summary of Regression Results: Bond Issuer

Note: Asterisks denote the following significance levels: *** 1%, ** 5%, and *10%.

Dependent Variable	Control	TRACE	ZEN	Combined
Number of Trades	European issuer	0.58115479	1.5236109***	1.9447367**
	Non-EU Non-US issuer	0.59175572	1.1574979***	1.5788225**
Zero Trading Days	European issuer	−0.00242479	−.44050759***	−0.12214505
	Non-EU Non-US issuer	0.07990088	−.3041931***	0.00233382
Par Value Traded	European issuer	−0.1378113	2.9132466***	2.4996817**
	Non-EU Non-US issuer	0.26802004	1.4499613***	1.4851893
Round-Trip Cost	European issuer	0.00027631	−0.00010002	0.00017828
	Non-EU Non-US issuer	0.00066031***	−.00045351***	0.00054182***
Amihud $1M	European issuer	−0.00029136	0.00117914***	−.0007187**
	Non-EU Non-US issuer	−0.00021373	0.0012758***	−0.00042433
Composite Measure	European issuer	0.01252354	0.02384474	0.05441879**
	Non-EU Non-US issuer	0.05806235*	−.04899168*	0.07677364***

As can be seen in Table 5, based on TRACE we would conclude that the bonds of European and Other Non-US issuers in our sample (composed of USD-denominated bonds that trade in both markets) are just as liquid as bonds of US issuers. However, looking at trading in ZEN only, the bonds of these issuers are significantly more liquid than those of US issuers across a range of metrics. This finding also largely carries over to the combined dataset. One way to interpret this result is that trading in the US dataset contains less information for the bonds of European and Other Non-US issuers relative to US issuers. By extension, it is likely that the datasets of other regulators are also particularly informative for bonds issued by firms in their jurisdiction, but may suffer from biased data regarding foreign issuers.

8 Conclusions

To the best of our knowledge, this is the first paper to explore potential benefits of sharing regulatory data across jurisdictions. We computed various liquidity metrics ranging from simple measures of market activity such as number of trades, zero trading days and par value trade, to more complex metrics such as roundtrip costs, Amihud, and the composite measure based on the principal component analysis. These metrics were computed based on TRACE, ZEN, as well as the combined dataset at the weekly frequency. We then linked the liquidity metrics to lagged inventories while controlling for various issuer and bond characteristics, as well as macroeconomic variables that can affect the credit market. Our results show that neither of the individual datasets paints a complete picture of the bond market activity, and that more accurate results—both in terms of computing the liquidity metrics and building dealer inventories—can be obtained by leveraging access to both TRACE and ZEN. Given the level of integration of the capital markets, we believe that any research that informs policymaking can benefit from comprehensive data that covers multiple jurisdictions. Regulators have unique opportunity to facilitate the compilation of comprehensive data through sharing data across jurisdictions.

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Appendix A: Standardized dealer inventory

Our inventory measure follows Friewald and Nagler (2016). Start with the nominal dollar inventory for dealer i in bond j at time t:

$$Q_{i,t}^j = Q_{i,0}^j + \sum_{s=1}^{t} q_{i,s}^j,$$

where $Q_{i,t}^j$ is the nominal dollar inventory for dealer i in bond j at time t, and $q_{i,t}^j$ is the corresponding signed transaction volume (for principal trades only) for dealer i. Then compute the standardized inventory:

$$I_{i,t}^j = \frac{Q_{i,t}^j - \mu Q_i^j}{\sigma_{i,t}^j},$$

where μQ_i^j is the average nominal dollar inventory for dealer i in bond j over the rolling interval $(t-\tau, t)$ such that $\mu Q_i^j = \frac{\sum_{s=t-\tau}^{s=t} q_{i,s}^j}{\tau+1}$; μQ_i^j is set to 0 whenever it is constant (i.e., there are no dealer principal trades) in the relevant period. $\sigma_{i,t}^j$ is the standard deviation of inventory over the same interval as above. This allows for time variation in both a dealer's target inventory and risk tolerance by estimating conditional means and standard deviations using a rolling time window. We then aggregate the inventories across N dealers that provide liquidity in bond j at time t by defining the inventory measure I_t^j as:

$$I_t^j = \frac{1}{N_t^j} \sum_{i=1}^{N_t^j} I_{i,t}^j$$

where N_t^j is the number of dealers providing liquidity, as defined above, in bond j. This is an unweighted average, which reflects the inventory risk of the average dealer in a bond.

We compute I_t^j weekly, using a one-year rolling window (τ=52 weeks). Dealers are considered to provide liquidity in a bond if they have made at least one trade in the rolling 52-week window.

Appendix B: Principal component analysis

Table B1: Principal Component Analysis

Combined	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Comp7
Variable							
Number of Trades	−0.0041	−0.6234	0.0277	−0.0797	0.2644	0.4157	0.5218
Zero Trading Days	−0.1744	0.6955	−0.015	0.044	0.1269	0.4395	0.5239
Turnover	0.0353	0.0147	0.9871	0.159	−0.0093	−0.0047	0.0003
Amihud	0.5313	0.1072	−0.0142	0.0428	−0.7712	−0.1121	0.3113
Amihud std	0.2986	−0.078	−0.1561	0.9816	0.0659	0.0204	−0.0047
RTC mean	0.5796	0.2144	0.007	−0.0247	0.122	0.532	−0.5653
RTC std	0.5109	0.2527	0.0042	−0.0214	0.5477	−0.5814	0.1916
Variance Explained							
Proportion	26%	20%	14%	14%	10%	9%	6%
Cumulative	26%	46%	60%	74%	85%	94%	100%
TRACE	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Comp7
Variable							
Number of Trades	0.1379	−0.6764	0.0148	−0.0515	0.379	0.5955	0.1498
Zero Trading Days	−0.0272	0.691	−0.0088	0.2497	0.3327	0.5425	0.2331
Turnover	−0.0002	0.0149	0.9998	0.0078	−0.0092	−0.0021	0.003
Amihud	0.4548	−0.0807	−0.0089	0.482	−0.6714	0.2112	0.2425
Amihud std	0.4944	0.2152	0.0018	−0.5199	−0.1613	0.3267	−0.5534
RTC mean	0.4836	−0.0308	0.0013	0.5356	0.4758	−0.3027	−0.4005
RTC std	0.5433	0.1055	0.0008	−0.3815	0.2059	−0.3288	0.6306
Variance Explained							
Proportion	31%	21%	14%	12%	10%	7%	5%
Cumulative	31%	52%	67%	78%	88%	95%	100%
ZEN	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Comp7
Variable							
Number of Trades	−0.1316	0.694	−0.056	−0.025	0.0537	0.2674	0.6503
Zero Trading Days	0.1485	−0.6912	−0.0226	0.0059	0.0382	0.2832	0.6465
Turnover	−0.0108	0.0064	−0.4651	0.8849	−0.0139	−0.0114	−0.0092
Amihud	0.5243	0.1112	0.069	0.0279	−0.7133	−0.3906	0.2139
Amihud std	0.0545	0.0423	0.8731	0.4621	0.0991	0.0973	0.0106
RTC mean	0.6309	0.133	−0.0986	−0.0393	0.0023	0.6912	−0.3087
RTC std	0.5335	0.0928	−0.0574	−0.0179	0.6905	−0.4565	0.134
Variance Explained							
Proportion	23%	22%	14%	14%	12%	8%	7%
Cumulative	23%	45%	59%	73%	85%	93%	100%

Appendix C: Regression results

Higher values of number of trades and par value traded are indicative of higher liquidity. Thus, in the regressions with number of trades and par value traded as dependent variables, a positive coefficient on the dealer inventory would point to a positive relationship between inventories and liquidity. Conversely, higher values of zero trading days, roundtrip cost, Amihud, and the composite measure reflect lower liquidity. Therefore, in the regressions where these metrics are dependent variables, a positive coefficient on the dealer inventory would imply a negative relationship between inventories and liquidity.

Table C1: Regressions: Number of Trades

Note: Pooled OLS regressions with standard errors clustered by issuer. "***", "**" and "*" denote significance at the 1%, 5% and 10%, respectively.

Variable	TRACE	ZEN	Combined
avg std inv lag1	.73304916***	−0.00352232	1.0229469***
AMOUNT OUTSTANDING	3.329e-09***	6.869e-10**	3.902e-09***
OFFERING AMOUNT	−2.833e-09***	−5.930e-10**	−3.309e-09***
BOND AGE	−.26406944***	−.07380317***	−.31809698***
TIME TO MATURITY	0.00793605	.01115677***	.01731956**
COUPON	0.04345689	.02876794**	0.064605
d inv grade	−0.36840548	−0.05818671	−0.50729877
d rule 144a	−3.7466119***	−1.0150736***	−4.5336463***
d asset backed	−3.0573337***	−.33204541***	−3.3003293***
d convertible	−0.09980493	0.03403649	−0.09129801
d putable	−1.2084525***	−.17154015**	−1.3151501***
d finance	0.33997284	0.10576749	0.46196771
d utility	−2.1203754***	−.39364599***	−2.4429804***
D EUROPE ISSUER	0.58115479	1.5236109***	1.9447367**
D NON EU NON US	0.59175572	1.1574979***	1.5788225**
OFFERED GLOBAL	2.0249034***	.50822922***	2.524519***
CREDIT ENHANCEMENT	0.40793321	0.16777484	0.53256853
HAS COVENANTS	0.16107266	−0.0001867	0.23186622
credit spread	0.06929536	−.05460532**	0.02309175
ted spread	−2.3152559***	−.35331465***	−2.5796585***
term spread	1.6499026***	.15823247**	1.7142296***
swap curve level	−1.5135685***	−.59188496***	−2.0377287***
swap curve slope	.47138189**	.44475316***	.93651208***
Year:			
2013	0.18970297	−.11481303**	.29827587**
2014	.45855647***	0.06468786	.73406126***
2015	.73636903***	.32214018***	1.276793***
2016	1.6176921***	.59556433***	2.4639801***
Constant	6.3150932***	1.0385787***	6.8122945***
N	2468452	1997118	2481773
Adjusted R^2	0.08685273	0.05903546	0.08770958

Table C2: Regressions: Zero Trading Days

Note: Pooled OLS regressions with standard errors clustered by issuer. "***", "**" and "*" denote significance at the 1%, 5% and 10%, respectively.

Variable	TRACE	ZEN	Combined
avg std inv lag1	−.21742414***	−0.00813854	−.18924892***
AMOUNT OUTSTANDING	-6.335e-10***	−2.104e-10***	−6.361e-10***
OFFERING AMOUNT	5.496e-10***	1.783e-10***	5.494e-10***
BOND AGE	.05951363***	.02826356***	.0609078***
TIME TO MATURITY	−.00246525**	−.00247624***	−.00189735*
COUPON	.04033896***	−0.0003956	.04274325***
d inv grade	.15787287***	0.04487183	.14792843***
d rule 144a	.85616565***	.36914022***	.8912803***
d asset backed	.99224146***	.184519***	.97140786***
d convertible	.28409209***	.05282231**	.2779573***
d putable	.43785107***	.09470546***	.42940878***
d finance	−.11684497**	−0.04427494	−.10777576*
d utility	.43223099***	.16240848***	.43548219***
D EUROPE ISSUER	−0.00242479	−.44050759***	−0.12214505
D NON EU NON US	0.07990088	−.3041931***	0.00233382
OFFERED GLOBAL	−.49629867***	−.15884651***	−.52273268***
CREDIT ENHANCEMENT	−0.02070236	−0.03241849	−0.01938583
HAS COVENANTS	−.11396933*	0.00012364	−0.09203839
credit spread	.0802757***	.03067598***	.08255363***
ted spread	.4159064***	.16894777***	.41715942***
term spread	−.3716971***	−.08184304***	−.36635056***
swap curve level	.40309791***	.16582711***	.41326771***
swap curve slope	−.21129511***	−.10532588***	−.22633***
Year:			
2013	−.02186529**	.06630184***	−.03148852***
2014	−0.01366019	0.00233916	−.02790921**
2015	−.1121044***	−.08550414***	−.13028354***
2016	−.26061814***	−.18776227***	−.28864347***
Constant	4.8130899***	6.4102029***	4.7794369***
N	2468452	1997118	2481773
Adjusted R^2	0.1879846	0.10403413	0.19475875

Table C3: Regressions: Par Value Traded (Million)

Note: Pooled OLS regressions with standard errors clustered by issuer. "***", "**" and "*" denote significance at the 1%, 5% and 10%, respectively.

Variable	TRACE	ZEN	Combined
avg std inv lag1	1.7789769***	0.02370208	1.8159465***
AMOUNT OUTSTANDING	7.414e-09***	1.182e-09***	8.307e-09***
OFFERING AMOUNT	−6.238e-09***	−9.863e-10**	−6.930e-09***
BOND AGE	−.52181556***	−.10311086***	−.59357173***
TIME TO MATURITY	−0.0231586	0.00476528	−0.01913255
COUPON	−.16915242*	−0.04700286	−.20466037**
d inv grade	2.1017264	0.52408764	2.2957151*
d rule 144a	−5.4099959***	−1.586766***	−6.5999693***
d asset backed	−4.4426263***	−.38407397**	−4.7342457***
d convertible	0.3775322	0.17142691	0.51324303
d putable	−0.83556722	−0.12598742	−0.91207385
d finance	−0.40668797	−0.09165627	−0.38189631
d utility	−2.8037236***	−.43211876***	−3.1456496***
D EUROPE ISSUER	−0.1378113	2.9132466***	2.4996817**
D NON EU NON US	0.26802004	1.4499613***	1.4851893
OFFERED GLOBAL	3.294726***	.90655776***	4.1638648***
CREDIT ENHANCEMENT	1.3316868***	0.47360932	1.6851643***
HAS COVENANTS	−2.7715889**	−.76001017*	−3.2223831***
credit spread	−0.09497142	−0.04677913	−0.15930247
ted spread	−4.1703824***	−.95583622***	−5.0241251***
term spread	3.9060855***	.6468412***	4.323442***
swap curve level	−4.5927848***	−.8340707***	−5.3224517***
swap curve slope	2.1683255***	.43446414**	2.6591251***
Year:			
2013	.67595431***	−0.19934205	.87332342***
2014	1.5611995***	0.18474825	2.0815879***
2015	2.2016717***	.53049455**	3.078988***
2016	3.4595785***	.88835932***	4.7732578***
Constant	14.424027***	2.3775343***	15.76071***
N	2468452	1997118	2481773
Adjusted R^2	0.01292374	0.00958756	0.01603843

Table C4: Regressions: Roundtrip Costs

Note: Pooled OLS regressions with standard errors clustered by issuer. "***", "**" and "*" denote significance at the 1%, 5% and 10%, respectively.

Variable	TRACE	ZEN	Combined
avg std inv lag1	0.00002517	0.0002298	.00009045*
AMOUNT OUTSTANDING	−2.392e-13**	3.81e-13	−2.162e-13**
OFFERING AMOUNT	2.163e-13**	−4.58e-13	1.908e-13*
BOND AGE	0.00001112	−.00005093**	0.00001071
TIME TO MATURITY	.00004341***	.00006193***	.00004145***
COUPON	.00029863***	.00048351***	.00029579***
d inv grade	−0.00008214	−.0002912*	−0.00008143
d rule 144a	−.00028659**	.00048442*	−.00021563**
d asset backed	−0.00003356	−0.00086905	0.00127114
d convertible	.00243654***	.00265499***	.00240978***
d putable	−.00084717***	−0.00028246	−.00082288***
d finance	−.00017289*	−.00052612***	−.00019309**
d utility	−0.00013542	−0.00020372	−0.00011792
D EUROPE ISSUER	0.00027631	−0.00010002	0.00017828
D NON EU NON US	.00066031***	−.00045351***	.00054182***
OFFERED GLOBAL	−0.00009301	−0.00011655	−0.00012483
CREDIT ENHANCEMENT	0.00011056	.00031679**	0.00012599
HAS COVENANTS	0.0001147	−0.00001874	0.00011219
credit spread	.00127228***	.00208865***	.00124769***
ted spread	−.00185333***	0.00023813	−.0017232***
term spread	.0002344*	−0.00065046	0.00020004
swap curve level	.00058959***	−0.00021295	.00054483***
swap curve slope	−.00080297***	0.00079234	−.00072462***
Year:			
2013	0.0000247	0.00039	0.00002177
2014	0.00016578	−0.00048033	0.00013347
2015	−0.00008706	−0.00014514	−0.00009066
2016	.00026266*	.00078961**	.00024008*
Constant	−.00098531***	−.00214181***	−.00098783***
N	368132	40413	383756
Adjusted R^2	0.04381704	0.04674981	0.0436938

Table C5: Regressions: Amihud Measure

Note: Pooled OLS regressions with standard errors clustered by issuer. "***", "**" and "*" denote significance at the 1%, 5% and 10%, respectively.

Variable	TRACE	ZEN	Combined
avg std inv lag1	−.00024716***	.00019994***	−0.00004397
AMOUNT OUTSTANDING	−1.798e-12***	8.74e-14	−1.728e-12***
OFFERING AMOUNT	1.599e-12***	−6.43e-14	1.544e-12***
BOND AGE	.0002212***	−.00011337***	.00021563***
TIME TO MATURITY	.00028473***	.00006866***	.00026645***
COUPON	.00067782***	.00051149***	.00068465***
d inv grade	−0.00029556	−.00065715***	−0.00033415
d rule 144a	−.00564307***	−.00190718***	−.0051499***
d asset backed	−.00265099**	0.001205	−.00271844***
d convertible	.00158251***	.00220019***	.00177703***
d putable	−.00333566***	−.00084797*	−.00326414***
d finance	0.00028072	−0.00005975	0.00031974
d utility	−.00127631***	−.00101264***	−.00116793**
D EUROPE ISSUER	−0.00029136	.00117914***	−.0007187**
D NON EU NON US	−0.00021373	.0012758***	−0.00042433
OFFERED GLOBAL	−0.00034581	−0.00001299	−.00048446*
CREDIT ENHANCEMENT	−0.00050684	0.00012721	−0.00047555
HAS COVENANTS	.00161962***	0.00025178	.00159155***
credit spread	.00399456***	.0022248***	.00392754***
ted spread	−.00322197***	.00178687***	−.00264239***
term spread	−.00198297***	−.00154945***	−.00184904***
swap curve level	.00069933**	−.00126046***	.00058611**
swap curve slope	0.00019646	.00190029***	0.0002611
Year:			
2013	−.0006229***	−.00141402***	−.00070052***
2014	−.00126271***	−.00143421***	−.00130461***
2015	−.00166898***	−.00131485***	−.00175432***
2016	0.0001568	−.00055329**	−0.00006369
Constant	−0.0000359	−0.00017938	−0.00019131
N	1007685	278740	1039942
Adjusted R^2	0.07473241	0.03267165	0.07201361

Table C6: Regressions: Composite Measure

Note: Pooled OLS regressions with standard errors clustered by issuer. "***", "**" and "*" denote significance at the 1%, 5% and 10%, respectively.

Variable	TRACE	ZEN	Combined
avg std inv lag1	−0.00186184	.03396809**	.01715353**
AMOUNT OUTSTANDING	−9.030e-11***	−3.62e-11	−5.331e-11***
OFFERING AMOUNT	7.779e-11***	3.41e-11	4.898e-11***
BOND AGE	.01614707***	0.00377909	.00831546***
TIME TO MATURITY	.01448019***	.00787824***	.00888076***
COUPON	.0695898***	.07152269***	.05299508***
d inv grade	−.05612498**	−.078978**	−.03248781*
d rule 144a	−.24267255***	−0.04984913	−.13529016***
d asset backed	−.14331391**	0.07962025	−0.03254437
d convertible	.50732691***	.46776602***	.39396691***
d putable	−.27129164***	−.21664517**	−.17011769***
d finance	−0.01973685	0.00462633	0.00838481
d utility	−0.03946725	−0.037344	−0.0474223
D EUROPE ISSUER	0.01252354	0.02384474	.05441879**
D NON EU NON US	.05806235*	−.04899168*	.07677364***
OFFERED GLOBAL	−0.01271936	0.02447355	−0.00247876
CREDIT ENHANCEMENT	0.01499418	0.00842676	0.00924666
HAS COVENANTS	.04115739*	0.01743024	0.02060953
credit spread	.12501118***	.21194182***	.13490436***
ted spread	−.22597975***	0.06134572	−.17623378***
term spread	0.0117737	−.0957187**	0.00348505
swap curve level	.05242968**	−0.06581328	.04906518***
swap curve slope	−.07210666***	0.09477967	−.05981254***
Year:			
2013	−.01753619*	−.0566367**	−.01427347*
2014	0.0056861	−.14085967***	−0.00806815
2015	−.03171135*	−.15772391***	−.04041489***
2016	0.00594886	−.12825794***	−0.00370755
Constant	−.57018658***	−.33724006***	−.4568007***
N	367981	39700	383508
Adjusted R^2	0.13083618	0.10549093	0.09868816