

# Transparency and Liquidity in the Structured Product Market

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We use a unique data set from the Trade Reporting and Compliance Engine (TRACE) to study liquidity effects in the U.S. structured product market. Our main contribution is the analysis of the relation between accuracy in measuring liquidity and the level of detail of the trading data employed. We find evidence that, in general, liquidity measures that use dealer-specific information can be efficiently proxied by means of measures that use less detailed information. However, when the level of trading activity in individual securities or overall market activity is low, measures based on more detailed trading data permit a more precise assessment of liquidity. These results provide us with a better understanding of the information contained in disseminated OTC trading data, in general. (*JEL* G12, G14)

## Introduction

The U.S. fixed-income structured product market, also referred to as the securitized product market, is an important financial market that has received

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much attention in the past two decades, especially since the financial crisis. With an average daily trading volume of more than \$32.7 billion in 2011–2013, it is the second-largest fixed-income market in the United States, after the Treasury bond market. Its products are traded over-the-counter (OTC), with no central market place, or even a clearing house, thus far. Following the financial crisis, in which structured financial products played an important role, the opacity implied by this OTC architecture has been widely criticized, since traded prices and volumes are not readily observable. Thus, liquidity in the structured product market, with its complex financial instruments, has only been measurable based on potentially unrepresentative or biased information, such as quotations from individual dealers.

The Financial Industry Regulatory Authority (FINRA) has, therefore, launched a project with the aim of improving transparency in the structured product market. Since May 16, 2011, virtually all trades in the fixed-income structured product market have been required to be reported to TRACE by broker/dealers.<sup>1</sup> However, FINRA has not yet released this information to the market.<sup>2</sup> This unique data set allows us to analyze liquidity effects based on a complete information set *before* the potential dissemination of the data to the broader market and, thus, before the possible reaction of market participants to a new regime.

So far, there has been only a modest literature analyzing liquidity effects in the fixed-income structured product market, mostly focusing on liquidity at the market-wide level. However, this type of analysis, dictated by the constraints of data availability, provides only a limited view of the structured product market's liquidity. Moreover, in contrast with other fixed-income markets, an aggregate analysis of structured products masks several issues of detail, since this market consists of rather diverse instruments with potentially different liquidity characteristics. Following FINRA's definitions, these products are classified into three main segments: asset-backed securities (ABS), collateralized mortgage obligations (CMO) and mortgage-backed securities (MBS).<sup>3</sup> In particular, in contrast with corporate or Treasury bonds, structured products allow investment in various pools of assets, often consisting of loans to retail customers, which, in most cases, cannot be traded on an individual basis. Thus, the credit risk of an individual security stems from the cash flows of the relevant pool, and not from the creditworthiness of the particular issuer, alone. A second important point is that

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<sup>1</sup> This project has followed on from an earlier FINRA project, that resulted in the establishment of the U.S. corporate bond Trade Reporting and Compliance Engine (TRACE) database.

<sup>2</sup> FINRA started to release information on individual market segments for mortgage-backed securities specified pool transactions on July 22, 2013 and asset-backed securities on June 1, 2015. FINRA is continuing to study the other segments before deciding on its overall information dissemination policy. However, during our observation period, no product-specific information had been released to the market for any of the segments.

<sup>3</sup> Note that we do not analyze to-be-announced securities (TBA) in this paper as these products essentially represent a forward market for MBS contracts and thus cannot be directly compared with the other segments.

structured products have rather diverse cash-flow structures, ranging from simple pass-through instruments to tranches with very complex risk structures. Overall, structured products constitute a unique fixed-income market with distinct features compared to other important markets. Hence, a comprehensive study of liquidity for individual instruments in this structured product market will be of special interest to all market participants.

Our study fills this gap in the literature by exploring a broad range of liquidity proxies for the structured product market (e.g., the Amihud and Roll measures) that have been proposed in the academic literature in the context of OTC markets. In particular, we study liquidity effects in the three main segments of the structured product market (i.e., ABS, MBS, and CMO), covering virtually all products. We deepen our understanding of the market by further analyzing the relations between various product characteristics (such as credit ratings or seniority) and liquidity. Finally, we explore the link between our liquidity metrics and observed yield spreads.

Our main contribution is the analysis of the relation between the measurement of liquidity and the level of detail of the trading data utilized. As we have privileged access to all the relevant trading information, we can examine whether detailed transaction data provide valuable information, beyond that offered by aggregated information. This is important as the various liquidity measures presented in the academic literature require different information sets for their estimation, with varying levels of detail. For example, measuring liquidity based on the *round-trip cost* uses the most detailed information, that is, each transaction needs to be linked to a particular dealer, on each side of the trade. Other liquidity metrics, such as the *effective bid-ask spread*, do not require such detailed trade information for their computation, but transactions need to be flagged as *buy* or *sell* trades. Many alternative liquidity measures rely on trading data as well: However, they only use information regarding the price and/or volume of each transaction. On the other hand, simpler proxies use either static or aggregated data.

Thus, a question arises as to which information sets allow market participants to reliably estimate measures of liquidity/transaction costs. In addition, it is relevant to understand whether measures based on less information are less reliable in certain market environments, for example, when the trading activity in individual securities or overall market activity is low. For this analysis, we compare various liquidity proxies with the round-trip cost. We use this measure as our benchmark because it reflects actual transactions costs most closely. Of course, the round-trip cost itself relies on data that would likely compromise trader confidentiality and, therefore, the required data set will, most likely, not be disseminated to market participants. Thus, it is of importance to study whether other measures using less detailed data are still reliable proxies for liquidity. This issue is relevant for improving market transparency and fostering our understanding of the information contained in the disseminated transaction data on OTC markets, in general. To address

this issue, we present a regression analysis discussing the explanatory power of various liquidity measures based on different sets of information in diverse market environments.

For our empirical analysis, we use all traded prices and volumes in the fixed-income structured product market, along with security characteristics provided by FINRA, and credit ratings from Standard & Poor's (S&P). Our data set is comprised of information on nearly 340,000 structured products in the United States, for which about 3.6 million trades were conducted over the period from May 16, 2011 to June 17, 2013. Hence, our data cover the whole structured product market during this period, including even those securities with very little trading activity.

Overall, we find an average daily trading volume of around \$32.7 billion in the structured product market and an average transaction cost across the three market segments of around 73 bp for a round-trip trade. The daily turnover per security in relation to its amount outstanding is 0.32%, on average. Thus, this market has a considerable higher daily trading volume than the U.S. corporate bond market (\$23 billion), whereas the daily turnover per security is comparable. However, in all market segments, we find more dispersed trading activity than in other important fixed-income markets, that is, fewer trades per security, but with higher volumes. The ABS and MBS segments have round-trip costs of 43 and 58 bp, respectively, which are comparable to that of the U.S. corporate bond market, whereas the CMO segment (118 bp) is considerably less liquid. We analyze these differences in greater detail using regression analyses, showing that securities that have greater seniority, are guaranteed by a federal authority, have lower credit risk or are less exposed to dealer market power, tend to be more liquid. In addition, we explore the relation between yield spreads and liquidity measures, showing that liquidity is an important factor. In particular, we provide evidence that the round-trip cost (our benchmark measure) is indeed the liquidity variable with the highest explanatory power. When comparing it with the other measures, we find that the imputed round-trip cost, in particular, has similar explanatory power, whereas the Roll measure has the lowest predictive power.

Analyzing the relation between the measurement of liquidity and the level of trading data in detail, we show that simple product and pool characteristics, as well as trading activity variables, may not be sufficient statistics by themselves for measuring market liquidity. In particular, when regressing state-of-the-art liquidity measures on these variables, we find that the various liquidity measures offer significant idiosyncratic information. Thus, the dissemination of detailed transaction data, necessary for the estimation of liquidity measures, is of importance in the fixed-income structured product market. We present evidence that liquidity measures based on price and volume information alone (e.g., the imputed round-trip cost) can account

for most of the variation observed in the benchmark measure, which uses significantly more information, including confidential trader identities.

In a second set of regressions, we show that liquidity measures based on less information are less efficient proxies for the benchmark measure in certain market environments. In particular, we analyze the cross-sectional variation by separately exploring securities with different levels of trading activity, and time-series aspects, by considering trading periods with different levels of market activity. Along both dimensions, we find pronounced differences in the ability of the liquidity measures to accurately estimate transaction costs. For liquidity metrics that use only price information (e.g., the Roll measure), the explanatory power is about 40% lower for securities with low trading activity than for securities that trade more actively. For measures that use both price and volume, the difference is less severe in terms of magnitude (about 25%), whereas measures that use buy/sell side indicators or a proxy for the round-trip trading cost (e.g., the imputed round-trip cost) show the lowest reduction in explanatory power. We find similar results when analyzing overall market activity. In addition, we analyze the economic significance of these results. We find significant deviations between the benchmark measure and the liquidity proxies, confirming that measures based on less information are significantly less precise when trading activity is low. For example, in the case of the price dispersion measure, the absolute deviation compared to the benchmark measure is around 70 bp for less actively traded securities, whereas it is around 30 bp when trading activity is high. Thus, detailed transaction data including price, volume and trade direction indicators are particularly important in such market environments, permitting a more precise assessment of transaction costs. This is an important result for all market participants, even in other securities, as it provides valuable insights concerning the information content of reported transaction data.

## **1. Transparency in the Structured Product Market**

In this section, we discuss the trading structure of the U.S. structured product market and its deficiencies with regard to market transparency. We do so in the context of the relevant literature and motivate our research questions accordingly. Similar to most other fixed-income markets, the U.S. structured product market has an OTC architecture. Thus, trading activity is opaque, since transactions take place through a one-to-one contact between an investor and a broker/dealer, or between two broker/dealers. However, in contrast with other fixed-income markets (i.e., the Treasury, municipal and corporate bond markets), the market segments and products in the structured product market are quite diverse (see Section 2). Given the OTC structure of this market, traded (or even quoted) prices and volumes are generally not observable by market participants that are not directly involved in the particular trades. In such an opaque market environment, the observation of

market activity and liquidity is difficult, and many market participants may be severely disadvantaged, for example, incurring high transaction costs for certain types of trades.

In response to such concerns about the opacity of this market, especially during the financial crisis, FINRA started a transparency project for structured fixed-income products, making the reporting of trading activity mandatory for broker/dealers. In the first phase of this project, which started on May 16, 2011, *all* trades have had to be reported to the TRACE database for structured products, although the information collected had not been fully released to the market during our sample period.<sup>4</sup>

FINRA's transparency project for structured products is comparable to its earlier introduction of the TRACE database for the U.S. corporate bond market. TRACE was introduced in the corporate bond market in multiple phases starting in July 2002, and set in place in its current form in October 2004. There was much debate, to begin with, concerning the dissemination of the transaction data. In the end, information about all trades was disseminated, but without the identity of the dealer or the precise volume (the volume being capped at one or five million, depending on the credit quality of the bond) being revealed.<sup>5</sup> A similar transparency project was launched for the municipal bond market by the Municipal Securities Rulemaking Board (MSRB). Initiatives aimed at improving trade transparency for this market started in 1998, and rules similar to those for the corporate bond market were adopted in 2005. The TRACE and MSRB initiatives are milestone transparency projects in the context of OTC markets, and have justifiably received a lot of attention in the academic literature. Many studies have used these data sets to quantify and analyze liquidity effects in the various stages of their implementation.<sup>6</sup>

The main focus of our research in this context is the relation between the level of detail in the disclosure requirements and the accuracy of the liquidity measure(s) that can be computed from the resultant data. For instance, during the implementation phases of the MSRB and TRACE projects, some controversial discussion took place regarding whether an increase in transparency (i.e., the dissemination of more detailed transaction data) would

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<sup>4</sup> Note that there was a limited increase in transparency during our sample period when FINRA released their structured product tables in October 2011. These tables contain aggregate information about daily market activity.

<sup>5</sup> More recently, the precise volume of trading has been disclosed, with an 18-month delay.

<sup>6</sup> Papers using data from early stages of the data release include those by Harris and Pivowar (2006), Green, Hollifield, and Schürhoff (2007b), Bessembinder, Maxwell, and Venkataraman (2006), Goldstein, Hotchkiss, and Sirri (2007), and Edwards, Harris, and Pivowar (2007). These papers focus on the quantification of transaction costs and the relationship between transaction costs and credit risk and trading activity. More recent papers quantifying liquidity in these markets rely on other sets of liquidity measures and study different sample periods. See, for example, Mahanti et al. (2008), Jankowitsch, Nashikkar, and Subrahmanyam (2011), Bao, Pan, and Wang (2011), Nashikkar, Subrahmanyam, and Mahanti (2011), Lin, Wang, and Wu (2011), Feldhütter (2012), Friewald, Jankowitsch, and Subrahmanyam (2012), Dick-Nielsen, Feldhütter, and Lando (2012), and Ronen and Zhou (2013).

have a positive effect on market liquidity. Some market observers argued that such transparency in rather illiquid OTC markets would expose dealers' inventory and trading strategies to other market participants, which could lead dealers to reduce their trading activity to avoid the resultant disadvantages in the price negotiation process. However, more recent research on price discovery and liquidity, using controlled experiments, finds clear evidence of an increase in liquidity when transparency is improved. For example, Bessembinder, Maxwell, and Venkataraman (2006) compare transaction costs in the U.S. corporate bond market for a sample of insurance company trades before and after the implementation of the TRACE transparency project in that market. They find that transaction costs decreased dramatically (by 50%); even for bonds not subject to the reporting requirements, trading costs reduced (by 20%). Goldstein, Hotchkiss, and Sirri (2007) find similar results in their study of a BBB-rated bond sample. They report that medium-to-small trades benefit more from transparency. Furthermore, they show that trading volume does not decrease with greater transparency of disclosure.<sup>7</sup>

Overall, these papers come to the conclusion that the chosen level of detail of the disseminated data has a positive effect, compared to the regime in which no transaction data is disseminated. However, most of these papers solely focus on one individual liquidity measure, due to the limitations on data availability. Thus, these papers do not ask the broader question of how informative transaction data are to market participants in terms of market liquidity conditions, as they do not comprehensively compare liquidity measures based on different information sets.

In this paper, we remedy this lacuna by focusing on the relation between the measurement of liquidity and the level of detail of the employed trading data in OTC markets, beyond merely quantifying liquidity. Thus, we ask how much information is needed to enable the accurate measurement of liquidity, compared to our benchmark measure that uses the *most* detailed information, in particular trader identity and trade direction, which would almost certainly compromise the identities of individual traders and/or their trading strategies. Therefore, we measure the efficacy of liquidity metrics that require different levels of detail in terms of the information used to compute them. In this respect, we explore to what extent liquidity measures using less detailed trading data can proxy for the benchmark measure that is based on *all* available information. Second, we analyze in which market environments liquidity measures based on less information act as less efficient proxies for the benchmark measure. In particular, we separately explore the liquidity measures of

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<sup>7</sup> For the primary municipal and corporate bond markets, Green (2007), Green, Hollifield, and Schürhoff (2007a), and Goldstein and Hotchkiss (2007) provide similar evidence. They show, both theoretically and empirically, that transparency reduces underpricing following the dissemination of trading data. In addition, Schultz (2012) shows that transparency considerably reduces the dispersion of purchase prices, while the effect on markups (due to commissions) is small.

securities with different levels of trading activity, and time periods with different levels of overall market activity.

Interestingly, in the context of exchange traded markets, several papers discuss the effects of less detailed data on the quality of liquidity estimates. For example, [Holden and Jacobsen \(2014\)](#) explore liquidity measurement problems when using the Monthly Trade and Quote (MTAQ) database compared to the daily version and present an interpolation technique to improve the results of the less detailed data set. Furthermore, [Easley, de Prado, and O'Hara \(2016\)](#) discuss the performance of trade and order-flow classification techniques when noise in the data is present in the context of the CME E-mini S&P 500 futures contract. Both papers demonstrate that measures based on less detailed information show substantial deviations depending on the market microstructure noise. Thus, it is important to understand this relation in the context of less liquid OTC markets.

However, only a few papers have analyzed liquidity effects in the fixed-income structured product market in general, due to the aforementioned constraints on data availability. In one example, [Vickery and Wright \(2013\)](#) use aggregated trading volumes for the *whole* market to analyze liquidity effects. Given the complexity and diversity of the fixed-income structured product market, an aggregate analysis of this sort may yield only limited insights into issues of liquidity and market microstructure.

Therefore, the second focus of this paper is to close this gap by employing a wide range of liquidity measures developed in the academic literature (see Section 3) and providing a detailed analysis of liquidity in the structured product market based on its segments (i.e., ABS, CMO and MBS). In this context, we explore the relationship between various product and trading characteristics and liquidity. In particular, we quantify and analyze two aspects that are unique to the structured product market. First, an important fraction of products such as ABS and CMO have risk structures offering different tranches based on certain pools of underlying securities (see Section 2). Therefore, we analyze these tranches expecting to find that more senior claims tend to be more liquid.<sup>8</sup> Second, many products are guaranteed by federal agencies, that is, government sponsored enterprises (GSE), which provide implicit or explicit government guarantees (see Section 2). Hence, we compare such products to nonagency issues and test whether agency securities are more liquid, given the potentially lower credit risk and higher degree of standardization.<sup>9</sup> In addition, we explore the interaction between credit and liquidity, based on the credit rating and the effect of trading activity and dealer market power on liquidity. In a further analysis, we explore the relation between observed yield spreads and liquidity, providing us with a better

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<sup>8</sup> [Friedwald, Hennessy, and Jankowitsch \(2016\)](#) provide detailed evidence of a relation between seniority and liquidity for the ABS market.

<sup>9</sup> See [Vickery and Wright \(2013\)](#) for a discussion of agency guarantees and their liquidity-enhancing effects.

understanding regarding which measures are related to differences in bond prices.

It should be noted that the new TRACE data set also has been analyzed simultaneously by other authors covering certain aspects of liquidity: [Atanasov, Merrick, and Schuster \(2014\)](#) show that the prices of agency MBS consistently “cross” and thus indicate violations of arbitrage conditions. They attribute these pricing patterns to impediments to aggregating small positions and a suitability restriction on recommending small positions to retail customers. [Hollifield, Neklyudov, and Spatt \(2014\)](#) analyze the structure of the interdealer network and its relation to bid-ask spreads. They find evidence that central dealers face relatively lower transaction costs than peripheral dealers, with the discount being stronger for “144a securitizations” that are on the “shelf.” The paper that is perhaps closest to ours in spirit is by [Bessembinder, Maxwell, and Venkataraman \(2013\)](#), who also analyze trading activity and transactions costs in the structured product market.

However, our paper is different from that of [Bessembinder, Maxwell, and Venkataraman \(2013\)](#) for at least five important reasons, relating to various aspects of liquidity effects in the structure product market: First, while their analysis is based only on *one* single estimate of liquidity, we, in contrast, rely on a much broader set of liquidity proxies, which allows us to discuss the information contained in measures employing reported data at different levels of detail. Second, while [Bessembinder, Maxwell, and Venkataraman \(2013\)](#) use a regression-based estimate of liquidity, our round-trip cost measure (which serves as our benchmark) reflects the cost of trading more accurately, since it is based on detailed dealer-specific transaction costs, which are straightforward to compute, and does not depend, in any way, on modeling assumptions. Third, in their analysis, they solely focus on customer-to-dealer trades which constitute only a rather small fraction of all trades in the structured product market, whereas our analysis is based on all customer-to-dealer *and* dealer-to-dealer transactions. Fourth, unlike their study, we analyze different subsegments (e.g., tranche seniority, issuing authority, credit rating) of the overall market in much more detail. These subsegments have either turned out to be important in other fixed-income markets, or are unique to the structured product market. Fifth, a novel contribution of our paper is that we analyze which of the liquidity measures best correlate with yield spreads in the structured product market.

## 2. Data Description

We use the new TRACE data set compiled by FINRA in the course of their recent transparency project for the fixed-income structured product market. This proprietary data set is comprised of *all* reported transactions made by dealers and brokers in the U.S. structured product market between May 16, 2011 and June 17, 2013. The complete information will be distributed to

market participants in due course, although the level of detail and the timetable for its release are yet to be decided.<sup>10</sup> The data set contains, as basic attributes, the price, volume, trade date and time of each individual transaction. Furthermore, in our data set, it is possible to link individual trades to dealers, as the data are comprised of specific broker/dealer information, although the identity of the individual dealers is coded, and hence concealed from us. In addition, we can distinguish buy- and sell-side trades in the data set, identifying the active customer in each transaction. We employ various cleaning and filtering procedures before analyzing the data (see the Appendix for a detailed description of these procedures) and end up with about 3.6 million reported transactions for nearly 340,000 structured products.

Structured products can be classified into three market segments according to FINRA's definitions, that is, ABS, CMO, and MBS. The instruments traded in these individual segments are rather diverse, as structured products can be based on substantially different cash-flow structures. Furthermore, the securities are issued/guaranteed by multiple federal agencies and nonagencies. In the following, we provide a brief summary description of each of the three market segments to place their distinguishing characteristics in perspective.

*ABS* are created by bundling loans, such as automobile loans or credit card debt, and issuing securities backed by these assets, which are then sold to investors. In most cases, multiple securities are offered on a given portfolio. Known as tranches, they are all based on a single pool of underlying loans, but have differing levels of risk. In general, payments are first distributed to the holders of the lowest-risk securities, and then sequentially to the holders of higher-risk securities, in a "waterfall" in order of priority, and hence risk. In most cases, *ABS* are issued by private entities ("nonagencies") rather than federal agencies. *CMO* are instruments similar to *ABS*, but backed by pools of mortgage loans. A substantial fraction of these securities offers investors multiple tranches with differing risk characteristics. As is to be expected, the prices of *CMO* tranches are often highly sensitive to property prices. Other products in this market segment are "pass-through" securities, which entitle the investor to a pro rata share of all payments made on an underlying pool of mortgages. These securities are often guaranteed by one of the three main GSEs, the Government National Mortgage Association (Ginnie Mae), the Federal National Mortgage Association (Fannie Mae), or the Federal Home Loan Mortgage Corporation (Freddie Mac).<sup>11</sup> In a few cases, the guarantee is provided by the Small Business Administration (SBA). (All these institutions

<sup>10</sup> The time period of our data sample is dictated by the fact that, during this period, no product-specific data were disseminated to the market. Since then, data on selected market segments of the structured product market have been disseminated in stages. Since our research focuses on the potential level of disclosure, we restrict our attention to the period when *no* data were disseminated. In subsequent research, we plan to examine the effects of the (staged) disclosure of information explicitly.

<sup>11</sup> Fannie Mae and Freddie Mac actually take in mortgages from banks and then issue and guarantee *CMO* and *MBS*, while Ginnie Mae provides guarantees only.

are backed by explicit or implicit guarantees from the U.S. government.) *MBS* are similar to *CMO* securities and represent claims on the cash flows from pools of mortgage loans. However, most *MBS* are guaranteed by one of the *GSEs*, and are “pass-through” participation certificates, entitling the investor to a pro rata share of future cash flows.

Based on information provided by *FINRA*, we can identify the market segment and the issuer/guarantor of each security, that is, one of the federal *GSEs* or a nonagency entity (private labeller). This difference is particularly interesting for the *CMO* market segment, in which both agencies and private labellers are active. Furthermore, we can determine whether a security is a pass-through certificate or represents one of the tranches based on a specific pool of loans. Securities that represent a tranche exist only in the *ABS* and *CMO* market segments. For these tranches, we calculate the seniority based on the “attachment point” of the security within the specific pool. We define the attachment point as the fraction of the sum of the tranche sizes that are subordinated (relative to the tranche considered) to the overall pool size. An attachment point close to 100% represents the most senior tranche, whereas an attachment point of zero represents the first loss piece. Furthermore, we use the overall pool size and the number of tranches as additional controls so as to consider the effects of the structure to which the security belongs. Note, however, that we have no information available concerning the composition of the underlying pool of loans.

Based on the transaction data, we calculate various controls based on the trading activity of the security. In particular, we calculate the number of trades observed for a product on a given day, and the associated trading volume (measured in millions of U.S. dollars). We separate these two variables into the customer-related and interdealer trading segments. Furthermore, we compute a measure for dealer market power, which we define as the ratio of the traded volume of the most active dealer (in terms of traded volume) in a security during a given day, to the overall trading volume on that day.

In addition, we have available to us basic data about the product characteristics of the securities in our database. In particular, we know the original amount issued, the coupon, the maturity and whether the security is traded under Rule 144a. We also obtain credit ratings from *S&P*. However, only a small fraction of the whole universe of securities is rated, especially in the case of agency instruments, which typically do not have ratings. Since these securities have either implicit or explicit guarantees provided by the government, we consider them to have the top ratings, in our empirical analysis. These variables and classifications of the overall sample allow us to analyze, in detail, the liquidity of the structured product market and its segments.

### 3. Liquidity Measures

In this section, we introduce the liquidity measures used in our empirical analysis. The proxies cover virtually all liquidity measures proposed in the related literature and are estimates of transaction costs or market impact based on detailed trading data. The comparison of these measures allows us to evaluate the performance of each measure, in terms of its efficacy in estimating liquidity.<sup>12</sup> We focus on the conceptual underpinnings of the liquidity proxies and their relation to the dissemination of data, and defer the technical details concerning computing the liquidity measures to the Appendix.

Most liquidity measures require transaction information for their computation. However, the level of detail concerning the required information set varies considerably across measures. The liquidity measure that uses the most detailed information and, thus, serves as our benchmark measure, is the *round-trip cost*, which can be computed only if the traded prices and volumes can be linked to the individual dealer (see, e.g., Goldstein, Hotchkiss, and Sirri, 2007). It is defined as the price difference, for a given dealer, between buying (selling) a certain amount of a security and selling (buying) the same amount of this security, within a particular time period, that is, one day.<sup>13</sup> Thus, it is assumed that, in a “round-trip” trade, the price is not affected by changes in the fundamentals during this period. Following the literature, we assume that the round-trip trade may either consist of a single trade or a sequence of trades, which are of equal size, in aggregate, on each side.<sup>14</sup> The *effective bid-ask spread*, proposed by Hong and Warga (2000), can be computed when information about the trade direction is available. The effective bid-ask spread is then defined as the difference between the daily average sell and buy prices (relative to the mid-price).

Many other liquidity measures use only the price and/or volume of each transaction, without relying on dealer-specific or buy/sell-side information. The *Amihud* measure is a well-known metric proposed by Amihud (2002) and conceptually based on Kyle (1985). It was originally designed for exchange-traded equity markets, but has since also become popular for measuring liquidity in OTC markets. It measures the price impact of trades on a particular day. That is, it is the ratio of the absolute price change (measured as a return) to the trading volume given in U.S. dollars. A larger Amihud measure

<sup>12</sup> Our methodology, thus, is similar in spirit to that of Goyenko, Holden, and Trzcinka (2009), who run horse races of various liquidity measures against a liquidity benchmark, albeit for the equity market.

<sup>13</sup> Of course, some round-trip trades may occur over several days. However, to be consistent in computing the various daily liquidity proxies, we rely on the same data sample; that is, we only use transactions within a single day. Robustness checks (not reported in this paper) reveal that extending the round-trip period to one week, for example, has only a minor effect on its magnitude. This is in line with prior empirical evidence that shows that a large fraction of round-trip trades occur within a single day, despite the fact that most structured products are traded rather infrequently.

<sup>14</sup> Note that, for computing the round-trip cost (similar to all other liquidity proxies), we use both customer and interdealer trades, since a round trip (as we define it) may consist of both types of trades.

implies that trading a financial instrument causes its price to move more in response to a given volume of trading and, in turn, reflects lower liquidity. An alternative method for measuring the bid-ask spread is the *imputed round-trip cost*, introduced by Feldhütter (2012) and applied in Dick-Nielsen, Feldhütter, and Lando (2012) for OTC markets. The idea here is to identify round-trip trades, which are assumed to consist of two or three trades on a given day with exactly the same traded volume. This likely represents a pre-matched arrangement in which either one or two dealers match a buy and a sell order from a customer. Thus, the dealer identity is not employed in this matching procedure. The *price dispersion* measure is a liquidity metric recently introduced for OTC markets by Jankowitsch, Nashikkar, and Subrahmanyam (2011). This measure is based on the dispersion of traded prices around the market-wide consensus valuation and is derived from a market microstructure model with inventory and search costs. A low dispersion around this valuation indicates that the financial instrument can be bought for a price close to its fair value and, therefore, represents low trading costs and high liquidity, whereas a high dispersion implies high transaction costs and, hence, low liquidity. The price dispersion measure is defined as the root mean squared difference between the traded prices and the average price, the latter being a proxy for the respective market valuation.

The *Roll* measure, developed by Roll (1984) and applied by Bao, Pan, and Wang (2011) and Friewald, Jankowitsch, and Subrahmanyam (2012), for example, in the context of OTC markets, is a transaction cost measure that is simply based on observed prices. The idea is that transactions randomly occur at the bid and the ask price which results in transitory price movements that are serially negatively correlated. The strength of this covariation is a proxy for the round-trip transaction costs for a particular financial instrument, and hence a measure of its liquidity. This measure requires the lowest level of detail as only traded prices, and not trading volume or dealer-specific information, are used in the computation. However, it requires knowledge of the precise sequence of trades, which may be difficult in the context of batch reporting.

#### 4. Results

In this section, we present the results of our analysis. We first discuss, in Section 4.1, the descriptive statistics of our liquidity proxies for the U.S. fixed-income structured product market, and its three market segments. We then use regression analysis to explore the relation between both product and pool characteristics, as well as trading activity variables, and liquidity. We present a second set of regressions in Section 4.2, where we study the effect of liquidity on the prices of structured products. Specifically, we empirically identify the liquidity measure that is most tightly linked to the yield spread and thus explains liquidity most appropriately. In Section 4.3, we present our main analysis of the relation between the measurement of liquidity and the

**Table 1**  
**Trading activity**

	Total	ABS	MBS	CMO
Traded products	3,296	345	1,866	1,158
Trades	6,470	599	3,290	2,728
Traded volume [mln USD]	32,683	4,468	17,168	11,794
Turnover [in bp]	32	35	31	36

This table presents aggregate data on the average daily number of traded products, number of trades, traded volume, and turnover for the whole structured product market, as well as for the market segments of asset-backed securities (ABS), mortgage-backed securities (MBS), and collateralized mortgage obligations (CMO), during the time period from May 13, 2011 to June 17, 2013, based on data on structured fixed-income products from the Trade Reporting and Compliance Engine (TRACE) provided by the Financial Industry Regulatory Authority (FINRA).

level of detail used in the trading data. Employing different sets of regressions, we explore whether liquidity measures using less detailed information can accurately proxy for our benchmark measure that uses the most detailed data. We elaborate further on this issue in Section 4.4, where we analyze whether certain liquidity measures based on less information are less reliable in certain market regimes.

#### 4.1 Liquidity effects in the structured product market

We first discuss the descriptive statistics of the trading activity in the structured products at a market-wide level. Table 1 presents the average daily number of products traded, the number of trades and the traded volume in the market as a whole. On average, we observe 3,296 different traded securities, 6,470 trades and an aggregate trade volume of \$32.7 billion, per day.

The structured product market has a much higher daily trading volume than the U.S. corporate debt market or the U.S. municipal bond market, each of which have an average daily trading volume of \$23 and \$11 billion, respectively.<sup>15</sup> In terms of daily turnover (i.e., the fraction of trading volume to the amount outstanding) all three markets exhibit a similar trading activity of around 0.32%. However, the average daily trading volume and turnover of the structured product market are much lower than those of the U.S. Treasury securities market, the latter being \$519 billion and 4.7%, respectively. Analyzing the three different market segments of the structured market, that is, ABS, MBS and CMO, we find that the average traded volumes in these segments are \$4.5 billion (ABS), \$17.2 billion (MBS), and \$11.8 billion (CMO), respectively.<sup>16</sup>

Table 2 provides details of the trading activity in the structured product market and reports the fractions of products that are traded, on average, at

<sup>15</sup> These figures are for the year 2012 and were obtained from [www.sifma.org](http://www.sifma.org).

<sup>16</sup> Note that other related surveys may provide different numbers as not all reports use the classification provided by FINRA. For example, in some cases, the MBS and TBA markets are added and simply referred to as the MBS segment.

**Table 2**  
**Trading frequency**

	Total	ABS	MBS	CMO
No trade	77.421	57.397	71.177	79.560
Trade at least once a year	15.136	32.961	20.896	13.184
Trade at least once a month	2.201	10.027	5.067	1.264
Trade at least once a week	0.507	2.957	1.324	0.232
Trade every day	0.050	0.187	0.112	0.030

This table shows, in percentage points, the fraction of active products that do not trade, and trade on average at least once a year, month, week, and every day for the whole structured product market, as well as for the market segments of asset-backed securities (ABS), mortgage-backed securities (MBS), and collateralized mortgage obligations (CMO). The time period of the sample runs from May 13, 2011 to June 17, 2013, and is based on data on structured fixed-income products from the Trade Reporting and Compliance Engine (TRACE) provided by the Financial Industry Regulatory Authority (FINRA).

least once a year, month, week, or day, or are never traded during our sample period. On average, 77% of all structured securities never trade at all, and only 2.2% are traded at least once a month. In comparison to the MBS and CMO market segments, products from the ABS market seem to be somewhat more actively traded. These numbers show that estimating liquidity in the structured product market is challenging, and it is important to analyze differences in trading activity, in general. Overall, we find that many more instruments exist in the structured product market than in other fixed-income markets, but they are traded less often, albeit with a higher volume per trade.<sup>17</sup>

Focusing on the liquidity of the individual securities, we present summary statistics (mean and standard deviation) for the pool and product characteristics, trading activity variables, and liquidity measures for the individual market segments (see Table 3). The average time-to-maturity is close to 20 years across all segments. The average pool size in the ABS segment is \$5.3 billion, with around 17 tranches, and in the CMO segment it is \$1.6 billion with close to 19 tranches, whereas the MBS pools consist of only one tranche. In the ABS segment, we observe an average amount issued of around \$722 million, compared with \$1.2 billion in the MBS, and \$71 million in the CMO segments, per issue. MBS securities have a AAA rating assigned to them since they are commonly issued by one of the federal-government-sponsored enterprises. ABS and CMO securities are, on average, rated somewhat lower, by one or two notches. The seniority of the MBS securities is zero as they do not consist of any tranches, that is, no subordinated claims exist; instead investors are immediately affected by losses on a pro rata basis. The average seniorities of traded ABS and CMO securities are 48% and 39%, respectively. That means that, for example, in the ABS segment the sum of all tranche sizes subordinated relative to the considered tranche (i.e., security) within the relevant pool is 48%.

Regarding trading activity and liquidity, we find around four trades per security across segments, on average, per day. The daily trading volume is

<sup>17</sup> See, for example, Friewald, Jankowitsch, and Subrahmanyam (2012) for trading activity in the U.S. corporate bond market.

**Table 3**  
**Security characteristics and liquidity**

	Mean			Standard deviation		
	ABS	MBS	CMO	ABS	MBS	CMO
<i>Pool characteristics</i>						
Pool size [bln USD]	5.347	1.192	1.623	4.455	2.634	3.352
Number of tranches	17.150	1.000	18.943	12.746	0.000	23.510
<i>Product characteristics</i>						
Amount issued [mln USD]	722.211	1,192.154	71.089	716.284	2,634.395	179.691
Time-to-maturity [years]	23.602	19.425	21.727	11.001	7.222	6.054
Coupon rate [%]	4.604	4.420	4.886	1.737	1.522	1.787
Rating number	2.363	1.000	1.631	1.720	0.000	1.798
Seniority	0.481	0.000	0.390	0.334	0.000	0.334
<i>Trading activity variables</i>						
Trades	3.630	4.431	4.160	2.736	4.228	4.954
Customer trades	2.559	1.933	2.109	1.531	2.060	3.126
Interdealer trades	1.071	2.498	2.050	2.177	2.705	2.835
Trading volume [mln USD]	18.505	16.293	6.871	35.538	71.693	29.630
Customer trading volume [mln USD]	14.190	8.365	3.755	27.779	44.681	18.909
Interdealer volume [mln USD]	4.315	7.928	3.116	19.918	41.649	16.826
Market power	0.819	0.691	0.728	0.199	0.166	0.187
<i>Liquidity measures</i>						
Round-trip cost [%]	0.426	0.583	1.180	0.708	0.580	0.865
Effective bid-ask spread [%]	0.362	0.368	0.896	0.656	0.454	0.860
Amihud [%/mln]	28.679	14.686	152.774	132.696	81.588	281.909
Imputed round-trip cost [%]	0.406	0.573	1.128	0.670	0.575	0.859
Price dispersion [%]	0.300	0.460	0.711	0.523	0.631	0.636
Roll [%]	0.701	0.729	1.127	1.090	1.239	1.474

This table shows the means and the standard deviations of pool characteristics, product characteristics, trading activity variables, and liquidity measures for the market segments of the structured product market of asset-backed securities (ABS), mortgage-backed securities (MBS), and collateralized mortgage obligations (CMO). The sample is based on data on structured fixed-income products from the Trade Reporting and Compliance Engine (TRACE) provided by the Financial Industry Regulatory Authority (FINRA) for the period from May 13, 2011 to June 17, 2013.

highest for the ABS segment, at \$18.5 million, and lowest for the CMO segment, at \$6.9 million, which is in line with the results given in Table 2 in that ABS products trade more frequently than securities in the other market segments. The dealer market power is quite high in all segments: 81.9% (ABS), 69.1% (MBS) and 72.8% (CMO) of all the daily traded volume is executed by just one dealer.

Analyzing the various liquidity measures, the round-trip cost in the ABS market is around 43 bp, compared to 58 bp in the MBS and 118 bp in the CMO segments, respectively. The ranking is basically preserved for all the alternative liquidity measures that we consider. For example, for the price dispersion measure, we find 30 bp for the ABS, 46 bp for the MBS and 71 bp for the CMO segments. Thus, securities in the ABS segment are more liquid than those backed by mortgages. Furthermore, we find that, within the market of mortgage-backed products, the MBS segment is much more liquid than the CMO segment, potentially because MBS typically have less complicated cash-flow structures and also provide credit guarantees. In

comparison, Friewald, Jankowitsch, and Subrahmanyam (2012) report for the U.S. corporate bond market a price dispersion of 42 bp, on average. Thus, according to this metric, the ABS segment is more liquid than the corporate bond market, while the other two markets are less liquid. The presented standard deviations of the pool and product characteristics, trading activity variables and liquidity measures indicate high cross-sectional variations.

In a second step, we study liquidity effects based on various characteristics, employing regression analysis, to shed light on the observed differences. We use a panel regression with month fixed effects based on the weekly averages of all the variables to explore whether each of our defined liquidity measures can be related to product and pool characteristics as well as trading activity variables.<sup>18</sup> For each liquidity measure, we estimate the regression specification

$$\begin{aligned}
 \text{liquidity measure}_{it} = & \alpha_0 + \sum_j \beta_j \cdot \text{product characteristic}_{ijt} \\
 & + \sum_k \gamma_k \cdot \text{pool characteristic}_{ikt} \\
 & + \sum_l \delta_l \cdot \text{trading activity}_{ilt} + \sum_m \kappa_m \cdot \text{month}_{mt} + \epsilon_{it},
 \end{aligned}
 \tag{1}$$

where the set of liquidity measures we are aiming to explain consists of, in turn, the round-trip cost, effective bid-ask spread, Amihud measure, imputed round-trip cost, price dispersion measure, and Roll measure of security  $i$  at time  $t$ . Table 4 presents the result of these six regressions. We first confirm the result that securities from the ABS segment are significantly more liquid, and those of the CMO segment less liquid, than the MBS securities. For example, the round-trip cost is 60 bp lower for products traded in the ABS market and 10 bp higher for those in the CMO market than it is for MBS securities. Comparing securities guaranteed by federal GSEs, i.e., Freddie, Fannie, Ginnie and SBA, with nonagency securities, we find that, in general, guaranteed securities are more liquid. For example, securities with a guarantee from Freddie or Fannie have round-trip costs that are around 30 bp lower, and Ginnie has costs that are 9 bp lower than nonagency securities, whereas SBA securities are slightly less liquid than nonagency securities.

Exploring the liquidity effects for different rating grades, we confirm that better-rated securities are more liquid, that is, have lower transaction costs.

<sup>18</sup> Note that there is a trade-off between using more and less frequent data. More frequent data improve the power of the statistical tests in our empirical analysis but may also imply larger measurement errors in our liquidity measures and a more unbalanced data set as not all securities necessarily trade each week. We therefore compute weekly averages of all variables used in our empirical analysis and consider this as the optimal sampling frequency. We use ordinary least-squares regressions based on robust standard errors clustered across time and products to account for time-series and product-specific differences.

**Table 4**  
**Liquidity measure regression**

	Round-trip cost	Eff. bid-ask spread	Amihud	Imp. round-trip cost	Price dispersion	Roll
Intercept	1.233*** (17.501)	0.509*** (7.005)	-41.942 (-1.537)	1.157*** (17.922)	0.744*** (6.388)	0.874*** (3.726)
Product-type dummies						
ABS	-0.595*** (-7.545)	-0.539*** (-7.026)	-4.887 (-0.198)	-0.546*** (-7.879)	-0.270*** (-5.219)	-0.569*** (-4.517)
CMO	0.096*** (3.956)	0.101*** (5.164)	105.296*** (12.070)	0.101*** (4.433)	0.112*** (6.761)	0.213*** (4.924)
Issuer dummies						
Fannie	-0.316*** (-8.722)	-0.273*** (-7.836)	-57.065*** (-2.682)	-0.294*** (-8.717)	-0.137*** (-6.142)	-0.422*** (-5.415)
Freddie	-0.300*** (-8.333)	-0.255*** (-7.319)	-39.957* (-1.891)	-0.281*** (-8.364)	-0.144*** (-6.750)	-0.434*** (-5.558)
Ginnie	-0.085** (-2.406)	-0.112*** (-3.261)	-84.329*** (-4.159)	-0.060* (-1.833)	-0.057*** (-2.805)	-0.410*** (-5.728)
SBA	0.151** (2.560)	0.147** (2.564)	-97.065*** (-6.149)	0.135*** (2.594)	-0.025 (-0.620)	-0.131 (-1.367)
Credit rating	0.040*** (5.341)	0.029*** (4.025)	-14.976*** (-4.611)	0.037*** (5.458)	-0.001 (-0.260)	-0.015 (-1.186)
Seniority	-0.228*** (-7.415)	-0.206*** (-6.797)	-62.442*** (-5.499)	-0.212*** (-7.402)	-0.149*** (-6.983)	-0.202*** (-3.362)
log(Amt issued)	-0.172*** (-19.552)	-0.127*** (-15.684)	-7.639*** (-2.716)	-0.157*** (-19.758)	-0.057*** (-9.683)	-0.020 (-1.458)
Time-to-maturity	0.006*** (5.651)	0.004*** (4.037)	-0.408 (-1.315)	0.005*** (5.430)	0.002*** (2.741)	-0.007*** (-3.305)
Coupon rate	0.090*** (21.457)	0.069*** (21.055)	26.284*** (18.946)	0.087*** (21.789)	0.096*** (25.610)	0.161*** (19.711)
Rule 144a	-0.118*** (-2.777)	-0.098** (-2.428)	-32.082*** (-3.681)	-0.124*** (-3.083)	-0.072** (-2.426)	-0.074 (-1.048)
log(Pool size)	0.091*** (11.976)	0.079*** (11.235)	-8.612*** (-2.801)	0.081*** (11.552)	0.051*** (8.797)	0.064*** (4.148)
N. of tranches	-0.004*** (-6.668)	-0.003*** (-6.409)	-0.226 (-1.321)	-0.004*** (-7.002)	-0.003*** (-7.730)	-0.004*** (-4.312)
Customer trades	0.022*** (5.324)	0.060*** (6.655)	2.132*** (3.406)	0.005** (2.243)	0.039*** (6.179)	0.035*** (4.624)
Customer volume	-0.002*** (-8.794)	-0.002*** (-8.890)	-0.182*** (-4.945)	-0.002*** (-8.903)	-0.001*** (-2.821)	-0.001*** (-2.972)
Interdealer trades	-0.008*** (-2.792)	-0.028*** (-5.845)	-0.381 (-0.805)	0.001 (0.398)	0.002 (0.319)	0.016 (1.627)
Interdealer volume	-0.001* (-1.903)	0.000** (2.047)	0.026 (0.671)	-0.001** (-2.262)	-0.001*** (-4.123)	-0.001*** (-3.415)
Market power	0.475*** (9.233)	0.993*** (16.170)	169.920*** (10.772)	0.514*** (10.545)	-0.264*** (-4.371)	0.645*** (6.528)
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R <sup>2</sup>	0.314	0.320	0.193	0.283	0.176	0.093
Num. obs.	47,174.000	47,174.000	47,174.000	47,174.000	47,174.000	47,174.000

This table reports the results of regressing, in turn, the round-trip cost, effective bid-ask spread, Amihud measure, imputed round-trip cost, price dispersion measure, and Roll measure on product characteristics, pool characteristics, and trading activity variables using a panel regression of weekly averages of all variables and month fixed effects. Values in parentheses are *t*-statistics based on robust standard errors clustered across time and products. \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% level, respectively. The sample is based on data on structured fixed-income products from the Trade Reporting and Compliance Engine (TRACE) provided by the Financial Industry Regulatory Authority (FINRA) for the period from May 13, 2011 to June 17, 2013.

For example, the round-trip costs for AAA-rated securities are about 24 bp lower than those for CCC/C-rated issues (based on the difference in the number of rating notches). In addition, we find that higher seniority of a security within its pool increases its liquidity. A one-standard-deviation increase toward higher seniority improves liquidity by 7.7 bp. As expected, we find securities with a larger amount issued to be more liquid. A one-standard-deviation increase in size reduces round-trip costs by 33 bp. Securities with a longer time-to-maturity are less liquid, as these instruments are often held by buy-and-hold investors. The coupon rate also significantly affects liquidity. The higher the coupon, the lower is the liquidity. The economic significance of the coupon rate is considerable, in that a one-standard-deviation increase in the coupon rate increases the round-trip cost by 16 bp. As expected, Rule 144a securities are more liquid (by 12 bp based on the round-trip cost) as these securities are traded mostly by institutional investors. As for the pool characteristics, we find securities from larger pools to be less liquid, potentially indicating more complex structures.

Concerning trading activity, we find higher (customer and interdealer) trading volume to improve liquidity, the effect being somewhat more pronounced for customer trading volume. A one-standard-deviation increase in customer volume decreases the round-trip cost by 5.3 bp. For the number of trades, we observe that only interdealer trades improve liquidity. However, the results for the number of trades are economically small at around 2 bp. Interestingly, dealer market power has a rather strong effect. For example, a security with a one-standard-deviation-higher concentration in dealer market power has round-trip costs that are 9 bp higher.

Overall, our results show product and pool characteristics as well as trading activity variables to be related to the liquidity measures. Important variables are seniority, the credit rating, coupon, guarantees by GSEs and dealer market power. The  $R^2$  of the regressions lie approximately between 10% and 30% for the different liquidity measures, showing a significant proportion of unexplained variation.

## 4.2 Liquidity effects and yield spreads

In this section, we explore the relation between the liquidity measures and the yield spreads in the structured product market. This analysis is important in the first place as it allows us to test empirically whether the round-trip cost is most closely related to the yield spread and should thus capture liquidity best. For this analysis, we compute, for each individual transaction, the related yield of the structured product, based on the trade price and expected coupon payments. Furthermore, we determine the yield of a synthetic risk-free bond based on the swap curve at the same time.<sup>19</sup> The dependent variable in our

<sup>19</sup> Feldhütter and Lando (2008) show that riskless rates based on swap rates are the best proxies to use as benchmarks.

analysis is the spread between the individual structured product's yield and the benchmark yield for the same duration.<sup>20</sup> We use a panel regression with month fixed effects based on the weekly averages of all variables to explore the observed yield spreads, given the liquidity measures and various controls. In doing so, we run the following regression:

$$yield\ spread_{it} = \alpha_0 + \sum_j \beta_j \cdot liquidity\ measure_{ijt} + \sum_k \gamma_k \cdot control_{ikt} + \sum_l \kappa_l \cdot month_{lt} + \epsilon_{it}, \quad (2)$$

where *liquidity measure* refers, respectively, to the round-trip cost, effective bid-ask spread, Amihud measure, imputed round-trip cost, price dispersion measure, and Roll measure of security *i* at time *t*. The controls represent product and pool characteristics.<sup>21</sup>

Table 5 presents the results of the above regressions for different specifications. Regressions (1) to (6) focus on the liquidity measures, including each one individually. Regression (7) includes all these measures and controls together. Starting with Regression (1), that is, including the round-trip cost, we find that the adjusted  $R^2$  is 10.7%, indicating that liquidity is an important factor in the pricing of structured products. A one-standard-deviation increase in this benchmark measure increases the yield spread by 53 bp (the standard deviation of the spread is 193 bp). As expected, the round-trip cost, which uses the most detailed information, produces the highest  $R^2$ . Thus, we find evidence that our benchmark measure is indeed better at capturing information that is relevant for pricing than are the other measures. It is noteworthy that, when we use either the imputed round-trip cost or the effective bid-ask spread as an explanatory variable, we obtain a similar level of explanatory power (around 10.0%). All the other measures, when used individually in the regression, provide explanatory power of between 8.3% and 9.0%.

Regression (7) is the full model, including all the explanatory variables, and the  $R^2$  increases to 88.1%. Since all the liquidity measures quantify similar aspects of liquidity, at least to some extent, not all of them turn out to be statistically significant in this full specification, due to potential multi-collinearity. We find similar explanatory power when we eliminate the round-trip cost from the regression equation.

<sup>20</sup> We compute the yield of a structured product based on its weekly mid-price, defined as the mid point between the weekly average bid and ask prices.

<sup>21</sup> Note that we do not use trading activity variables as controls, as information from these variables is already reflected in the liquidity measures, and this could, therefore, result in multicollinearity issues that would complicate the interpretation of the individual measures. In addition, all trading activity variables already contain dealer-specific information: We specifically want to analyze which liquidity measure would be the best proxy for this information, compared with the benchmark measure.

**Table 5**  
**Yield spread regression**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	0.561*** (8.240)	0.736*** (12.686)	1.049*** (20.064)	0.594*** (7.987)	0.793*** (16.731)	0.882*** (22.528)	-2.838*** (-27.185)
Round-trip cost	0.636*** (26.150)						0.005 (0.260)
Eff. bid-ask spr.		0.634*** (22.052)					0.057*** (3.628)
Amihud			0.002*** (17.875)				0.000* (1.705)
Imp. rtc				0.624*** (25.791)			0.017 (1.078)
Price dispersion					0.691*** (28.712)		-0.103*** (-8.506)
Roll						0.310*** (21.421)	0.022*** (4.074)
Product-type dummies							
ABS							-0.295*** (-3.318)
CMO							0.124*** (3.914)
Issuer dummies							
Fannie							-0.363*** (-8.998)
Freddie							-0.314*** (-7.941)
Ginnie							-0.435*** (-11.889)
SBA							-0.560*** (-7.560)
Credit rating							0.381*** (26.866)
Seniority							-0.066* (-1.900)
log(Amt issued)							-0.025** (-2.525)
Time-to-maturity							-0.037*** (-24.589)
Coupon rate							0.930*** (130.813)
Rule 144a							0.133 (1.632)
log(Pool size)							0.009 (0.931)
N. of tranches							-0.002** (-2.009)
Month fixed effects	Yes						
Adj. R <sup>2</sup>	0.107	0.098	0.090	0.102	0.086	0.083	0.881
Num. obs.	47,174.000	47,174.000	47,174.000	47,174.000	47,174.000	47,174.000	47,174.000

This table reports the results of regressing the yield spread (i.e., the difference between the yield of the structured product and the duration-matched swap rate) on liquidity measures (i.e., round-trip cost, effective bid-ask spread, Amihud measure, imputed round-trip cost, price dispersion measure, and Roll measure), product characteristics, and pool characteristics by using a panel regression of weekly averages of all variables and month fixed effects. Values in parentheses are *t*-statistics based on robust standard errors clustered across time and products. \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% level, respectively. The sample is based on data on structured fixed-income products from the Trade Reporting and Compliance Engine (TRACE) provided by the Financial Industry Regulatory Authority (FINRA) for the period from May 13, 2011 to June 17, 2013.

Analyzing the effects of the control variables in the full model, we find that the most relevant variables in the full model turn out to be the coupon and the credit rating. A one-standard-deviation-higher coupon results in an increase of 160 bp in the yield spread, while a one-standard-deviation change in the credit rating increases the yield spread by 59 bp. Thus, the coupon rate and credit rating have the highest explanatory power of all the variables, indicating that credit risk is an important factor, while a higher coupon is also associated with higher liquidity risk for many products.

Maturity exhibits important effects as well, with a one-standard-deviation increase leading to a 26 bp decrease in the yield spread, indicating that longer maturities are associated with lower spreads. Larger issues have lower yield spreads as well. However, compared with the other product characteristics, the issue size is of minor importance. As for the market segment and the issuer dummies, we find similar results, in line with their impacts on liquidity in the previous analysis. Thus, ABS have lower yield spreads (−29.5 bp) and CMO slightly higher yield spreads (12.4 bp) than MBS. Securities with guarantees from GSEs have significantly lower yield spreads of around 30 to 60 bp, reflecting the lower credit risk of these products.

Overall, we find a clear relation between yield spreads and liquidity measures, highlighting the importance of liquidity for the pricing of structured products. More importantly, the round-trip cost, which incorporates the most detailed transaction data, exhibits the highest explanatory power.

### **4.3 Liquidity and the dissemination of information**

In this section, we discuss the relation between liquidity and the granularity of the dissemination of information. Overall, this analysis allows us to examine whether the dissemination of detailed transaction data provides valuable information to market participants, beyond that provided by liquidity measures based on more aggregated information. Furthermore, this analysis provides insights into the informational value of liquidity measures at different levels of granularity.

The results presented in Sections 4.1 and 4.2 provide a good starting point for our analysis. Recall from [Table 4](#) that liquidity measures contain significant idiosyncratic information that is not included in the simple product characteristics or trading activity variables. Given these results, it seems evident that the liquidity measures provide additional insights beyond those contained in the basic data on product characteristics and trading activity. Less obvious is the question of whether liquidity measures using more detailed data provide more insights into the liquidity effects than do those using less information. In our yield-spread regression based on [Equation \(2\)](#), we find that the different liquidity measures lead to similar explanatory power, which is a first indication that liquidity measures using less information are reasonable proxies for liquidity.

To analyze this question in more detail, we present a set of panel regressions with month fixed effects in which we regress our benchmark measure, that is, the round-trip cost, on all the other liquidity measures and various controls, in a nested fashion. Thus, we explore whether the liquidity measures based on *less* information can be good proxies for the round-trip costs. The regression equation is

$$\begin{aligned} \text{round-trip cost}_{it} = & \alpha_0 + \sum_j \beta_j \cdot \text{liquidity measure}_{ijt} + \sum_k \gamma_k \cdot \text{control}_{ikt} \\ & + \sum_l \kappa_l \cdot \text{month}_{lt} + \epsilon_{it}, \end{aligned} \quad (3)$$

where *liquidity measure* represents the effective bid-ask spread, Amihud measure, imputed round-trip cost, price dispersion measure, and Roll measure, respectively, of security *i* at time *t*. The controls are the same as in the regression analysis based on Equation (2).

Table 6 presents the results of this analysis, presenting the six specifications. In Regressions (1) to (5), we use each of the liquidity measures in turn, plus all controls, to analyze the round-trip costs. When we add just one individual proxy to the regression analysis, we find that the imputed round-trip cost is the best proxy by far, with an  $R^2$  of 88.9%. The effective bid-ask spread and the price dispersion measure show high explanatory power as well, with  $R^2$  of 70.4% and 51.1%, respectively, whereas the  $R^2$  of the Amihud and Roll measure is much lower at around 35%. Adding all the liquidity measures to the regression equation, in Regression (6), we obtain an  $R^2$  of 91.3%. That is, the explanatory power increases slightly when we include all these proxies, compared to the result with the imputed round-trip cost. We consider this level of explanatory power rather high, given the rather diverse nature of the instruments, with potentially different liquidity characteristics, and the low number of trades per security and day, in general. We obtain similar results (not reported here) when we explore the relationship between the effective bid-ask spread and liquidity measures using less information. Thus, there is evidence that, in general, liquidity measures using more detailed data can be proxied for reasonably well with similar measures using less data.

Overall, we find that dealer-specific information and buy/sell-side flags are not absolutely essential, in terms of incremental informativeness, for the purpose of computing reliable liquidity metrics in the context of OTC markets. Instead, reasonable estimates of the liquidity measures can be calculated based on prices and volumes of individual trades. In particular, the imputed round-trip cost, which tries to identify round-trip trades with price and volume information alone, does explain most of the variation observed in the benchmark measure. Thus, data dissemination comparable to that of TRACE for U.S. corporate bonds, where the focus is on the dissemination of the trading activity, seems appropriate in this context, and would incur little loss of informativeness.

**Table 6**  
**Round-trip cost measure regression**

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.637*** (15.436)	1.507*** (21.696)	0.197*** (7.218)	1.113*** (13.154)	1.442*** (19.014)	0.149*** (8.202)
Eff. bid-ask spr.	0.768*** (80.217)					0.224*** (22.119)
Amihud		0.001*** (23.324)				-0.000*** (-3.230)
Imp. rtc			0.917*** (250.249)			0.741*** (70.422)
Price dispersion				0.656*** (27.436)		0.063*** (10.617)
Roll					0.092*** (13.387)	-0.001 (-1.005)
Product-type dummies						
ABS	-0.217*** (-8.846)	-0.556*** (-8.365)	-0.083*** (-4.069)	-0.363*** (-6.956)	-0.500*** (-6.729)	-0.058*** (-4.933)
CMO	-0.000 (-0.011)	0.007 (0.318)	0.007 (1.386)	0.043** (2.422)	0.091*** (4.024)	-0.009* (-1.814)
Issuer dummies						
Fannie	-0.082*** (-5.243)	-0.284*** (-8.124)	-0.053*** (-4.395)	-0.266*** (-8.970)	-0.306*** (-8.322)	-0.026*** (-3.408)
Freddie	-0.079*** (-5.017)	-0.285*** (-8.148)	-0.049*** (-4.004)	-0.244*** (-8.204)	-0.289*** (-7.918)	-0.023*** (-2.757)
Ginnie	0.032** (2.131)	-0.030 (-0.866)	-0.040*** (-3.411)	-0.084*** (-2.734)	-0.078** (-2.189)	-0.010 (-1.274)
SBA	0.082*** (4.040)	0.214*** (4.435)	0.017 (1.174)	0.113*** (3.079)	0.124** (2.316)	0.024*** (2.738)
Credit rating	0.017*** (4.979)	0.052*** (7.393)	0.006*** (2.678)	0.037*** (6.452)	0.039*** (5.445)	0.006*** (3.526)
Seniority	-0.070*** (-5.740)	-0.170*** (-6.419)	-0.037*** (-4.382)	-0.117*** (-5.557)	-0.209*** (-7.241)	-0.019*** (-3.123)
log(Amt issued)	-0.082*** (-21.589)	-0.167*** (-22.383)	-0.028*** (-11.312)	-0.130*** (-20.958)	-0.171*** (-20.892)	-0.025*** (-13.558)
Time-to-maturity	0.003*** (6.175)	0.005*** (6.105)	0.001*** (4.610)	0.002*** (3.139)	0.005*** (5.752)	0.001*** (5.788)
Coupon rate	0.034*** (13.530)	0.075*** (19.941)	0.013*** (11.048)	0.040*** (13.000)	0.087*** (22.499)	0.005*** (4.879)
Rule 144a	-0.045** (-2.551)	-0.085** (-2.253)	-0.001 (-0.064)	-0.079*** (-2.903)	-0.111*** (-2.824)	0.000 (0.042)
log(Pool size)	0.030*** (8.433)	0.100*** (14.330)	0.018*** (8.577)	0.053*** (9.324)	0.085*** (11.929)	0.010*** (6.398)
N. of tranches	-0.001*** (-4.216)	-0.004*** (-6.733)	-0.000*** (-2.804)	-0.002*** (-4.195)	-0.003*** (-6.128)	-0.000 (-1.238)
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R <sup>2</sup>	0.704	0.354	0.889	0.511	0.314	0.913
Num. obs.	47,174.000	47,174.000	47,174.000	47,174.000	47,174.000	47,174.000

This table reports the results of regressing the round-trip cost on all other liquidity measures (i.e., effective bid-ask spread, Amihud measure, imputed round-trip cost, price dispersion measure, and Roll measure), product characteristics, and pool characteristics by using a panel regression of weekly averages of all variables and month fixed effects. Values in parentheses are *t*-statistics based on robust standard errors clustered across time and products. \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% level, respectively. The sample is based on data on structured fixed-income products from the Trade Reporting and Compliance Engine (TRACE) provided by the Financial Industry Regulatory Authority (FINRA) for the period from May 13, 2011 to June 17, 2013.

#### 4.4 Measuring liquidity in different market environments

In this section, we analyze whether liquidity measures based on less information are less reliable in certain market environments. In particular, we focus on the impact of the trading activity in the individual securities and overall market activity. In the first analysis, we rely on the regression setup presented in Section 4.3. That is, again we use the round-trip cost as our benchmark measure and regress it on all the other liquidity measures and various controls. As we are interested in the performance of these liquidity measures, we use them only individually in the analysis, together with all controls and month fixed effects. The regression equation is

$$\begin{aligned} \text{round-trip cost}_{it} = & \alpha_0 + \beta_1 \cdot \text{liquidity measure}_{it} + \sum_k \gamma_k \cdot \text{control}_{ikt} \\ & + \sum_l \kappa_l \cdot \text{month}_{lt} + \epsilon_{it}, \end{aligned} \quad (4)$$

where *liquidity measure* represents either the effective bid-ask spread, Amihud measure, imputed round-trip cost, price dispersion measure, or Roll measure of security *i* at time *t*. The controls are the same as in the regression analysis based on Equation (2).

We implement this regression analysis repeatedly, splitting our sample into two subsamples defined in various ways, based on high and low trading activity in securities, or on regimes with low and high overall market activity. In particular, we employ the trading volume to form subsamples based on trading activity, that is, each week, we separate the securities, using the cross-sectional median, into low- and high-trading-activity subsamples. In addition, we form subsamples based on the ABS (most liquid) and CMO (least liquid) market segments. Further, we compare samples of small and large issues. Regarding overall market activity, we separate our time period into weeks with low and high activity. We use the VIX index for this purpose and split our data sample into weeks in which the index was above, and weeks in which it was below, the median for our sample period.<sup>22</sup>

Table 7 provides the results of this analysis. The table shows the parameters and the *t*-statistics of the liquidity measures employed, and the resultant  $R^2$  (the parameters of the controls are not shown to conserve space).<sup>23</sup> Focusing on the imputed round-trip cost, we find an  $R^2$  of 89.0% for high trading volume compared to 84.0% for low volume. Regarding market segments, we find an  $R^2$  of 85.5% for CMO as the least liquid segment and 91.3% for ABS as the most liquid segment. Thus, there is a difference in the explanatory

<sup>22</sup> We use the VIX index as our market volatility measure as there is no volatility index specifically available for the structured product market. However, we also have used a volume-weighted volatility measure constructed from our data set, and the results are virtually identical to those obtained using the VIX index.

<sup>23</sup> The results of a regression specification without controls allow for a similar conclusion since the relative ranking based on the explanatory power remains basically unchanged.

**Table 7**  
**Analysis of the round-trip cost measure for various subsegments**

	Eff. bid-ask spread		Amihud		Imp. round-trip cost		Price dispersion		Roll	
	Low	High	Low	High	Low	High	Low	High	Low	High
<i>Average trading volume</i>										
Liquidity measure	0.675*** (60.884)	0.862*** (59.774)	0.001*** (20.865)	0.003*** (7.411)	0.886*** (139.977)	0.927*** (182.029)	0.540*** (23.091)	0.692*** (20.415)	0.048*** (9.054)	0.106*** (14.792)
Adj. R <sup>2</sup>	0.606	0.700	0.229	0.282	0.840	0.890	0.368	0.485	0.179	0.277
<i>Product type</i>										
Liquidity measure	CMO 0.742*** (77.118)	ABS 0.933*** (32.977)	CMO 0.001*** (24.535)	ABS 0.003*** (9.761)	CMO 0.897*** (222.617)	ABS 0.945*** (43.423)	CMO 0.744*** (27.249)	ABS 0.827*** (11.235)	CMO 0.090*** (14.065)	ABS 0.231*** (7.289)
Adj. R <sup>2</sup>	0.667	0.831	0.262	0.531	0.855	0.913	0.462	0.649	0.218	0.465
<i>Amount issued</i>										
Liquidity measure	Small 0.735*** (64.479)	Large 0.808*** (49.041)	Small 0.001*** (23.819)	Large 0.001*** (12.965)	Small 0.886*** (161.323)	Large 0.955*** (202.807)	Small 0.739*** (24.516)	Large 0.540*** (19.730)	Small 0.087*** (12.176)	Large 0.079*** (11.576)
Adj. R <sup>2</sup>	0.643	0.684	0.247	0.305	0.841	0.918	0.447	0.450	0.196	0.270
<i>Market volatility</i>										
Liquidity measure	Low 0.776*** (59.530)	High 0.759*** (62.413)	Low 0.001*** (18.028)	High 0.001*** (20.703)	Low 0.928*** (205.843)	High 0.902*** (174.900)	Low 0.586*** (22.871)	High 0.770*** (26.451)	Low 0.078*** (9.828)	High 0.104*** (13.526)
Adj. R <sup>2</sup>	0.670	0.736	0.332	0.364	0.898	0.875	0.481	0.544	0.296	0.323

This table reports the results of regressing the round-trip cost on the liquidity measure given in the corresponding column (i.e., effective bid-ask spread, Amihud measure, imputed round-trip cost, price dispersion measure, and Roll measure), product characteristics, and pool characteristics by using a panel regression of weekly averages of all variables and month fixed effects. We report only the coefficient for the corresponding liquidity measure given in each column and the adjusted R<sup>2</sup>. The regressions are conducted for the subsegments of low versus high average daily trading volume, collateralized mortgage obligations (CMO) versus asset-backed securities (ABS), small versus large bonds as defined by the amount issued, and low versus high market volatility as defined by the VIX index. We use weekly cross-sectional medians as the cutoff values for the subsegments based on average trading volume and the amount issued. For the market volatility regression, we split our total sample into two periods as defined by the median value of the VIX index. Values in parentheses are t-statistics based on robust standard errors clustered across time and products. \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% level, respectively. The sample is based on data on structured fixed-income products from the Trade Reporting and Compliance Engine (TRACE) provided by the Financial Industry Regulatory Authority (FINRA) for the period from May 13, 2011 to June 17, 2013.

power of around 5% when considering trading volume and the market segment. We find a similar effect for the subsamples based on the amount issued. Analyzing the other liquidity measures, the results show relative reductions in the  $R^2$  of about 15% for the effective bid-ask spread when going from the high to the low trading-activity regimes. Exploring the Amihud measure and price dispersion measure, we find relative reductions of more than 25%, when comparing the different trading-activity subsamples. Thus, measures based solely on price and volume information show a more severe decrease than do the imputed round-trip cost and effective bid-ask spread, which use buy/sell-side indicators or try to identify round-trip trades. For the Roll measure, the relative reduction in the  $R^2$  is more than 40%. Thus, we find even more pronounced differences for measures that focus on price information alone. As for the overall market activity, we find that, for the imputed round-trip cost, there is basically no difference between the two subsamples. However, for all the other liquidity measures, we find that the  $R^2$  falls by around 10% in a regime of low overall market activity.

Given the large variation in the explanatory power across the subsamples, we additionally explore the economic significance of the previous results. In doing so we compute the signed and absolute deviation of the various liquidity measures to our benchmark measure. This allows us to quantify any potential biases in the liquidity measures with respect to the round-trip cost measure as well as its absolute magnitude. Table 8 reports the results in a similar fashion as Table 7.<sup>24</sup> First, we find all measures across subsegments to be lower than our benchmark measure, albeit for the imputed round-trip cost, the deviation is economically small (on average less than 5 bp). Second, both the signed and the absolute deviation of the liquidity measures to the round-trip cost measure tend to be weaker for the subsegments of high trading activity compared to low trading activity, in line with our previous results. For example, the effective bid-ask spread is, on average, 33.8 bp below the round-trip cost in the subsegment with low average trading volume, but only 15.5 bp, in the subsegment with high trading volume. Third, we find that measures that are based on buy/sell-side indicators (i.e., effective bid-ask spread) or try to identify round-trip trades (i.e., imputed round-trip cost) decrease less in precision when moving from a high to a low trading activity segment. For example, the absolute deviation of the effective bid-ask spread compared to the round-trip cost measure is 22.7 bp higher in the low trading volume segment, compared to the high trading volume segment. On the contrary, the corresponding absolute deviation for the price dispersion measure is 39.2 bp. Again, these results confirm that measures based on less information

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<sup>24</sup> Note that we leave out the Amihud measure in this type of analysis because, contrary to our benchmark measure, the Amihud measure is a price impact measure and thus is not directly comparable in terms of magnitude to the round-trip cost measure.

**Table 8**  
**Quantification of potential biases in the liquidity measures for various subsegments**

	Eff. bid-ask spread		Imp. round-trip cost		Price dispersion		Roll	
<i>Average trading volume</i>								
	Low	High	Low	High	Low	High	Low	High
Deviation	-0.338***	-0.155***	-0.053***	-0.022***	-0.492***	-0.193***	-0.031***	0.091***
Abs. deviation	0.456***	0.229***	0.079***	0.044***	0.717***	0.325***	1.184***	0.606***
<i>Product type</i>								
	CMO	ABS	CMO	ABS	CMO	ABS	CMO	ABS
Deviation	-0.284***	-0.064***	-0.053***	-0.020***	-0.470***	-0.126***	-0.053***	0.275***
Abs. deviation	0.397***	0.120***	0.083***	0.044***	0.622***	0.236***	1.010***	0.519***
<i>Amount issued</i>								
	Small	Large	Small	Large	Small	Large	Small	Large
Deviation	-0.330***	-0.163***	-0.058***	-0.018***	-0.504***	-0.181***	-0.147***	0.207***
Abs. deviation	0.439***	0.246***	0.087***	0.036***	0.655***	0.388***	1.030***	0.761***
<i>Market volatility</i>								
	Low	High	Low	High	Low	High	Low	High
Deviation	-0.256***	-0.231***	-0.032***	-0.047***	-0.292***	-0.427***	0.018**	0.049***
Abs. deviation	0.348***	0.334***	0.053***	0.076***	0.487***	0.578***	0.854***	0.964***

This table reports the average signed and absolute deviation between the liquidity measure reported in the corresponding column and the round-trip cost for the subsegments of low versus high average daily trading volume, collateralized mortgage obligations (CMO) versus asset-backed securities (ABS), small versus large bonds as defined by the amount issued, and low versus high market volatility as defined by the VIX index. We use weekly cross-sectional medians as the cutoff values for the subsegments based on average trading volume and the amount issued. For the market volatility analysis, we split our total sample into two periods as defined by the median value of the VIX index. \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% level, respectively. The sample is based on data on structured fixed-income products from the Trade Reporting and Compliance Engine (TRACE) provided by the Financial Industry Regulatory Authority (FINRA) for the period from May 13, 2011 to June 17, 2013.

are significantly less precise when estimated in low trading activity subsegments.

Overall, we conclude that detailed transaction data, including price, volume and trade-direction indicators, are particularly important in illiquid markets represented by low trading activity in individual securities and low general market activity, as this information, in general, allows for a more precise assessment of transaction costs. This is an important result for all market participants, as it provides valuable insights concerning the information content of reported transaction data.

## 5. Conclusion

The U.S. market for structured financial products played an important role during the global financial crisis. The opacity of its OTC trading architecture has been widely criticized, especially as this market represents the second-largest fixed-income market in the United States, after the Treasury bond market. To address this concern, FINRA introduced a transparency project to close this information gap. Since May 16, 2011, virtually all trades in the

structured product market have had to be reported to the TRACE database, which we use in this study, including reported transactions up to June 17, 2013. However, this information has not yet been finally released to the general market.

We analyze the liquidity effects in the structured product market and in the three main market segments (ABS, MBS, and CMO), which cover rather different products, and compare these results to the liquidity in other fixed-income markets. We employ a wide range of liquidity proxies proposed in the academic literature, which have not been used previously, mainly due to the nonavailability of transaction data. Our main contribution is the analysis of the relation between the accuracy in measuring liquidity and the level of detail of the employed trading data. In particular, we explore whether liquidity measures based on less detailed information may still be reasonable proxies for liquidity. This analysis fosters our understanding of the information content of disseminated transaction data and is an important issue in improving market transparency.

In our empirical analysis, we find a high trading volume in the fixed-income structured product market, with a daily average of around \$32.7 billion and an average transaction cost across the three market segments of 73 bp for a round-trip trade. The liquidity of the ABS and MBS markets is comparable to that of the U.S. corporate bond market, whereas the CMO market is considerably less liquid. In all three segments, we find more dispersed trading activity than in other fixed-income markets, i.e., fewer trades per security but with higher volumes.

Exploring the relation between the various liquidity proxies and the depth of information, we find that product characteristics or variables based on aggregated trading activity, by themselves, are not sufficient proxies for market liquidity. The dissemination of the price and volume of each individual trade is important for the quantification of liquidity effects, particularly for explaining yield spreads. However, we also provide evidence that liquidity measures that use additional dealer-specific information (i.e., trader identity and sell/buy-side categorization) can be efficiently proxied for using measures that are based on less information. In particular, the imputed round-trip cost can account for most of the variation observed in our benchmark measure. In addition, we analyze whether measures based on less information are less reliable in particular market environments. We find that more detailed trading data permit a more precise assessment of liquidity when the trading activity in individual securities or overall market activity is low. These results are important for all market participants in the context of OTC markets, as they lead to a better understanding of the information contained in the disclosure of trading data.

## Appendix A. Data Cleaning and Liquidity Measures

This Appendix explains the data cleaning and filtering procedures employed and contains the exact definitions of the liquidity measures that we explore in our empirical analysis.

### A.1 Data Cleaning and Filtering

Our filtering procedures are similar to, but more detailed than, those that are normally applied for the U.S. corporate bond TRACE database (see, e.g., Dick-Nielsen, 2009). The filtering procedure starts with accounting for (1) same-day trade corrections and cancellations and (2) trade reversals that refer to corrections and cancellations conducted, not on the trading day, but afterward.

We then correct *give-up* and *locked-in* trade reports, which are of particular relevance when computing the round-trip cost. In a *give-up* trade, one party reports on behalf of another party, who has reporting responsibility. In a *locked-in* trade, one party is responsible for reporting for both sides of a trade in a single report, thus satisfying the reporting requirements on both sides. This *locked-in* trade can either refer to a transaction between the reporting party and its correspondent (single *locked-in*) or to a transaction occurring between two correspondents (two-sided *locked-in*).

Finally, since the transaction data most likely contain erroneously reported trades, we apply two types of filters, a *price median filter* and a *price reversal filter*, similar to the filters suggested for the U.S. corporate bond market data (see, e.g., Edwards, Harris, and Piwowar, 2007). While the median filter identifies potential outliers in the reported prices within a certain time period, the reversal filter identifies unusual price movements. The median filter eliminates any transaction in which the price deviates by more than 10% from the daily median or from a nine-trading-day median centered on the trading day. The reversal filter eliminates any transaction with an absolute price change deviating from the lead, lag, and average lead/lag price change by at least 10%. These filters are designed to remove most, if not all, errors arising from data entry.

### A.2 Liquidity Measures

We compute the liquidity measures for each financial instrument individually, using the following notation: We represent the trade price and volume of a transaction observed at time  $t_{i,j}$  on trading day  $i$  for trade  $j$  by  $p(t_{i,j})$  and  $v(t_{i,j})$ . We use  $n(t_i)$  to refer to the observed number of trades of a financial instrument on trading day  $t_i$ .

#### A.2.1 Round-trip cost

This uses the most detailed information. Each transaction needs to be assigned to a particular dealer  $d$ . The round-trip cost is then defined as the price difference, for the same dealer, between buying (selling) a certain amount of a security and selling (buying) the same amount of this security. More precisely, for a given trading day  $t_i$ , we define a round-trip trade  $q$  of dealer  $d$  as a sequence of consecutive buy transactions with trade prices  $p_{d,q}^b(t_{i,j})$ , followed by a sequence of sell transactions with prices  $p_{d,q}^s(t_{i,j})$  (or vice versa) conducted by the same dealer  $d$  such that  $\sum_j v_{d,q}^b(t_{i,j}) = \sum_j v_{d,q}^s(t_{i,j})$ , where  $v_{d,q}^b(t_{i,j})$  and  $v_{d,q}^s(t_{i,j})$  denote the trading volumes belonging to the round-trip trade  $q$  of dealer  $d$ . Thus, the round-trip trade may either consist of a single trade on each side or a sequence of trades on trading day  $t_i$ , where  $pv_{d,q}^s(t_i) = \sum_j p_{d,q}^s(t_{i,j})v_{d,q}^s(t_{i,j})$  and  $pv_{d,q}^b(t_i) = \sum_j p_{d,q}^b(t_{i,j})v_{d,q}^b(t_{i,j})$  denote the dollar amount sold and bought, respectively, in round-trip  $q$  of dealer  $d$  on trading day  $t_i$ . The round-trip cost is then given by

$$rtc(t_i) = \frac{1}{m(t_i)} \sum_{d,q} \frac{pv_{d,q}^s(t_i) - pv_{d,q}^b(t_i)}{1/2 \cdot (pv_{d,q}^s(t_i) + pv_{d,q}^b(t_i))}, \quad (5)$$

where  $m(t_i)$  denotes the number of round-trip trades on trading day  $t_i$  for a particular financial instrument.

### A.2.2 Effective bid-ask spread

This is the difference between the daily average sell- and buy-prices relative to the average mid-price. Thus, transactions need to be flagged as *buy* or *sell* trades. It is formally defined as

$$ebas(t_i) = \frac{\bar{p}^s(t_i) - \bar{p}^b(t_i)}{1/2 \cdot (\bar{p}^s(t_i) + \bar{p}^b(t_i))}, \tag{6}$$

where  $\bar{p}^s(t_i) = 1/n^s(t_i) \sum_{j=1}^{n^s(t_i)} p^s(t_{i,j})$  and  $\bar{p}^b(t_i) = 1/n^b(t_i) \sum_{j=1}^{n^b(t_i)} p^b(t_{i,j})$  refer to the average sell and buy prices on trading day  $t_i$ .

### A.2.3 Amihud measure

This quantifies the average price impact of trades on a particular trading day  $t_i$ . It is defined as the ratio of the absolute price change given as the return  $r(t_{i,j}) = \frac{p(t_{i,j})}{p(t_{i,j-1})} - 1$  to the trading volume  $v(t_{i,j})$ , measured in U.S. dollars:

$$ami(t_i) = \frac{1}{n(t_i)} \sum_{j=1}^{n(t_i)} \frac{|r(t_{i,j})|}{v(t_{i,j})}. \tag{7}$$

### A.2.4 Imputed round-trip cost

This is an alternative way of measuring bid-ask spreads. The idea here is to identify round-trip trades that are assumed to consist of two or three trades on a given day, with exactly the same traded volume. This likely represents a prematched arrangement in which either one or two dealers match a buy and a sell order from a customer. Formally, for a given trading day  $t_i$ , we define an imputed round-trip trade  $w$  as a sequence of two or three transactions with trade prices  $p_w(t_{i,j})$  and identical volumes  $v_w(t_{i,j})$ . The imputed round-trip cost is then defined as

$$irc(t_i) = \frac{1}{b(t_i)} \sum_w \left( 1 - \frac{\min_j p_w(t_{i,j})}{\max_j p_w(t_{i,j})} \right), \tag{8}$$

where  $b(t_i)$  refers to the total number of imputed round-trip trades on trading day  $t_i$  for a financial instrument.

### A.2.5 Price dispersion measure

This is defined as the root mean squared difference between the traded prices and the respective market valuation weighted by volume. Thus, for each day  $t_i$  it is defined as

$$pdisp(t_i) = \sqrt{\frac{1}{n(t_i)} \sum_{j=1}^{n(t_i)} (p(t_{i,j}) - u(t_i))^2 \cdot v(t_{i,j})}, \tag{9}$$

where  $u(t_i)$  refers to the market valuation for trading day  $t_i$ , which we assume to be the average traded price on that day. We require at least four observations on a given day to calculate the price dispersion measure (i.e.,  $n(t_i) \geq 4$ ).

## A.2.6 Roll measure

This is a proxy for the round-trip transaction costs and is defined as

$$\text{roll}(t_i) = 2 \cdot \sqrt{-\text{Cov}(\Delta p(t_k), \Delta p(t_{k-1}))}, \quad (10)$$

where  $\Delta p(t_k)$  is defined as the change in the consecutive prices  $p(t_{k,j})$  and  $p(t_{k,j-1})$  on trading day  $t_k$  with  $t_k \leq t_i$ . We compute the Roll measure based on the available price changes within a time frame of 60 days (i.e.,  $\forall t_k$  with  $i - k \leq 60$ ). Since we interpret the Roll measure as a transaction-cost metric, we bound the measure at zero whenever the covariance turns out to be positive.

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