

Herrmann, Markus; Hibbeln, Martin

Article — Published Version

Trading and liquidity in the catastrophe bond market

Journal of Risk and Insurance

Provided in Cooperation with:

John Wiley & Sons

Suggested Citation: Herrmann, Markus; Hibbeln, Martin (2022) : Trading and liquidity in the catastrophe bond market, Journal of Risk and Insurance, ISSN 1539-6975, Wiley, Hoboken, NJ, Vol. 90, Iss. 2, pp. 283-328, <https://doi.org/10.1111/jori.12407>

This Version is available at:

<https://hdl.handle.net/10419/287980>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



<http://creativecommons.org/licenses/by/4.0/>

Trading and liquidity in the catastrophe bond market

Markus Herrmann  | Martin Hibbeln 

Mercator School of Management,
University of Duisburg-Essen, Duisburg,
Germany

Correspondence

Martin Hibbeln, Mercator School of
Management, University of Duisburg-
Essen, Lotharstr. 65, 47057 Duisburg,
Germany.

Email: martin.hibbeln@uni-due.de

Funding information

German Insurance Science Association

Abstract

We provide first insights into secondary market trading, liquidity determinants, and the liquidity premium of catastrophe bonds. Based on transaction data from TRACE (Trade Reporting and Compliance Engine), we find that cat bonds are traded less frequently during the hurricane season and more often close to maturity. Trading activity indicates that the market is dominated by brokers without a proprietary inventory. Liquidity is high in periods of high trading activity in the overall market and for bonds with low default risk or close to maturity, which results from lower order processing costs. Finally, using realized bid-ask spreads as a liquidity measure, we find that on average, 21% of the observable yield spread on the cat bond market is attributable to the liquidity premium, with a magnitude of up to 141 bps for high-risk bonds.

KEYWORDS

alternative risk transfer, catastrophe bonds, liquidity, yield spreads

JEL CLASSIFICATION

G12, G22, G32

This is an open access article under the terms of the Creative Commons Attribution License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited.

© 2022 The Authors. *Journal of Risk and Insurance* published by Wiley Periodicals LLC on behalf of American Risk and Insurance Association.

1 | INTRODUCTION

The link between yield spreads and default risk of catastrophe bonds (“cat bonds”) has been extensively analyzed in the theoretical and empirical literature (e.g., in actuarial models such as Jarrow, 2010, and Lee & Yu, 2002, and in empirical models such as Braun, 2016, Galeotti et al., 2013, and Gürtler et al., 2016). For corporate bonds it is known that liquidity is another important driver of yield spreads, second only to default risk; though, the magnitude of the spread components is controversial (Bai et al., 2020; Feldhütter & Schaefer, 2018; Huang & Huang, 2012; Longstaff et al., 2005). Chordia et al. (2004) defines liquidity as the ability to buy and sell large quantities of an asset quickly and at a low cost. Investors are willing to pay a premium on liquid assets compared to less liquid assets of similar default risk. Although cat bonds are much less liquid than corporate bonds (see e.g., Lane & Roger, 2016), which indicates a potentially substantial liquidity premium in the cat bond market, there is only very limited knowledge of cat bond trading and liquidity.

Braun (2016) and Gürtler et al. (2016) have implemented the issue volume and maturity as liquidity measures but results are inconclusive. Zhao and Yu (2019) attempt to proxy cat bond liquidity through various cat bond specific and pricing related variables; however, due to the lack of observable trade characteristics, they are unable to compute established liquidity measures from the corporate bond literature which rely on trading volume and/or trading frequency.¹ Instead, Braun et al. (2019) state that the separation of the liquidity premium from other yield spread components is currently not possible for Insurance Linked Securities (ILS) due to limitations in ILS data. On the contrary, we are now able to separate the liquidity premium from other yield spread components through the increasing availability of ILS data in the Trade Reporting and Compliance Engine (TRACE) where we observe bid-ask spreads based on individual secondary market trades on the over-the-counter (OTC) market; such bid-ask spreads are frequently used as liquidity measures in the empirical corporate bond pricing literature (e.g., Hong & Warga, 2000; Schestag et al., 2016). Hence, this paper is able to shed light on actual trading, liquidity determinants, and the liquidity premium in the secondary cat bond market.

For corporate bonds, estimating the liquidity premium is notoriously difficult, because default risk and liquidity are endogenously linked. Chen et al. (2018) theorize a spiral of deteriorating default risk and liquidity: Default risk is negatively correlated with liquidity when firms have difficulty to roll over debt. A low liquidity makes rolling over debt more costly which makes a default more likely. At the same time, an increase in default risk can increase inventory costs for dealers which in turn reduces liquidity. Ericsson and Renault (2006) show that equity holders have an incentive to default sooner when debtholders have fewer opportunities to sell their bonds in an illiquid market. Previous empirical research has dealt with the problem of endogeneity by identifying pairs of assets that have the same default risk but different liquidity. The difference in yield spreads between these assets is generally interpreted as the non-default component. Examples of these pairs include CDS and corporate bonds (Longstaff et al., 2005), BUNDS and Pfandbriefe (Kempf et al., 2012) or BUNDS and KfW-Bonds (Schwarz, 2019). Alternatives include the creation of baskets of different rating categories (Dick-Nielsen et al., 2012) or simultaneous equations models (Chen et al., 2007).

¹Examples are the Amihud measure (Amihud, 2002), Roll’s daily measure (Roll, 1984), and the Zero Returns measure (Lesmond et al., 1999).

However, most of these approaches are only as good as their underlying counterfactual which quantifies the default risk component. On the contrary, cat bonds default events (e.g., hurricanes or earthquakes) are strictly exogenous. A natural disaster is not more likely to occur nor is a natural disaster more severe if a cat bond is less liquid. Therefore, the spiral of deteriorating default risk and liquidity is broken. This allows for an accurate identification of the liquidity and default components in cat bond spreads.

The liquidity of cat bonds is important to issuers and investors alike. Issuers need to be informed about the potential illiquidity premium they pay to investors when they issue a new cat bond while investors, such as specialized cat bond funds, draw from the cat bond market as a source of liquidity when they readjust their investments.² These funds also invest in purely illiquid alternative tools of catastrophe risk transfer, such as sidecars and collateralized reinsurance, and they often sell cat bonds when faced with trapped capital after catastrophe events or redemptions (Aon Securities, 2019; Swiss Re, 2019). This highlights the importance of the cat bond market's liquidity in downturn scenarios stemming from catastrophe events but also crash scenarios on the general financial markets. Post Covid-19, Aon expects even more emphasis on liquidity leading to more growth in liquid investment strategies (Aon Securities, 2020).

We acquire the TRACE data set on cat bond trading from Refinitiv Eikon that contains dates, clean prices and a dealer buy/sell indicator for all trades from January 2015 to March 2019. During this period, we observe the bid-ask spread of 3341 trade pairs from 229 cat bonds. This information is supplemented by specific bond information from Refinitiv Eikon, Lane Financials, and artemis.bm. We employ pooled ordinary least squares and fixed effects regression models; in addition to the exogeneity of default events, we support our results with simultaneous equations models to account for possible dealer yield spread interactions.³ By using a data set from TRACE we are able to contribute to the literature in four ways: First, we shed light on the actual trading on the secondary cat bond market by identifying trade patterns and dealer behavior. Second, we investigate trading of cat bonds around adverse events and compare it to corporate bonds of insurers issuing cat bonds. Third, using bid-ask spreads as a liquidity measure, we identify the bond characteristics that influence the liquidity of cat bonds. Fourth, we quantify the liquidity premium on bond level and on the aggregate market through observable bid-ask spreads.

First, concerning trading on the secondary market, we find that cat bonds are more strongly traded outside of the US hurricane season. Trading is especially low August through September when the hurricane season reaches its peak.⁴ Additionally, trading increases as a bond nears its maturity. It appears that the secondary market of cat bond is dominated by dealers who do not hold an inventory as indicated by the large share of round-trip trades that are concluded within 60 min. Second, we analyze the observable trades of selected cat bonds with respect to adverse events (hurricanes Harvey, Irma, and Maria as well as hurricane Michael). We find that only very few trades took place during these adverse catastrophe events, whereas the trading of corporate bonds issued by the same insurance companies is elevated during these events. This

²In 2019, specialized cat funds held the lion's share of 59% of the cat bond market (Aon Securities, 2019).

³We consider this model because a dealer could nevertheless set his bid-ask spread in relation to the observed yield spread rather than the other way around. For example, a dealer could observe increased yield spreads due to a change in cat bond investor sentiment and adjust his bid-ask spread without a change in exogenous default risk.

⁴For a detailed discussion on seasonal effects in the yield spreads of cat bonds, please refer to Herrmann and Hibbeln (2021).

underlines that the seasonality-implied increase of default risk leads to a substantial reduction of cat bond trading even in periods with much new information arriving in the market, which is contrary to the trading behavior of corporate bonds where the information effect dominates. Third, we identify the following major liquidity determinants: A bond's liquidity is low when its default risk is high, it is more expensive to execute trades of large volume, and liquidity is increasing when a bond approaches its maturity. Fourth, we find that a lower liquidity causes a substantially increasing yield spread: A 1 basis point (bp) increase in bid-ask spreads is associated with 10 bps increase in yield spread. On average, the liquidity component of a cat bond is 98 bps. Overall, 21% of the yield spread of cat bonds can be attributed to the liquidity premium. This liquidity premium is even larger for bonds with a high default risk, which is driven by a time-series and a cross-sectional determinant: Liquidity is low in time periods of high default risk, and liquidity is more strongly priced for risky cat bonds. We measure the latter effect by forming subsamples of different rating categories. In addition, we find evidence for a positive relationship between market liquidity—measured by the mean bid-ask spread of the current quarter—and yield spreads.

Many of our findings are generally in line with the previous empirical literature on corporate bonds. Concerning the determinants of liquidity, the finding that liquidity is higher when a cat bond is closer to maturity or when there is much trading in the market is in line with Amihud and Mendelson (1986) and Goyenko et al. (2011). Concerning the overall liquidity of the cat bond market, our finding that yield spreads are lower when the general liquidity of the market is high is supported by Lin et al. (2011).⁵ While the corporate bond literature, thus, generally supports the effects we have identified for cat bonds, our results also contribute to the corporate bond literature: Exploiting the exogenous default risk of cat bonds, we identify and quantify many liquidity related effects.⁶ This way we can verify previous findings for corporate bonds where default risk and liquidity are endogenously linked. Thus, while previous attempts have mainly dealt with these endogeneity concerns by means of the econometric design, we are able to estimate the liquidity premium based on bonds with exogenous default risk implied by strictly exogenous catastrophe events.⁷ By doing so, we also contribute to the ongoing debate on the credit spread puzzle (see, e.g., Huang & Huang, 2012), which suggest that structural models underpredict credit spreads for high-yield but not investment-grade bonds (Feldhütter & Schaefer, 2018) and vice versa (Bai et al., 2020). In this context, researchers have found very

⁵Aligned with the individual liquidity of a bond, the risk that the level of liquidity worsens (“liquidity risk”) is priced in the corporate bond market (Acharya & Pedersen, 2005; Lin et al., 2011). Due to limitations in the quantity of data, we are unable to quantify liquidity risk in the cat bond market.

⁶In the empirical finance literature, natural disasters are frequently used as exogenous treatments. For example, Cortés and Strahan (2017) look into credit supply in the aftermath of a multitude of different natural disasters. Schüwer et al. (2019) use hurricane Katrina to investigate how affected banks react to a local shock depending on their affiliation with a holding company. Koetter et al. (2020) find that banks in flood areas increase lending after floods to support recovery; this effect is especially pronounced when the bank is affiliated with another bank in an area that was not affected by the flood. Berg and Schrader (2012) find that demand for credit increases after volcanic eruptions in Ecuador but the access to credit is restricted; a pre-existing borrower-bank relationship reduces this mismatch.

⁷Until the default of Lehman Brothers in 2008, it was common in the structure of a cat bond to include a total return swap (TRS) which in turn was exposed to the default risk of the associated counterparty. According to the artemis.bm cat bond default database, four cat bonds were pushed into default in 2008 when Lehman Brothers as the TRS counterparty defaulted. However, the typical postcrisis structure does not include a TRS anymore. Because our data set begins in 2015, the TRS structure is not present in our sample and, thus, exposed to this type of counterparty risk. For a deep discussion on cat bond structure and lessons learned from the Financial Crisis, please refer to Braun (2016) and Towers Watson (2010).

different results for the fraction of the default risk versus the illiquidity component. For example, Longstaff et al. (2005) find that, depending on the rating, 50%–80% of the credit spread is explained by default risk, whereas the nondefault component is nearly constant across rating categories with values of 50–72 bps. While the nondefault component is mainly liquidity related, this component can, though, include various other factors like call and conversion features or an asymmetric tax treatment of corporate and Treasury bonds (Huang & Huang, 2012). On the contrary, using more direct liquidity measures, Bao et al. (2011) find that liquidity is by far the most important yield spread component for corporate bonds, and Huang and Huang (2012) conclude that the fraction due to credit risk is typically only around 20%.⁸ We find that 21% of the yield spread of cat bonds can be attributed to the liquidity premium, which is in line with Dick-Nielsen et al. (2012), who determine that the fraction of the liquidity component is around 23% for speculative grade bonds.⁹

The remainder of this paper is structured as follows: Section 2 provides further details on the (re-)insurance and the cat bond market and derives hypotheses. Section 3 illustrates the TRACE data set and the econometric model. Section 4 contains empirical results and Section 5 concludes.

2 | INSTITUTIONAL BACKGROUND AND HYPOTHESES

2.1 | Institutional background

Usually, insurers turn to reinsurers for large loss event coverage. Reinsurance companies are able to cover large risks because they offer a broad within industry diversification, which is unavailable to individual insurers. However, reinsurers' ability for within industry diversification has limits, especially for perils with extreme loss potential such as earthquakes, wildfires or hurricanes. The latter two are even expected to worsen in the wake of climate change. With increasing frequency, the (re-)insurance industry draws from the financial markets for additional diversification, when within industry diversification is exhausted or becomes too expensive.¹⁰ This growing demand for additional diversification is reflected in the size and growth of the cat bond market. According to artemis.bm, it has reached a record size of US\$ 51 billion in 2021 up from US\$ 27 billion in 2016.

If a (re-)insurance company ("sponsor") wants to get extreme-event coverage in form of a cat bond, it sets up the following structure:¹¹ A special purpose vehicle (SPV) engages in a reinsurance contract with the sponsor, selling reinsurance coverage. To cover potential losses, the SPV issues bonds that contain a default trigger that mirrors the reinsurance contract's payment clauses. This reinsurance contract can cover a certain layer of the sponsor's actual losses for a given time period for a specified peril type (or for multiple perils). Alternatively, the SPV and the sponsoring (re-)insurer can agree upon specified catastrophe parameters such as

⁸Though, the fraction is substantially increasing for low-rated bonds.

⁹While we do not decompose the non-liquidity component, the large impact of the modeled expected loss on yield spreads identified in previous studies implies that it is mainly related to default risk (see Braun, 2016; Gürtler et al., 2016; Herrmann & Hibbeln, 2021). Other factors include, for example, the regulatory treatment of cat bonds or, given the complexity of modeling the expected loss, a compensation for model risk.

¹⁰In addition, the severity of catastrophe events like hurricanes is increasing due to higher sea surface temperatures, leading to higher (insured) damages and inflated insured losses (Döhrmann et al., 2017).

¹¹For an illustration and discussion on cat bond design, please refer to Braun (2016).

wind speed or an earthquake severity on the Richter scale that trigger the default of the cat bond. The underwriting risk in the reinsurance contract is fully collateralized through the issued bonds. The collateral is kept in a trust account, usually invested in short term treasuries or assets of similar quality and liquidity.¹² Thus, credit risk from the sponsor is largely excluded in a cat bond transaction.¹³ Cat bonds are floating-rate notes that pay the investors a fixed coupon over the flexible interest from the trust account. This fixed coupon is fully covered by premium payments, which the sponsor pays to the SPV in exchange for the catastrophe coverage. These fixed payments reimburse the investors for the cat bond's inherent underwriting risk.

For example, if a (re-)insurance company demands coverage against extreme losses from hurricanes in Florida in the volume of US\$ 150 million, it can set up the described structure and have its SPV issue cat bonds with this volume. If the specified hurricane losses in Florida do not manifest for the (re-)insurance company during the cat bond's duration, the collateral is liquidated and returned to the investors. If the (re-)insurer incurs losses from a hurricane in Florida that exceed specified attachment points, the collateral is not returned to the investors but instead used to cover the (re-)insurer's reimbursements; the cat bond defaults. A default can be complete or partial depending on the specified default trigger and the occurred loss event. The cat bond structure breaks down when the sponsoring (re-)insurance company becomes insolvent or goes out of business. In this case the principal is returned to the investors; the bond is repaid at par value. The repayment at par value is possible because the principal is kept in a trust account that is legally and physically separate from the sponsor. Hence, a cat bond does not bear any credit risk from the sponsor. Instead, all default risk of a cat bond can be attributed to the inherent underwriting risk.

Not only (re-)insurance companies but also government institutions can sponsor cat bonds. In 2019, the World Bank has issued cat bonds with nominal value of US\$ 1685 million to cover emergency payments and rescue efforts of emerging economies such as Mexico, Chile, Columbia, and Peru for earthquakes but also for the Philippines, which are badly affected by reoccurring typhoons. Overall, natural catastrophe damages are expected to rise substantially in the wake of climate change. For some perils, such as hurricanes, insurability will depend on the insurance industry's ability to diversify. Hence, the efficiency of the cat bond market that covers extreme events could prove vital in the insurability of coastal areas. Additional knowledge about the liquidity premium on the cat bond market could, thus, supplement risk management efforts in climate change.

When pricing this type of risk transfer, the empirical cat bond literature has focused on the explanation of yield spreads through default risk and other components such as financial market conditions or cat bond-specific properties such as peril types or trigger types. A bond's liquidity has not been one of these components beyond rudimentary liquidity measures such as issued volume and remaining maturity. Braun (2016) finds a negative relationship of issued volume and yield spread while Gürtler et al. (2016) find the opposite effect, and none of these studies finds a significant effect for the remaining maturity. Overall, these results are inconclusive. Similar to corporate bonds, the individual cat bond's default risk is the primary driver of yield spreads (e.g., Braun, 2016; Gürtler et al., 2016; Lane & Mahul, 2008; Major &

¹²The collateral is usually highly liquid and not traded during the duration of the cat bond. Hence, we abstract from modeling the liquidity of the collateral.

¹³Nevertheless, Götze and Gürtler (2019) find that some sponsor characteristics can affect yield spreads in hard and neutral market phases.

Kreps, 2002). For corporate bonds, default risk is typically determined by credit rating agencies. For cat bonds, a credit rating from one of the established rating agencies only plays a subordinated role in bond pricing.¹⁴ Instead, specialized risk modeling firms determine a cat bond's inherent underwriting risk through sophisticated earthquake and weather models (e.g., for hurricanes, wildfires, and hailstorms). Their efforts culminate in a risk report that contains a detailed probability distribution of loss potential.¹⁵ The expected loss (EL) as the first moment of this distribution is typically used to account for default risk in empirical cat bond research. Abstracting from model risk, the more granular nature of the EL allows for a more detailed quantification of default risk than the ordinal scale of rating categories. Empirical evidence indicates that a linear relationship between yield spread and EL is most appropriate (Galeotti et al., 2013).

While the default risk in cat bonds is well-understood in the empirical cat bond literature, it is important to first discuss cat bond trading and its participants before further investigating the cat bond market's liquidity. Cat bonds are exclusively held and traded by institutional investors. This investor audience includes reinsurers, hedge funds, mutual funds, specialized cat funds, and other institutional investors. In 2019, specialized cat funds held the lion's share of 59% of the cat bond market (Aon Securities, 2019); hence, we presume this investor type dominates cat bond trading. These funds do not only invest in cat bonds but also in industry loss warranties, collateralized reinsurance, and sidecars. Braun et al. (2019) introduce a factor model to explain the returns of these specialized cat bond funds shedding light on their investment decisions. For several reasons, the liquidity of the cat bond market is very important to these investors. Instead of following a simple buy-and-hold strategy, they heavily rely on the possibility to trade cat bonds on the secondary market. First, investors regularly readjust their portfolios: They often sell cat bonds on the secondary market to release capital and to invest into new issuances on the primary market (Aon Securities, 2017). Second, investors utilize the liquidity of the secondary market during adverse events. The need for liquidity in the secondary market for cat bonds during this time can even stem from other ILS classes: Capital invested in collateralized reinsurance and sidecars can become trapped in these vehicles while losses from an adverse event are assessed. This process can take years to complete. In consequence, this capital is unavailable for reinvestment and investor redemption. For example, Swiss Re (2020) reports that liquidity was at a premium in the cat bond market of 2019 as capital was tied in collateralized reinsurance transactions. Instead, investors sell cat bonds to release capital when faced with redemptions (Aon Securities, 2019). Contrary to collateralized reinsurance, a distressed cat bond can often still be bought and sold on the secondary market, though at a discount; hence, its capital is not completely trapped when its maturity was extended.¹⁶ Similar effects can be observed during downward scenarios on the financial markets: During the crash associated with the Covid-19 pandemic in March 2020, several key investors moved away from sidecars towards more liquid instruments, such as cat bonds (Aon Securities, 2020). In line with this, Swiss Re (2021) reports a strong uptick in cat bond trading in March 2020. Post Covid-19, Aon expects more emphasis on liquidity leading to more growth in liquid investment strategies

¹⁴Many cat bond issues do not receive a rating. In our data set, only about 30% of all cat bond issues have received a rating from Standard & Poors or other rating agencies, with a decreasing share over time.

¹⁵Notable risk modeling firms are AIR, RMS, and CoreLogic. In our sample, AIR has over 80% market share. For a discussion on risk modeling in ILS please refer to Poliquin and Lalonde (2012).

¹⁶Similar to collateralized reinsurance, the maturity of a cat bond can be extended for multiple years for loss assessment.

(Aon 2020). Although the liquidity of the cat bond market is very important to specialized cat funds and other ILS investors, the actual secondary market trading is almost completely unexplored. We fill this gap with insights from the actual trades reported in TRACE.

2.2 | Liquidity on the OTC market

Liquidity forms through trading among market participants. However, little is known about the trading of cat bonds on the OTC market.¹⁷ As opposed to exchange traded stocks, corporate bonds are usually traded directly between investors. Traders in these markets search for counterparties and then bargain for a price reflecting their need for liquidity and outside alternatives (Duffie et al., 2007). Often traders do not search for possible counterparties individually but employ the services of a broker or dealer to execute trades. A dealer often serves as a market maker with a proprietary inventory of securities. Market makers immediately sell or buy securities from traders before searching for a counterparty to offset the trade (Goldstein & Hotchkiss, 2020). They rebalance their inventory sometime after the trade by offloading to or buying from other dealers or traders. Market makers can significantly improve a market's liquidity and efficiency (Eldor et al., 2006). For their services, dealers are compensated by the bid-ask spread of the trade. Usually, the costs that a dealer incurs has three elements: (a) adverse selection costs, (b) inventory cost, and (c) order processing cost (Huang & Stoll, 1997). Adverse selection costs occur when traders have an informational advantage over dealers and trade an asset to the dealers' disadvantage. Inventory costs stem from capital requirements for dealer inventory. Additionally, a dealer can incur losses through adverse price movements (Schultz, 2017). Searching for counterparties and executing trades causes order processing costs.

Dealers set bid-ask spreads according to these cost elements: Bid-ask spreads are usually high for risky bonds where informational asymmetry is large driving adverse selection costs. Bid-ask spreads are also high when trading is infrequent, driving up inventory costs. Finally, bid-ask spreads are high when matching buyers and sellers of an asset is difficult, making the execution of a trade expensive. However, not all three of these cost elements must be present in the bid-ask spread: Goldstein and Hotchkiss (2020) indicate that dealers forgo an inventory altogether when trading is so infrequent that inventory costs are prohibitive. They find that over half of all dealer trades are offset within the same day. In this case, an inventory was not involved; instead, dealers without inventories for infrequently traded bonds serve as brokers who only match sellers and buyers without taking a bond onto their own balance sheet. Goldstein and Hotchkiss (2020) find that the share of within-day trade pairs increases when a bond is generally more rarely traded. Dealers who act as brokers are not exposed to adverse selection costs and inventory costs. Although the lack of these cost elements is often associated with lower bid-ask spreads for brokered trades, this advantage comes at a price for traders: The bond price can change while the trader waits for the execution of the trade, or the trade can even fail if no counterparty can be found. For cat bonds, Risk Management Solutions (2012) reports that cat bond trades are usually made on a matched basis with no inventory involved. Towers Watson (2017) states that dealers sometimes hold inventory.¹⁸ We expect dealers to

¹⁷For corporate bonds, Duffie et al. (2005) offers a variety of theoretical implications of OTC trading and the bid-ask spread.

¹⁸No market reports have provided any numbers of possible inventory involvement.

behave in such a way as Goldstein and Hotchkiss (2020) describe when trading is scarce: Dealers rarely hold an inventory of cat bonds because they are so infrequently traded. Instead, they mostly act as brokers who only match buy and sell orders. This has the disadvantage that cat bond traders are not guaranteed an immediate execution when they choose to submit an order but can experience long holding periods before a trade can be executed.¹⁹

2.3 | Hypotheses

The bid-ask spread of a trade compensates the dealer for adverse selection costs, inventory costs, and order processing costs (Huang & Stoll, 1997). However, as the trading of cat bonds is scarce, it is likely that cat bonds dealers mostly act as brokers. As such brokers are not exposed to adverse selection costs and inventory costs (Goldstein & Hotchkiss, 2020), we expect that order processing cost, due to searching for counterparties and executing trades, are the main driver of bid-ask spreads of cat bonds.²⁰ It is plausible that searching for counterparties and executing trades is easier for bonds with a larger investor audience, which rather applies to bonds with low default risk. For example, many institutions have investment restrictions that only allow investing into bonds up to some rating-based threshold (e.g., only investment grade rating, which would not be fulfilled for most cat bonds); similarly, regulatory capital requirements are higher for more risky investments, which reduces the attractiveness of investing into more risky bonds (e.g., if a bank used the standardized approach, the risk weight for corporate bonds is 100% for BB rating vs. 150% for B rating; see CRE20 in BCBS, 2019).²¹ This implies that order processing costs are lower if default risk is low, which implies higher liquidity. Similarly, Edwards et al. (2007) finds for corporate bonds that transaction costs are lower for highly rated bonds. Hence, we hypothesize that liquidity is lower for cat bonds with high default risk.

H1.1: *Liquidity determinants—default risk: Liquidity is low if default risk is high.*

Similarly, when an investor submits a large order, it is more difficult for the commissioned broker to find a counterparty. The broker may even have to involve multiple investors if he does not find a single counterparty willing to fill the order. This economic reasoning is in line with Huang and Stoll (1997) who find that search costs are disproportionately larger for large trades. Thus, we hypothesize that bid-ask spreads are larger for individual trades with a large trading volume.

¹⁹Please refer to Section 3.2 for information on the trading on the cat bond market. We find that at least 86% of all trades are offset within the same day and do not involve an inventory.

²⁰Please note that while a potential adverse selection between dealer and its counterparty are not relevant for dealers acting as brokers, there might still be adverse selection between a potential buyer and seller, which could increase the search cost of the dealer, ultimately leading to higher bid-ask spreads.

²¹Even if such capital requirements do not apply to all financial institutions (e.g., hedge funds or mutual funds), the economic argument still holds: First, many investment funds formulate some investment restrictions in the investment prospectus (either prohibiting investments into high-risk securities or restricting the investment share of such instruments). Second, assume that there is a regulated industry A (only allowed to invest into a low-risk security 1) and an unregulated industry B (allowed to invest into both low-risk and high-risk securities 1 and 2). Consequently, the potential investor audience for high-risk security 2 is only $B/(A + B)$, as opposed to 100% for low-risk security 1.

H1.2: Liquidity determinants—trade size: *Liquidity is low if the volume of an individual trade is high.*

The model of Amihud and Mendelson (1986) implies that bonds with a shorter time to maturity are more liquid, which is due to a clientele effect of different investor types. Their model predicts that assets with higher spreads yield higher expected returns, and investors with a longer holding periods select assets with higher spreads whereas short-term investors invest into more liquid assets with lower spreads. The underlying economic reason of the clientele effect is that long-term investors trade less often per period, so that trading costs, even if these are comparably high for longer maturities, would have a small negative impact on their overall returns. Consequently, long-term investors can profit from higher expected returns (net of trading costs) for bonds even if trading costs are high. Conversely, short-term investors, which trade more often on a per period basis, refrain from investing into assets with high trading costs as net expected returns would be low. Thus, in equilibrium, long-term investors rather invest into bonds with a long time to maturity and high trading costs, whereas short-term investors invest into bonds with short time to maturity and low trading costs.

In line with this model, Edwards et al. (2007) empirically find that corporate bonds with a shorter time to maturity have lower transaction costs, leading to higher liquidity. Similarly, various papers investigate the term structure of the liquidity premium and find increasing liquidity premia for longer maturities (see Goyenko et al., 2011; Gehde-Trapp, 2018; Kempf et al., 2012). Hence, we hypothesize that liquidity is higher if a cat bond nears its maturity.

H1.3: Liquidity determinants—remaining maturity: *Liquidity is low if time to maturity is high.*

The liquidity component in yield spreads on the corporate bond market has been thoroughly investigated in the empirical literature (e.g., Bao et al., 2011; Chen et al., 2007; Longstaff et al., 2005). Considering that trading of cat bonds is rather scarce, it is plausible that the yield spread of cat bonds also contain a significant liquidity component: Cat bonds with low liquidity should exhibit a high yield spread. In line with the empirical evidence for a liquidity premium on the corporate bond market, we formulate the following hypothesis:

H2.1: Liquidity premium—general: *Bonds with low liquidity are associated with high yield spreads.*

Additionally, it is often argued that the liquidity premium is larger for non-investment grade bonds than for investment grade bonds. For example, Chen et al. (2007) find a liquidity effect that is 8 to 10 times larger for non-investment grade bonds than for investment grade bonds. Furthermore, the liquidity premium is more pronounced in downturn scenarios (Acharya et al., 2013), especially in times of a crisis (see Dick-Nielsen et al., 2012, and Friewald et al., 2012 for the financial crisis or Schwarz, 2019 for the sovereign debt crisis). A flight-to-liquidity in downturn scenarios can have opposing effects for investment grade and speculative grade bonds. Prices for investment grade bonds can rise as they are considered safe havens, while prices on speculative grade bonds fall (Acharya et al., 2013). Hence, we hypothesize that bonds with a high default risk have a high liquidity premium.

H2.2: Liquidity premium—default risk: *Bonds with a high default risk have a high liquidity premium.*

The liquidity premium for an individual bond could also be related to the general liquidity of the cat bond market. In a theoretical framework, the Liquidity CAPM relates an asset's liquidity premium and return to the general market's liquidity (Acharya & Pedersen, 2005). Empirical results for the general corporate bond market confirm such an effect (Lin et al., 2011). Hence, we hypothesize that cat bonds exhibit a high yield spread during times of low market liquidity.

H3: *Liquidity premium—market liquidity: During a less liquid bond market, bonds exhibit higher yield spreads.*

3 | DATA AND ECONOMETRIC MODEL

3.1 | Data

In the cat bond literature, this article is the first to use TRACE data on a broad scale. Generally, there are two versions of TRACE data: “Standard TRACE” and “Enhanced TRACE.” Refinitiv Eikon is our vendor for standard TRACE data. We use standard TRACE because enhanced TRACE data on SEC 144a issues are not yet contained in Refinitiv Eikon or WRDS.²² Beyond what is reported in standard TRACE, enhanced TRACE essentially only contains uncapped trading volume (Dick-Nielsen, 2014). We use the following steps to construct the TRACE data set and obtain specific information from Refinitiv Eikon: First, we obtain a list of all cat bonds traded on the secondary market from January 2015 to March 2019 from Lane Financials LLC.²³ Second, we search for these names in Refinitiv Eikon;²⁴ after we have found a cat bond, we can access all of its important information such as specific issue and maturity dates and coupon payment dates as well as its CUSIP. Third, we obtain standard TRACE data for each of these bonds by entering the identified CUSIPs into the Trace Viewer from Refinitiv Eikon. From this source for standard TRACE data, we acquire clean prices, trading dates, and trading volumes, which are capped at US\$ 1 million.²⁵ Dealer buy and dealer sell indicators allow for the computation of bid-ask spreads. Detailed intraday trading times allow for a reliable matching of dealer sells and buys. Spanning from January 2015 to March 2019, we have 51 months of secondary market trading, where we observe 8883 trades for 245 cat bonds.²⁶ The original list of cat bond names contained 297 entries. However, some of these cat bonds are not TRACE

²²The enhanced TRACE data set from WRDS, which we use to investigate corporate bonds in Sections 4.1 and 4.2.2, does not contain any cat bonds. Therefore, we have no specific information on volume if the trade size is larger than US \$ 1 million. But even if we could use enhanced TRACE data, we would lose 18 months of trading information because enhanced TRACE is only published with an 18-month lag. This would severely limit our data set, which is currently 51 months long.

²³Once a year Lane Financial LLC publishes a market report in its Trade Notes that contains information on all newly issued cat bonds and surveyed quoted spreads for all live cat bonds on a quarterly basis.

²⁴If we cannot find a match, we obtain the CUSIPs through an online search, and search for these CUSIPs in Refinitiv Eikon.

²⁵When dealing with standard TRACE data, a filter from Dick-Nielsen (2009) is often used to deal with corrections and cancelations in reported standard TRACE trades. These errors can be identified in WRDS data and original TRACE trade reports. However, we did not identify any of these errors in Refinitiv Eikon TRACE data. It appears plausible these errors have already been corrected in the data set.

²⁶Cat bonds already became available in standard TRACE in July 2014 (Lane & Roger, 2016). However, in Refinitiv Eikon, we cannot observe TRACE data before January 2015.

eligible;²⁷ hence, they are not part of our sample. We supplement this data with additional cat bond information: Lane Financial LLC also provides EL, sponsor, volume, and rating for all cat bonds in our data set. From the deal directory on artemis.bm we obtain trigger types, peril types and peril locations. Matching is performed based on cat bond names. Additionally, we use the Treasury Yield Curve and the Bank of America Merrill Lynch BB Yield Spread Index from the Federal Reserve Bank of St. Louis. We use the Guy Carpenter Global Property Catastrophe Rate-On-Line Index to proxy general reinsurance rates. We supplement this data with another enhanced TRACE data set from WRDS to investigate the trading in selected corporate bonds issued by selected cat bond sponsors.²⁸

3.2 | Measuring liquidity

In line with He and Milbradt (2014), we use the percentage bid-ask spread based on transaction prices as a liquidity measure.²⁹

$$L_{it} = \frac{p_{a,it} - p_{b,it}}{(p_{a,it} + p_{b,it})/2},$$

where $p_{a,it}$ and $p_{b,it}$ denote the ask and bid transaction prices of bond i at time t . We obtain the necessary transaction prices from trades recorded in standard TRACE. This data set contains a dealer sell/buy indicator, the specific volume if a trade was smaller than US\$ 1 million, and the specific time of the trade.³⁰ This information can be used to match dealer sells and buys of the same bond with the same volume in close timely proximity. The resulting high-frequency liquidity measure is also known as “round-trip measure”; this type of measure belongs to the most frequently implemented approaches to estimate trading costs in bond markets (Bessembinder et al., 2020).

If trading is very frequent, matching buy and sell trade pairs can be challenging. For corporate bonds, the bid-ask spread is often proxied from aggregate daily buy and sell activity. For example, Hong and Warga (2000) or Black et al. (2016) calculate effective bid-ask spread as the daily (volume-weighted) average price of buy transactions minus the daily average price of sell transactions. Because buy/sell indicators are sometimes unavailable, Feldhütter (2012) and Dick-Nielsen et al. (2012) use an imputed round-trip measure that match trades in close timely proximity (e.g., 15 min), and identify the highest and lowest prices of matched trades as buy and sell trades. Since our TRACE data set does contain dealer buy and dealer sell indicators, we do not have to use the imputed round-trip measure. Instead, we generate a measure for actual round-trips similar to Green et al. (2007). We use the following matching algorithm: We match

²⁷For example, they were issued under European jurisdiction.

²⁸When dealing with enhanced TRACE data on corporate bonds, we use the filter from Dick-Nielsen (2014) to deal with corrections and cancelations in reported enhanced TRACE trades.

²⁹Schestag et al. (2016) and Black et al. (2016) use a similar bid-ask spread measure where the only difference is that they use the average ask price minus average bid price divided by average mid-price for each trading day. They both refer to Hong and Warga (2000) when they introduce their bid-ask spread measures. Schuster and Uhrig-Homburg (2015) use the ask price minus the bid divided by the mid-price; in that sense, they use the same measure as we do, albeit for quoted prices. Macchiavelli/Zhou (2022) calculate the bid ask-spread from transaction prices based on the daily volume-weighted buy and sell prices for each dealer-bond pair.

³⁰Please refer to Section 3.1 for a brief discussion on the differences between standard TRACE and enhanced TRACE.

two trades in the data set as a buy/sell pair under the following conditions: (a) They are for the same bond, (b) one trade is a dealer buy while the other trade is a dealer sell, (c) the volume of both is the same,³¹ and (d) the two trades occur within 60 min of each other.³²

In the context of matching trades, the infrequent nature of cat bond trades plays into our hands: There is rarely more than one buy/sell trade pair per day and bond. Hence, matching buy and sell trades for an individual bond is simple.³³ In rare cases, a trade did not just involve two parties and a dealer (hence one buy and one sell trade) but multiple parties expressed by a multitude of buy and sell orders. If these multi-party trades could be identified by close timely proximity and a matching aggregate volume of buy and sell trades, we have matched these trades by hand. For multi-party trades, we calculated the means of buy and sell orders to determine bid-ask spreads.

The empirical literature offers many alternative liquidity measures, which are typically categorized as high-frequency or low-frequency measures. Calculating high-frequency measures is much more demanding in terms of computation and the required granularity of the data. These measures are mostly calculated based on transaction data from TRACE and include, for example, the effective bid-ask spread (Hong & Warga, 2000), the interquartile range (Han & Zhou, 2007; Pu, 2009), or round-trip transaction costs (Feldhütter, 2012). Low-frequency proxies include, for example, Roll's daily measure (Roll, 1984), the zero returns measure (Lesmond et al., 1999), the high-low spread estimator (Corwin & Schultz, 2012), or bid-ask spreads from indicative or executable quotes. Schestag et al. (2016) offer a comprehensive discussion and comparison of these and further liquidity measures. They find that all analyzed high-frequency transaction cost measures are highly correlated so that it should not matter which exact high-frequency measure is used in an empirical study; in addition, they show that low-frequency liquidity measures can be a good approximation of transaction costs, which circumvents the extensive data handling with intraday trading data. Based on these findings, we conclude that relying on the discussed round-trip liquidity measure, which measures the realized bid-ask spreads based on round-trip trades using buy and sell transactions in TRACE, is well-suited for the purpose of our study.³⁴ Nevertheless, we also implement the effective bid-ask spread from Hong and Warga (2000) as an alternative liquidity measure. Thus, instead of matching individual trades, we determine bid-ask spreads by subtracting the daily (volume-weighted) average price of buy transactions from the daily average price of sell transactions. However, we find that the overall results remain robust and

³¹When trade size is below the US\$ 1 million cap, we can perform a very precise matching. If the volume of a trade is above the US\$ 1 million cap, we continue matching with the above US\$ 1 million label.

³²Feldhütter (2012) matches trades within 15 min. However, his data set lacks dealer buy and dealer sell indicators, so that close timely proximity is more important to reduce the risk of matching buys with buys and sells with sells. We choose 60 min because buy and sell indicators greatly improve matching precision.

³³Our data set does not contain dealer identifiers. So, in theory it is possible that we match dealer buys and dealer sells from different dealers. However, we believe this scenario is very unlikely: In total we have 3884 bond-days in the data set where at least one trade took place. In 2640 of these bond-days we only observed two trades. If these two trades occur within 60 min and have one dealer buy and one dealer sell indicator, it seems highly unlikely they are from different dealers. For another 696 of bond-days, we observe only three or four trades, for which it is very unlikely, too, that the matching algorithm matches trades from different dealers. Only 167 bond-days have five trades or more, whereas 134 bond-days have only one trade.

³⁴Moreover, Black et al. (2016) finds that about 80% of the non-default component (as attributable to the liquidity dimensions trading cost, depth and resilience) in corporate bond premiums comes from the bid-ask spread, while order-flow shocks and the Amihud measure explain only the remaining 20%. Hence, relying on the percentage bid-ask spread from transaction prices as liquidity measure appears to be no major limitation.

the magnitude of the resulting effects is very similar for both liquidity measures; the detailed results are presented in the Appendix.

In January 2015, TRACE reporting rules of OTC trades expanded to SEC 144a rule bonds. Overall, we observe a total of 245 bonds with 8883 trades from January 2015 to March 2019.³⁵ For four of these cat bonds we do not observe any matches; these four bonds in total only have eight trades observable in TRACE.³⁶ Hence, we observe bid-ask spreads for almost all cat bonds in the data set. We drop bonds with missing information such as EL and maturity dates (one bond is perpetual). Additionally, we drop trades from 180 days before a bond became distressed.³⁷ We also drop all trades with negative or zero bid-ask spreads.³⁸ To not artificially inflate bid-ask spread information, we collapse the data set to the matched bid/sell trade pair level. Through this step, we keep roughly half of all remaining observations. We use the midpoint between buy and sell prices as bond prices. In total, we acquire a data set of 229 cat bonds with 3341 trade pairs.

Table 1 compares matched trades to unmatched trades for the initial data set to identify possible biases from the trade matching procedure since we only use paired trades for the remainder of our empirical analysis. Additionally, the detailed examination of matched and unmatched trades allows us to gain some insights into cat bond trading activity. The results for both subsamples indicate that matched and unmatched trades are similar: Mean trade size, share of capped trades, mean size of the traded bond, mean EL and mean coupon are very similar for matched and unmatched trades. This indicates that trade matching does not bias our sample.³⁹ Overall, we are able to match 85.7% of all trades to pairs of dealer buys and dealer sells within a 60 min timeframe. If we assume that these bonds were not kept on a dealer's balance sheet, because the sell and buy trades were executed in close timely proximity, this

³⁵Although TRACE reporting began in 2015, we observe six additional cat bonds in 2011 and 2012. However, we omit these six additional bonds because it is likely they were issued under different disclosure rules.

³⁶The low number of trades for the four bonds which lack matches indicates that these bonds are not preferred by dealers. Thus, there is no indication that dealers hold inventory for them.

³⁷Distressed means there was a complete or partial loss of principal. Additionally, a bond can be marked as distressed in anticipation of partial or complete loss of principal. Information on distressed bonds is acquired from Lane Financials and artemis.bm.

³⁸For example, this includes 57 interdealer trade pair. We define an interdealer trade pair as observations of one buy and one sell transaction for the same bond at the same time for the same price. Interdealer trades in the cat bond market appear to be extremely rare: they make up less than 2% of all trades on the cat bond market for the observed period. See Li and Schürhoff (2019) and Asquith et al. (2019) for a broader discussion of interdealer trades in bond markets.

³⁹We also consider a potential selection bias on bond-level: Dealers might choose which bonds to trade through and which bonds to trade into inventories (e.g., depending on liquidity and its premium). If a bond is always traded with inventory involvement, the corresponding bond would not be included in our analyses because the trades would not be matched by our algorithm. However, this potential selection bias would only be relevant if a substantial number of bonds was without matches. In the raw standard TRACE data set, we observe 245 cat bonds, and for the vast majority of them we observe bid-ask spreads: For 46 of these bonds, we were able to match all trades obtaining bid-ask spreads, and for another 195 bonds, we could match at least a part of the trades. Only the remaining four bonds, which have no matched trades at all, are not part of the main regressions because of lacking bid-ask spreads. These four bonds only have eight—in this case unmatched—trades. Moreover, in additional analyses we did not find evidence that seasonality has a significant impact on the decision to trade into inventory. In addition, we implemented the “effective bid-ask spread” as an alternative liquidity measure, which reduces the number of unused trades even further from 14% to 8%; we find that the summary statistics for the used versus the remaining unused trades are still very similar, and the overall results remain unchanged (detailed results are provided in the Appendix). Thus, we conclude that potential selection effects should not have an impact on our results.

TABLE 1 Matched and unmatched trades

	Matched trades	Unmatched trades
Number of Trades	7610	1273
Buys/Sells	3798/3812	381/892
Mean Trade Size	US\$ 785,000	US\$ 761,000
Share of Capped Trades	62.9%	56.2%
Mean Bond Size	US\$ 270 million	US\$ 272 million
Mean EL	2.1%	2.2%
Mean Coupon	5.5%	5.2%

Note: Comparison of matched and unmatched trades regarding Number of Trades, Buys/Sells, Mean Trade Size (Trade Size capped at US\$ 1 million), Mean EL and Mean Coupon. Buy and sell trades were matched if they were from the same bond, had the same volume and occurred within 60 min of each other. The share of capped trades is the number of trades larger than US\$ 1 million divided by the number of total trades.

means that no inventory was involved for the vast majority of trades. In line with Goldstein and Hotchkiss (2020) we deduce that the market for cat bonds is dominated by brokers who focus on matching buy and sell transactions without inventory involvement. Hence, the bid-ask spreads in our empirical models mainly represent search costs for matching and executing trades and not inventory costs or costs from adverse selection.

3.3 | Yield spread and expected loss

We apply basic theory on floating-rate notes from Fabozzi and Mann (2000) to determine yield spreads from clean prices. The typical method to price a corporate bond is simple: An investor looks for the yield spread of another corporate bond with a similar risk profile and maturity. He then uses this yield spread to discount the future cash flow of the bond at hand to obtain its price. To this end, he needs to identify a similar corporate bond to obtain a yield spread and he needs to know the complete future cashflow of the bond at hand. We can apply the same method from corporate bonds to price a cat bond. In our case, we already have the clean price from TRACE and can determine the future cash flow from the cat bond data set. The only difference is that we do not determine the price using the yield spread from another cat bond but instead use the clean price from TRACE to determine the yield spread of the cat bond at hand. To this end, we determine the remaining cash flow for every price observation of every cat bond. First, we obtain the specific payment dates. From Refinitiv Eikon we obtain the first and last coupon payment dates. Using the coupon frequency, we can then determine the specific payment dates between the first and last coupon payments.⁴⁰ Second, we determine every expected coupon payment for each payment date: Cat bonds pay a fixed quoted spread over a floating interest rate. Due to limited availability of information as to which underlying interest rate is used for individual cat bonds, we use treasury yields as the underlying interest

⁴⁰In our data set, 90.8% of all cat bonds pay a quarterly coupon, with monthly coupons and semiannual coupons trailing at 7.4% and 0.4%, respectively. 1.3% of all cat bonds are zero coupon bonds.

rates.⁴¹ However, although we know the fixed quoted spread for all future coupon payments, we do not know the future underlying interest rate for every future payment date. Following Fabozzi and Mann (2000), we estimate unknown future interest rates by generating the appropriate forward rate curve from the Treasury Yield Curve. Adding the estimated future interest rate from the forward rate curve to the fixed quoted spread then yields the expected coupon payment for every determined coupon payment date.⁴² After we have obtained this complete cash flow stream, determining the yield spread is straightforward: First, we determine the dirty price by adding the accrued interest to the clean price. Second, we numerically determine the same yield spread for each summand of the cash flow stream that results in the correct dirty price.

Risk modeling firms model the yearly loss distribution of cat bonds in relation to its inherent underwriting risk. The most important indicator for cat bond yield spreads is the first moment of this loss distribution, the EL.⁴³ Risk modeling firms only provide a static loss distribution for each calendar year. However, the likelihood of losses fluctuates dynamically for some peril types. For example, hurricanes do not occur in the first half of a calendar year and European winter storms do not occur in the summer,⁴⁴ so that the default risk of cat bonds can be zero outside of its respective risk season. Herrmann and Hibbeln (2021) offer a method to model seasonality effects in yield spreads for cat bonds. The methodology implements a fluctuating EL in accordance with seasonally fluctuating default risk:

$$EL_t = \frac{\text{Remaining Risk}_t}{\text{Remaining Time}_t} = \frac{EL_{\text{initial}} \cdot \int_{\tau=t}^T \lambda(\tau) d\tau}{T - t},$$

where EL_{initial} is the yearly average EL as provided by risk modelers, $\lambda(\tau)$ is the density function of arrival frequencies, which varies depending on the point in time τ , and the time of maturity is denoted by T . The relative shares of arrival frequency λ for hurricanes and European winter storms is provided by AIR on a monthly basis. To acquire a daily distribution of λ , we use linear interpolation. We do not directly use EL_t as Herrmann and Hibbeln (2021) but instead implement a seasonal EL adjustment variable $EL_{s,t}$:

$$EL_{s,t} = EL_t - EL_{\text{initial}}.$$

⁴¹In Refinitiv Eikon, this data is missing for around half of the data set. However, in most cases, either the LIBOR (3 or 6 months) or a treasury rate (1 day or 3 months) are specified as the underlying interest rates.

⁴²For very few cat bonds, we have an additional assumption: We assume cat bonds to only pay a coupon of 0.5% in the last calendar month of maturity. Often, a cat bond's risk period has already ended during its last calendar month of maturity and it only pays a very reduced coupon. This assumption affects only 14 observations.

⁴³We have three parameters from this loss distribution in our data set: The EL, the probability of first loss (PFL), and the conditional expected loss (CEL), with $EL = PFL \times CEL$ (see also M. Lane, 2000). We could also use the PFL instead of the EL as a measure for default risk throughout this paper but Galeotti et al. (2013) and Braun (2016) report that models that only employ the EL generally have a better model fit. Nevertheless, we have rerun our main regressions from Table 5 with PFL instead of EL but do not find any meaningful differences. Detailed results are available upon request.

⁴⁴Other seasonal perils could include pacific typhoons and US wildfires. However, typhoons and US wildfires occur throughout the whole calendar year. Additionally, these peril types are very rare. Overall, we have four bonds in the data set that insure against typhoons and six bonds that insure against US wildfires. We do not have bonds in the data set that insure against wildfires in other regions.

This way, we can separate the general EL premium from the premium that is due to seasonal changes in EL. More importantly, it allows for an unhindered modeling of EL in single-peril earthquake bonds that are not affected by seasonality.

Herrmann and Hibbeln (2021) also identify a reduced seasonal fluctuation for multi-peril and/or multi-location bonds. A cat bond may fluctuate less strongly with the hurricane or winter storm season if it also insures against earthquakes or in locations without seasonal fluctuations in peril arrival frequency. To allow for a reduced seasonal fluctuation in multi-peril and/or multi-location bonds, we interact $EL_{s,t}$ with a multi-peril/multi-location dummy. Additionally, we use separate $EL_{s,t}$ for the US hurricane season and the European winter storm season. For our purpose of identifying the liquidity premium for exogenous default risk, the present seasonality for cat bonds is a substantial advantage because it strongly increases heterogeneity in yield spreads and default risk. Hence, we are able to observe the liquidity premium for various different levels of default risk and its associated change in yield spreads.

3.4 | Summary statistics

Table 2 describes the sample in terms of cat bond properties whereas Table 3 contains descriptive statistics on continuous variables. Over 90% of cat bonds protect against perils in North America, and the majority protects against wind perils including hurricanes. Peril categories add up to more than 100% because roughly half of all cat bonds protect against multiple perils. Almost 80% of all cat bonds are exposed to seasonally fluctuating perils, highlighting the importance of thoroughly modeling the seasonality in default risk and yield spread. Only a third of all cat bonds has received a rating. All of these ratings are in the noninvestment grade category of either BB or B.

In line with economic theory, yield spreads are larger than ELs for all quantiles, which implies a risk compensation of investors beyond the actuarially fair premium. The seasonal EL adjustment factors reduce or increase the overall EL depending on the seasonal state of the hurricane season or the European winter storm season. Generally, the heterogeneity in bid-ask spreads is rather small, and 10 bps is the most commonly observed bid-ask spread.⁴⁵ However, there is no cat bond in the sample, where the bid-ask spread is constantly at 10 bps; hence, there is no bond in the data set, where the within bond heterogeneity is zero.

3.5 | Econometric model

We explain two dimensions of liquidity effects in cat bond spreads: pooled ordinary least squares (OLS) regressions to incorporate between-bond differences and fixed effects (FE) regressions to explain within-bond changes and to account for unobserved bond properties. In all models, standard errors are clustered at bond level and robust to heteroscedasticity.

⁴⁵Cat Bonds are usually issued under SEC rule 144a. Edwards et al. (2007) report that bonds issued under SEC rule 144a have lower transaction costs, potentially manifesting in lower bid-ask spreads.

TABLE 2 Cat bond specific information on 229 cat bonds

Variable	No. of bonds	Percentage
Region		
North America	207	90.39
Europe	25	10.92
Japan	18	7.86
Other	7	3.06
Peril		
Hurricane	77	33.62
Wind	145	63.32
Earthquake	152	66.38
Peril Number		
Single-Peril	106	46.29
Multi-Peril	123	53.71
Peril Location		
Single-Location	204	89.08
Multi-Location	25	10.92
Peril Number and Peril Location		
Single-Peril and Single-Location	97	42.11
Multi-Peril and/or Multi-Location	132	57.89
Seasonality Affected		
Yes	181	79.74
No	48	21.15
Rating		
BB	42	18.50
B	29	12.78
NR	158	69.60

Note: For region and peril, the percentages of the categories exceed 100% because multi-peril and multi-location bonds have multiple peril types and locations, respectively. All other categories add up to 100%.

$$\begin{aligned}
YieldSpread_{it} = & \beta_0 + \beta_1 Liquidity_{it} + \beta_2 EL_i + \beta_3 EL_{s-us,it} + \beta_4 MultiP/L_i \\
& + \beta_5 MultiP/L_i \cdot EL_{s-us,it} + \beta_6 EL_{s-eu,it} + \beta_7 ReinsIndex_t \\
& + \beta_8 SP500Return_t + \beta_9 BBYieldIndex_t + \beta_{10} OneMonthTreasury_t \\
& + \beta_{11} SlopeYieldCurve_t + \beta_{12} Maturity_{it} + \beta_{13} IssuedVolume_i \\
& + \beta_{14} TriggerType_i + \beta_{15} US_i + \beta_{16} HU_i + \beta_{17} Coupon_i + \psi_t + \varepsilon_{it}.
\end{aligned}$$

We regress the observed yield spreads on liquidity and various control variables including default risk measures, macroeconomic variables that affect the financial market,

TABLE 3 Summary statistics for continuous dependent and independent variables

	<i>n</i>	Mean	SD	q1	q10	q50	q90	q99
Yield Spread (bps)	3341	466	310	28	189	407	761	1564
Bid-ask Spread (bps)	3341	9	5	3	5	10	10	25
Bid-ask Spread Market Quarter (bps)	17	10	2	7	8	9	11	15
Market Trading Activity (trades)	17	220	90	126	126	161	406	411
Maturity Remaining (years)	3341	2.04	1.30	0.06	0.36	1.92	3.75	5.69
EL _{initial} (bps)	229	260	242	21	63	177	564	1407
Coupon (bps)	229	622	355	0	250	525	1150	1750
Volume (in USD million)	229	185	144	33	55	150	325	500
EL Seas. Adj. US (bps)	2376	-25	89	-282	-128	-8	40	190
EL Seas. Adj. EU (bps)	309	-15	85	-263	-79	-20	52	378
GC Reinsurance Index (points)	5	180.9	8.7	170.6	170.6	177.4	182.2	194.4
SP500 90-day Return (bps)	3341	152	540	-1403	-631	235	714	1482
BaAML BB Index (bps)	3341	296	76	203	223	276	408	519
1-Month T-Bill Yield (bps)	3341	104	90	0	2	89	236	246
Yield Curve Slope (bps)	3341	65	42	-14	2	58	123	142

Note: Summary statistics for continuous dependent and independent variables. Most variables are in basis points (bps). Remaining Maturity is in years. The GC Reinsurance Index represents the Guy Carpenter Global Property Catastrophe Rate-On-Line Index, where 100 points refer to reinsurance prices in the base year of 1990.

and bond-specific information. As a liquidity measure, we use the percentage bid-ask spread of a matched dealer buy and dealer sell pair (see Section 3.2). To control for exogenous default risk, we use the EL as provided by the risk modeling firms and implement the seasonal adjustment factors as well as an interaction term with a multi-peril/multi-location dummy $MultiP/L_i$. We use separate seasonal adjustment factors (see Section 3.3) for the US hurricane season $EL_{s-us,it}$ and the European winter storm season $EL_{s-eu,it}$. There is no interaction term of the European season and the multi-peril/multi-location dummy because we do not have single-peril bonds in the sample that insure against European winter storms. To control for macroeconomic changes on the financial markets, we include the return of the S&P500 performance index over the past 90 days, the Merrill Lynch BB Yield Spread index, the 1-Month Treasury yield and the slope of the yield curve measured as the difference between the 1-Year and the 5-Year Treasury yield. To control for other bond specific information, we use the remaining maturity and issued volume. Following the established empirical cat bond literature such as Braun (2016) and Gürtler et al. (2016), we also control for cat bond specific properties. To control for possible moral hazard, we include an indemnity trigger dummy.⁴⁶ We include US and hurricane dummy variables to control for peak locations and peak perils. Additionally, we include year-quarter fixed effects ψ_t to account for unobserved macroeconomic effects.

⁴⁶For a discussion on trigger types and associated moral hazard, please refer to Finken and Laux (2009).

For our within-bonds analyses, we perform fixed effects transformations by demeaning all explanatory variables:

$$\begin{aligned} \widehat{YieldSpread}_{it} = & \eta_0 + \eta_1 \widehat{Liquidity}_{it} + \eta_2 \widehat{EL}_{s-us,it} + \eta_3 \widehat{MultiP/Li} \cdot \widehat{EL}_{s,it} + \eta_4 \widehat{EL}_{s-eu,it} \\ & + \eta_5 \widehat{ReinsIndex}_t + \eta_6 \widehat{SP500Return}_t + \eta_7 \widehat{BBYieldIndex}_t \\ & + \eta_8 \widehat{OneMonthTreasury}_t + \eta_9 \widehat{SlopeYieldCurve}_t \\ & + \eta_{10} \widehat{Maturity}_{it} + \widehat{\psi}_t + \widehat{\epsilon}_{it}. \end{aligned}$$

Hence, all variables that have no heterogeneity across time are dropped. Fixed effects transformations also control for all unobserved constant properties on bond level.

3.6 | Endogeneity in default risk and liquidity

For corporate bonds, the default risk premium and the liquidity premium are endogenously linked. Chen et al. (2007) highlight that much of the liquidity cost could be due to asymmetric information on the credit quality of a traded bond. Chen et al. (2018) describe a possible spiral of worsening credit and liquidity. According to Campbell and Taksler (2003), investors may also deduce credit risk information from observed yield spreads. Hence, it appears plausible that dealers set bid-ask spreads after they have deduced additional information on credit risk or other unobserved factors before the actual trade occurs. If this additional information is positively related to yield spreads, it drives bid-ask spreads upwards, which would lead to upward biased effects due to reversed causality. As stated before, there are various approaches in the literature to address the endogeneity issue. While many approaches attempt to find two assets that have the same default risk but differ in liquidity (Black et al., 2016; Kempf et al., 2012; Longstaff et al., 2005; Schwarz, 2019), Chen et al. (2007) implement three structural equations to explain yield spreads, liquidity, and credit ratings. They estimate all three equations simultaneously through a simultaneous equations model (SEM). However, we believe the endogeneity problem is much less severe for cat bonds than it is for corporate bonds. It is plausible to assume that cat bond defaults are strictly exogenous events because the occurrence of natural catastrophes cannot be influenced by financial market conditions; neither is the likelihood of a natural disaster amplified by deteriorating liquidity nor does a change in investor sentiment make a natural catastrophe more likely. Hence for cat bonds, there is only one channel of causation between default risk and liquidity: The likelihood and the severity of natural catastrophes dictate cat bond trading. However, the trading of cat bonds does not influence the likelihood or severity of natural catastrophes in any way. This accounts for the endogeneity stemming from default risk and liquidity. Nevertheless, there could still be some endogeneity stemming from unobserved factors that dealers observe through the yield spread, which are unrelated to default risk. Dealers could set their bid-ask spread according to the expected yield spread from the trade. Yield spread and bid-ask spread would form simultaneously. To account for this endogeneity dimension, we alter the SEM from Chen et al. (2007) to reflect the exogeneity assumption of default risk in the cat bond market. Instead of using three equations to explain yield spread liquidity and credit rating, we use two equations to simultaneously estimate yield spread and liquidity. We use the EL and the seasonal EL adjustment factors as exogenous variables to reflect default risk.

$$\begin{aligned}
YieldSpread_{it} = & \vartheta_0 + \vartheta_1 Liquidity_{it} + \vartheta_2 EL_i + \vartheta_3 EL_{s-us,it} + \vartheta_4 MultiP/L_i \\
& + \vartheta_5 MultiP/L_i \cdot EL_{s-us,it} + \vartheta_6 EL_{s-eu,it} + \vartheta_7 ReinsIndex_t + \vartheta_8 SP500Return_t \\
& + \vartheta_9 BBYieldIndex_t + \vartheta_{10} OneMonthTreasury_t + \vartheta_{11} SlopeYieldCurve_t \\
& + \vartheta_{12} TriggerType_i + \vartheta_{13} US_i + \vartheta_{14} HU_i + \vartheta_{15} Coupon_i + \psi_i + \varepsilon_{it},
\end{aligned}$$

$$\begin{aligned}
Liquidity_{it} = & \zeta_0 + \zeta_1 YieldSpread_{it} + \zeta_2 EL_i + \zeta_3 EL_{s-us,it} + \zeta_4 MultiP/L_i \\
& + \zeta_5 MultiP/L_i \cdot EL_{s-us,it} + \zeta_6 EL_{s-eu,it} + \zeta_7 Maturity_{it} \\
& + \zeta_8 IssuedVolume_i + \psi_i + \varepsilon_{it}.
\end{aligned}$$

For the yield spread, we consider *Reinsurance Index*, *SP500 Return*, *BB Yield Index*, *OneMonth Treasury*, *Slope Yield Curve*, *Trigger Indemnity*, *US*, *HU* and *Coupon* as exogenous variables. For the liquidity, we use *Maturity* and *Issued Volume* as exogenous variables. We estimate the SEM with maximum-likelihood estimation. Standard errors are again clustered at bond level and robust to heteroscedasticity. Analogously to the FE model described in the previous section, we also apply fixed effects transformations to the SEM.

4 | EMPIRICAL RESULTS

4.1 | Secondary market cat bond trading—General patterns

Figure 1 shows a strong fluctuation of trading activity over the sample period. Trading is relatively strong during the first half of 2015 but drops by more than 50% in the second half. From Q2-2016 to Q1-2018 trading fluctuates at a relatively low level before spiking in Q2-2018 and Q4-2018. Generally, we can see an increase in trades after Q1-2018. However, that does not necessarily imply an increased trading volume. The bottom panel indicates that the share of large trades has substantially declined just as the number of trades increased. The mean bid-ask spread fluctuates just below 10 bps for most quarters. However, Q3-2017 and Q4-2017 experienced a sudden spike in bid-ask spreads. This increase coincides with the landfall of hurricane Irma in September 2017 causing multiple cat bonds to default. For this month, the Eurekahedge ILS Advisers Index saw its worst monthly ILS return of -8.61% , with the second worst month being November 2018 trailing with -3.68% .⁴⁷

Herrmann and Hibbeln (2021) highlight the importance of seasonality on the cat bond market.⁴⁸ Cat bonds that insure against hurricanes are virtually risk free during the first half of a calendar year but are strongly exposed to default risk from the hurricane season in the second half. Figure 2 illustrates the within-year trading of cat bonds. The number of trades indicates that from March to June, in the prelude to the hurricane season, trading activity is high. From

⁴⁷Many defaulted cat bonds had already been affected by hurricane Harvey 2 weeks before hurricane Irma. In this context, it is important to note that we dropped all observations for defaulted cat bonds from 180 days before its default date. The observed spikes in bid-ask spreads are observed for bonds that did not default in the aftermath of the 2017 hurricane season.

⁴⁸The hurricane season can also impact traditional derivatives. Ben Ammar (2020) identifies a catastrophe risk premium in the implied volatility of OTM put options written on P&C insurers and finds that the implied volatility smile exhibits a seasonal pattern due to the hurricane season.

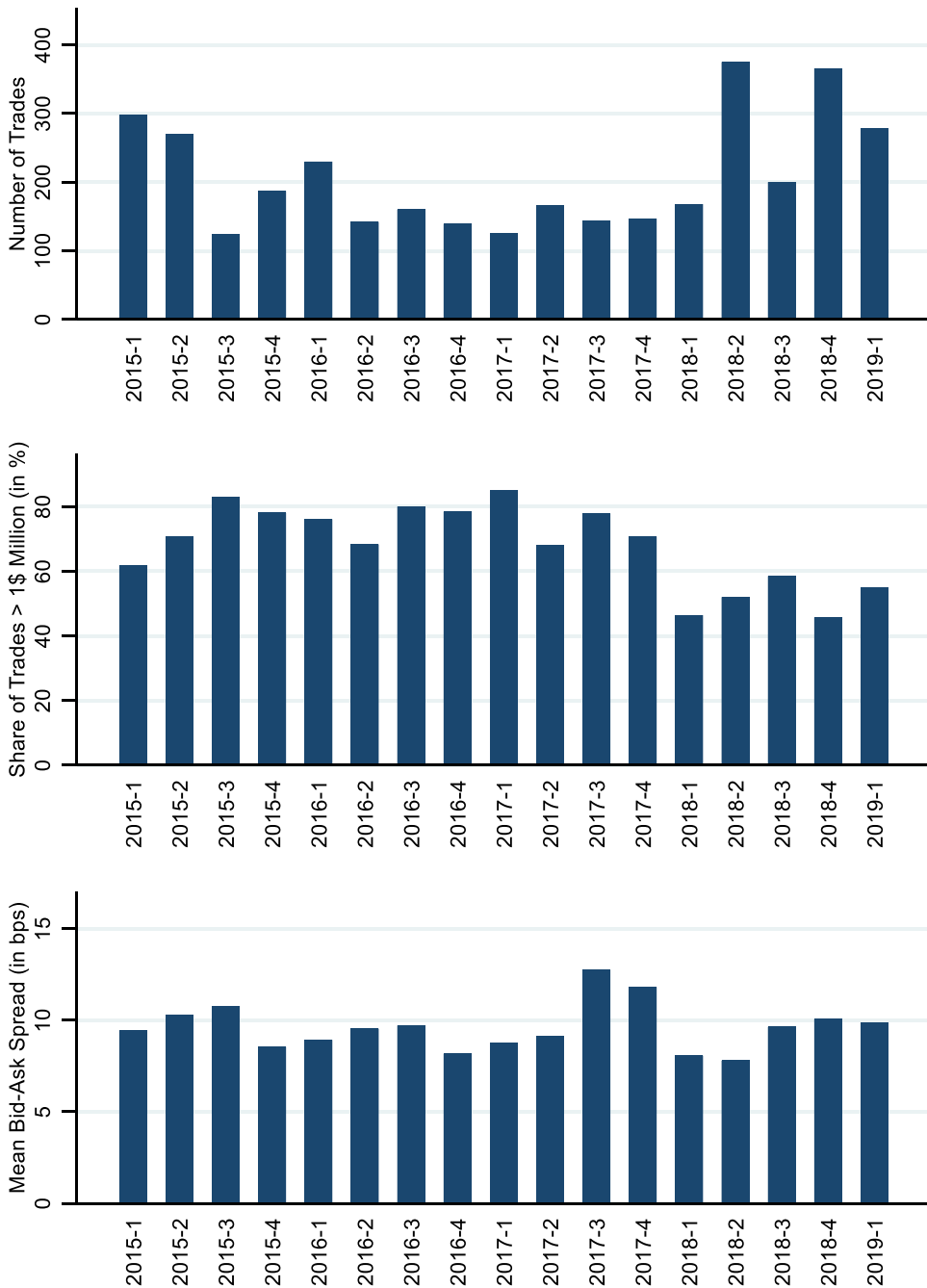


FIGURE 1 Trading activity per quarter—Cat bonds. This figure depicts trading activity on the secondary cat bond market over the sample period. The number of trades per quarter has been fluctuating strongly with peaks in the second and fourth quarter of 2018. Trading has generally been low from mid-2016 to early 2018. The mean bid-ask spread per trade has been fluctuation just below 10bps with two peaks in the second half of 2017. The share of trades above US\$1 million has been declining over the sample period.

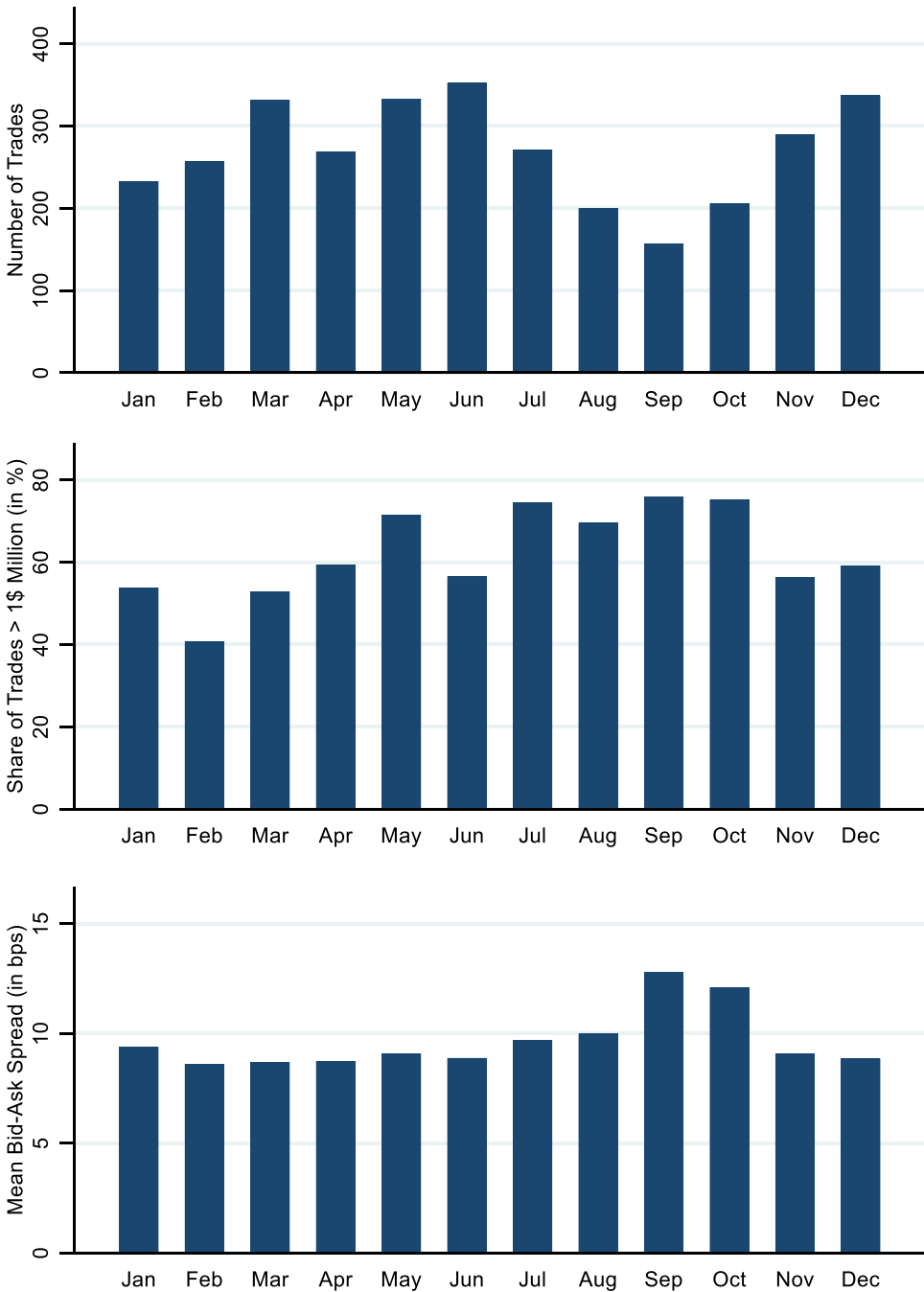


FIGURE 2 Trading activity within year—Cat bonds. This figure depicts trading activity on the secondary cat bond market within year. The share of trades fluctuates throughout the first half of each calendar year and rapidly declines throughout the first half of the risk season (June–September) to roughly half its previous size. Trading activity recovers throughout the remainder of the year as the risk season subsides. The mean bid-ask spread per trade fluctuates just below 10bps through most of a calendar year but peaks in September and October before it declines as the risk season subsides. The share of trades above US\$ 1 million is generally larger in the second half of a calendar year.

its peak in June, trading activity steadily declines to half its previous level in September until it recovers until December. The lowest point in September precisely coincides with the peak of the hurricane season. The trading activity is smaller during the peak months of the hurricane season—in August, September and October—with a joint significance at the 0.1%-level ($F = 11.16$). Mean bid-ask spreads fluctuate slightly below 10 bps. Only September and October experience average bid-ask spreads that are larger than 10 bps. However, it is unclear whether this increase is due to increased default risk, lower trading activity or a combination of both. A one-way analysis of variance (ANOVA) test reveals that the differences in means of bid-ask spreads for these calendar months are significant at the 0.1%-level ($F = 13.65$).

To compare some of these results to the corporate bond market, we have obtained an enhanced TRACE data set from WRDS that spans the same sample period from January 2015 to March 2019. We apply the enhanced TRACE filter from Dick-Nielsen (2014) to account for artefacts in the data set stemming from same-day corrections and cancelations or reversals.⁴⁹ The upper diagram in Figure 3 contains the number of trades in the corporate bond market for each quarter of the sample period. We can observe a clear trend over the sample period: While trading appears to be slightly more pronounced in the first quarter, the number of trades has generally increased throughout the sample period. In the first quarter of 2019 around 50% more trades were recorded than in the first quarter of 2015. This is quite contrary to the cat bond market, where we observe fluctuating trade numbers from one quarter to the next without a clear time trend. Not surprisingly, there are many more trades in the corporate bond market than in the cat bond market. The lower diagram contains the average number of trades per calendar month within each year. We observe slightly elevated trading in March and slightly depressed trading in April, July, and September. Overall, trading activity is quite constant irrespective of the calendar month. Compared to its median, it only drops by 9% to its lowest point in July. This is in stark contrast to the cat bond market, where we observe significantly reduced trading during the US hurricane season: Compared to its median, trading declines by 42%. As trading is quite evenly distributed for corporate bonds, we conclude that the observed intra-year trading pattern is unique to the cat bond market.

4.2 | Trading and adverse events

4.2.1 | Trading and adverse events—Cat bonds

On the one hand, the default risk is substantially increased during the hurricane season, which should reduce trading activity. On the other hand, the frequency of news related to catastrophe events is higher compared to off season, particularly if adverse events actually occur, which could increase trading activity. However, as the impact of the risk season on default risk can be quite substantial for cat bonds (see Herrmann & Hibbeln, 2021), we expect that the effect of increased default risk is relatively stronger than the information effect. Subsequently, we empirically investigate the overall effect on cat bond trading around adverse events. In terms of the numbers of defaults, 2017 and 2018 have been particularly bad years for the cat bond market. 2017 saw large losses from hurricanes Irma, Harvey, and Maria, while 2018 was strongly affected by hurricane Michael. These two hurricane seasons pushed multiple cat bonds

⁴⁹For more details on the filter, please refer to Dick-Nielsen (2014).

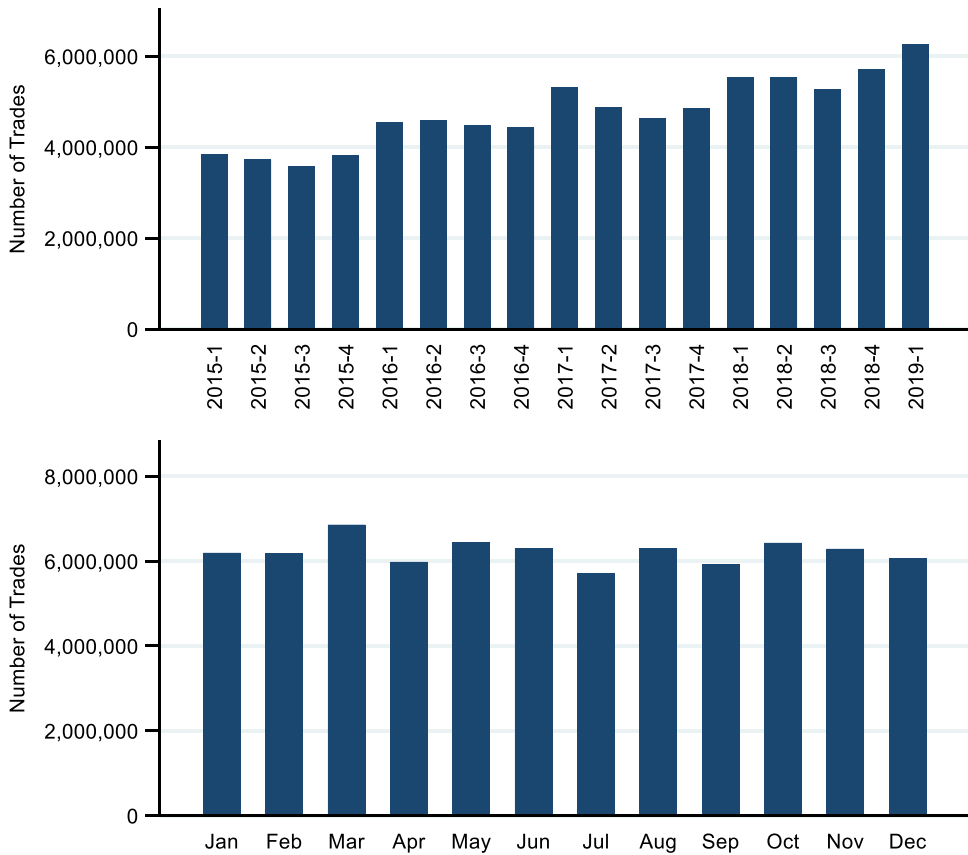


FIGURE 3 Trading activity—Corporate bonds. This figure depicts trading activity on the secondary corporate bond market over the sample period and within year. The two diagrams depict all OTC-trades reported in enhanced TRACE as provided by WRDS. Observable trades in enhanced TRACE have generally increased. The number of trades does not fluctuate strongly from one quarter to the next. Within the year, we observe slightly elevated trading in March and slightly depressed trading in April, July, and September.

into default according to the artemis.bm “Cat Bond Losses & Bonds at Risk” directory. Therefore, these events are well-suited to further investigate how the secondary market trading reacts to adverse events. In the following section, we further support this analysis by using enhanced TRACE data on corporate bonds to investigate the trading of corporate bonds of associated insurance companies.

First, we select a set of cat bonds from the data set to illustrate actual trading around these events. Since many cat bonds are traded very rarely, we select bonds that are relatively often traded in the time frame from March 2017 to March 2019. In addition, the selected bonds must have exposure to US hurricanes. Out of all cat bonds that meet these criteria, the nine bonds which were most often traded during this period are (in descending order): Alamo Re 2017-1A, Northshore Re II 2017-1A, Galilei Re 2016-1 E-1, Kilimanjaro II Re 2017-1 C-1, Cranberry Re 2017-1A, Alamo Re 2015-1 B, Sanders 2017-1, Long Point Re III 2018-1A, and Everglades Re II 2017-1. For example, we observe 54 trades for Alamo Re 2017-1A and 26 trades for Everglades Re II 2017-1A. Second, we mark the respective events: (a) overlapping Hurricanes Harvey, Irma, and Maria and (b) Hurricane Michael. Harvey formed August 17, 2017 and dissipated

September 2, 2017, Irma formed August 30, 2017 and dissipated September 14, 2017, and Maria formed September 16, 2017 and dissipated September 30, 2017. Thus, we define the event horizon of “Harvey/Irma/Maria” from August 17, 2017 to September 30, 2017. Hurricane Michael formed October 7 and dissipated October 16, 2017; we define this event horizon as “Michael.”

Figure 4 contains diagrams where each trade for these nine cat bonds is marked as a dot. The event periods “Harvey/Irma/Maria” and “Michael” are marked in gray. Similarly to evidence from the previous section, where we observed relatively few trades during the hurricane season in general, we observe almost no trades during adverse hurricane events for these nine bonds in particular: We only observe eight trades during Harvey/Irma/Maria across these bonds. We record trades for only four bonds: Alamo RE 2017-1A, Galilei Re 2016-1 E-1, Kilimanjaro II Re 2017-1 C-1, and Alamo Re 2015-1 B. For the latter two bonds, these trades highlight temporary losses, most notably for Alamo Re 2015-1 B. On August 24, 2017, its price

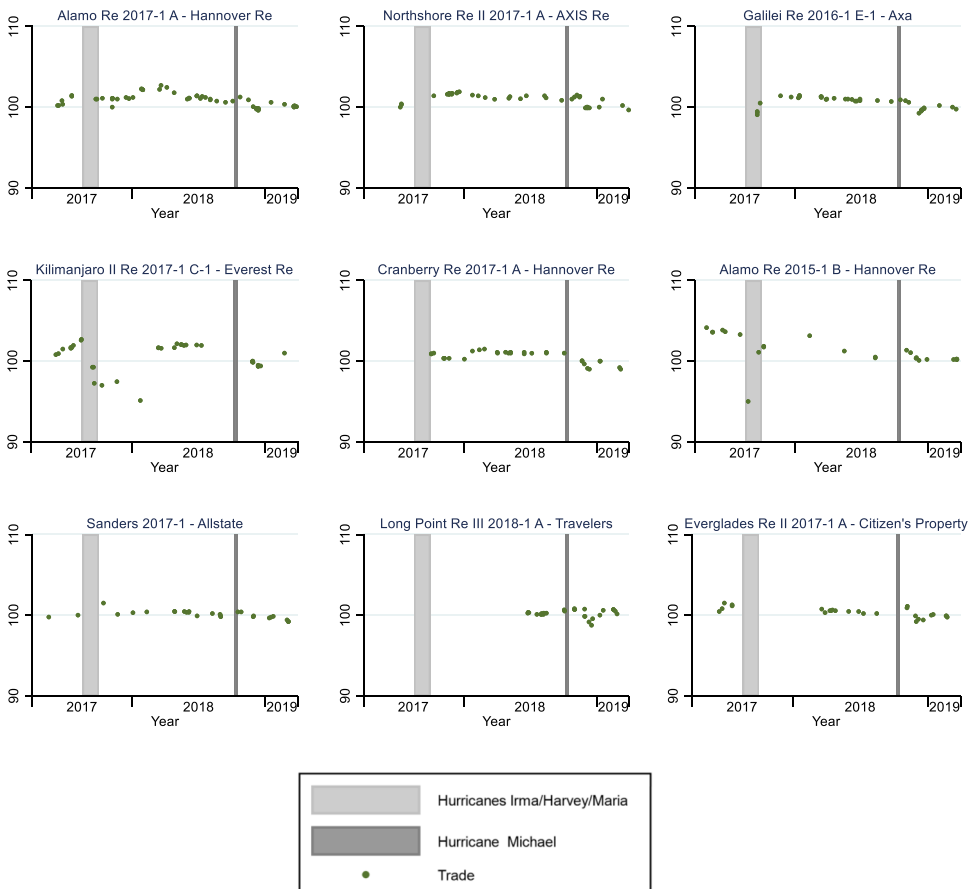


FIGURE 4 Trading around adverse events—Cat bonds. This figure depicts the trades that have taken place between March 2017–March 2019 for a set of nine cat bonds that were most often traded during this period. Two events are marked: (a) Hurricanes Irma, Harvey, and Maria from August 17, 2017 to September 30, 2017 and (b) Hurricane Michael from October 7, 2018 to October 16, 2018. Each dot represents one trade. Long Point Re II 2018-1A was issued May 2018, Northshore Re II 2017-1A and Cranberry Re 2017-1A were issued in June 2017. All other bonds were issued May 2017 or earlier.

is 95, which is a significant drop from the previous observable trade on August 02, 2017 at a price of 103.3. However, the bond quickly recovers to a price of 101.1 on September 22, 2017. It appears that one investor decided to reduce its exposure just as hurricane Harvey was about to make landfall in Texas. According to the Deal Directory on artemis.bm, Alamo Re 2015-1 B protects exclusively against named storms in Texas. This cat bond probably recovered after Harvey dissipated as it became apparent that it was not going to default. Alamo Re 2015-1 B matured 07 June 2019 without a loss. For other bonds, such as Alamo Re 2017-1A and Northshore Re II 2017-1A, it seems trading was very frequent before and after Harvey/Irma/Maria but almost paused completely during the event itself. Although we do not observe a single trade during Hurricane Michael, we can observe a cluster of trading just a few weeks later towards December 2019. During this time, some bonds such as Alamo Re 2017-1A, Northshore Re II 2017-1A, Galilei Re 2016-1 E-1 and Long Point Re III 2018-1A experienced some price decline but quickly recovered just a few weeks later. It is possible that the market was first surprised by potential losses from hurricane Michael a few weeks after the events, which could explain the price decline but then recovered a few weeks later. To put these observations into perspective, we also look at selected corporate bond trading in relation to the two catastrophe events Harvey/Irma/Maria and Michael but also earnings announcements of the associated corporations.

4.2.2 | Trading and adverse events—Corporate bonds

We further investigate our observations from the previous section by investigating the trading of selected corporate bonds that most closely match the nine cat bonds from the previous section. We utilize corporate bonds from the same insurance companies that sponsored these nine cat bonds.⁵⁰ This way, we can observe corporate bonds that are affected by the same adverse event information (Harvey/Irma/Maria and Michael);⁵¹ similarly, we can study how these corporate bonds react to new corporate information in the form of regular earnings announcements. In this context, we are particularly interested if such corporate bonds react similarly to catastrophe events or if reduced trading activity is only observable for cat bonds. While related corporate bonds could be negatively affected by catastrophe risk, too, these bonds are also exposed to various other types of risk (e.g., demand risk or management risk). It is even possible that adverse events lead to positive outcomes for insurers because the demand for new catastrophe insurance increases. Thus, in contrast to cat bonds, we expect for related corporate bonds that the trading activity during adverse events is rather increasing due to the information effect.

If possible, we select one corporate bond for each of the nine cat bonds from the previous section. This corporate bond (a) needs to be issued by the sponsoring insurance company, (b) must be observable in the enhanced TRACE data set from WRDS, and (c) should be traded during the same sample period from March 2017 to March 2019. From the corporate bonds complying with these criteria, (d) we choose the bond with the shortest remaining duration to achieve a similar duration as for the cat bonds. The nine aforementioned cat bonds were issued by the following seven (re-)insurance companies: Citizen's Property, Hannover Re,⁵² Everest

⁵⁰We note that corporate bonds and cat bonds are not necessarily issued by the same companies. A closer matching is not possible, though, because the specific company that sponsors a cat bond is often unknown.

⁵¹Strong catastrophe events can put (re-)insurance companies in jeopardy.

Re, Allstate, XL Bermuda,⁵³ Travelers, and Axis Re. In Refinitiv Eikon, we do not find any corporate bonds for Citizen's Property matching the correct time period; its last corporate bond was called in 2007. For Hannover Re, we do not find any corporate bonds that are TRACE eligible because Hannover Re has only issued corporate bonds in European jurisdiction during our time period. This leaves us with Everest Re, Allstate, Axa, Travelers, and Axis Re. For each sponsoring entity, we select one corporate bond following the abovementioned criteria.⁵⁴

Figure 5 depicts the trading of the five selected corporate bonds for the time frame of March 2017 to March 2019 as in the previous section. The catastrophe events Irma/Harvey/Maria and Michael are marked in gray. We additionally look at trading around earnings announcements, marked by dashed lines.⁵⁵ This allows us to compare the market's reaction to arrival of new information (1) from catastrophe events and (2) from the events of corporate disclosure.

Comparing the general trading of cat bond bonds in Figure 4 to the general trading of associated corporate bonds in Figure 5, we observe that corporate bonds are much more frequently traded than cat bonds. For Allstate, Axa, Travelers, and Axis, their respective corporate bonds are so frequently traded during this 2-year time period that we cannot make out any differences in trading during the catastrophe events by a visual inspection. We also cannot observe any obvious market reaction to earnings announcements. However, for Everest Re, there is a very long period around Irma/Harvey/Maria in 2017 where its corporate bond was not traded. On the contrary, the same corporate bond was more strongly traded during Michael and experienced a strong price drop.

Since the multitude of trades makes a visual inspection of corporate bond trading so difficult, we also determine the specific trading during the catastrophe events and around earnings announcements. This means for the catastrophe events we use the previously specified event horizon, and for earnings announcements we define a time window of 15 days before and 15 days after the respective announcement. Assuming that trades are evenly distributed across a calendar year as supported by Figure 3, we can expect roughly $44/365 \approx 12.1\%$ of all trades per bond in 2017 to take place during the defined time window of Irma/Harvey/Maria. If this share of trades is above (below) 12.1%, the specific corporate bond was more (less) often traded than expected. For Michael we expect $14/365 \approx 2.5\%$ of all trades in 2018 to take place during the defined time window, whereas for earnings announcements with four 30-day long time windows, we expect $4 \times 30/365 \approx 32.9\%$ of all trades per year to take place during one of the earnings announcement time windows.⁵⁶

For many corporate bonds, results are the opposite from cat bonds where we observed dampened trading during the catastrophe events. For Irma/Harvey/Maria, the shares of trades for each corporate bond as of the total trades in 2017 range from 12.8% for Axis Re up to 20.9% for Axa. The share for Allstate is 15.2%, while Travelers and Everest Re both have shares of 17.4%. All of these shares are above the 12.1% threshold.⁵⁷ For Michael, these shares fluctuate: Everest Re (2.7%) and Travelers (3.7%) have shares above the 2.5% threshold, while Allstate

⁵²Hannover Re has issued three of the nine cat bonds, while each of the remaining six (re-)insurance companies have issued one of the remaining cat bonds.

⁵³XL Bermuda is a subsidiary of Axa. We mark this sponsor as "Axa" from here on.

⁵⁴The selected corporate bonds have the following CUSIPs: Allstate (020002AX9), Travelers (020002AX9), Everest Re (020002AX9), Axa (020002AX9), and Axis Re (020002AX9).

⁵⁵The dates of earnings announcements stem from Refinitiv Eikon. Axa only provides earnings announcements with semiannual frequency, whereas Allstate, Travelers, Everest Re, and Axis Re announce earnings with quarterly frequency.

⁵⁶For Axa, we expect only a share of 16.4% because Axa reports earnings on a semiannual basis.

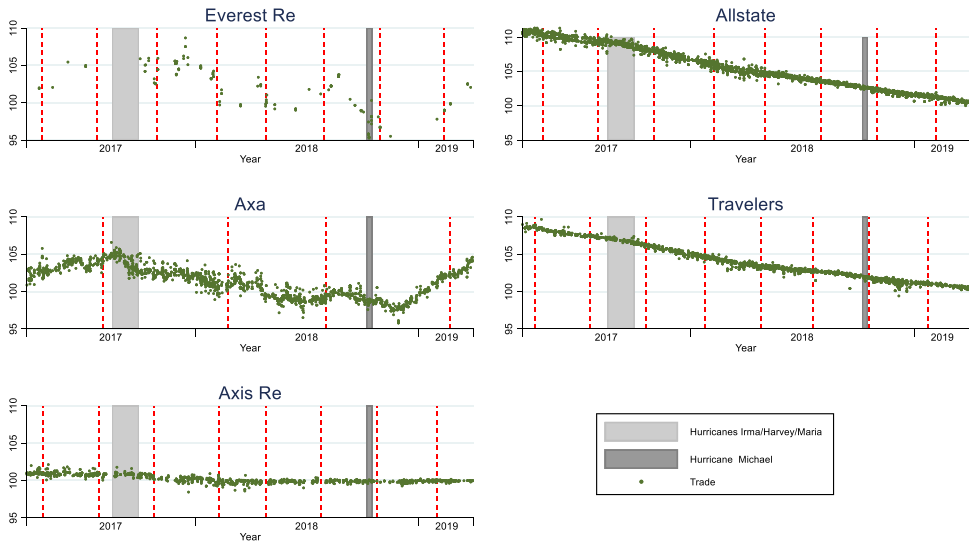


FIGURE 5 Trading around adverse events—Corporate bonds. This figure depicts the trades that have taken place between March 2017 – March 2019 for a set of five corporate bonds that belong to sponsoring entities of some of the cat bonds depicted in Figure 4. Two events are marked: (a) Hurricanes Irma, Harvey, and Maria from August 17, 2017 to September 30, 2017 and (b) Hurricane Michael from October 7, 2018 to October 16, 2018. The dashed lines mark earnings announcements. Each dot represents one trade.

(2.4%), Axis Re (0.9%), and Axa (1.9%) are below the threshold.⁵⁸ However, the results for Michael are less reliable due to the relatively short time frame. During the 30-day time frame of earnings announcements, all four corporate bonds were more often traded than expected and surpass the 32.9% threshold. Shares range from 35.6% for Everest Re to 40.0% for Axis Re; the shares for Travelers and Allstate are 35.9% and 38.2%; Axa surpasses its 16.4% threshold with 17.4%.⁵⁹

Overall, we can conclude that corporate bonds are more often traded during catastrophe events and around earnings announcements. This means that, in line with our expectation, corporate bonds of (re-)insurance companies are more frequently traded when new information arrives in the market in the form of catastrophe events or earnings announcements. On the contrary, cat bonds are less frequently traded during catastrophe events because the effect of increased default risk dominates the information effect. This makes the reduced trading during the hurricane season, which is clearly visible in Figure 2 and discussed in Section 4.1, even more meaningful because we can rule out that this is simply a consequence of overall reduced bond trading in this period but indeed a consequence of increased default risk. This is also in line with hypothesis H1.1 that liquidity is lower for bonds with high default risk, particularly regarding the seasonality-implied increase of default risk. In the next section, we will study the liquidity-related hypotheses from Section 2.3 in more detail.

⁵⁷All differences in shares from 12.1% for Irma/Harvey/Maria are statistically significant at least at the 0.1%-level except for Axis Re, where the difference is not statistically significant.

⁵⁸Differences in shares from 2.5% for Michael are statistically significant for Travelers, Axis Re and Axa at least at the 1%-level. Differences are not statistically significant for Everest Re and Allstate.

⁵⁹All differences in shares from 32.9% (and 16.4% for Axa) are statistically significant at least at the 5%-level.

4.3 | Determinants of liquidity

Next, we shed light on the drivers of liquidity on the cat bond market measured by bid-ask spreads. The models in Table 4 regress the bid-ask spreads on default risk and other liquidity-related variables such as maturity and traded volume. The bid-ask spread in Table 4 is related to the EL, both measured by yearly EL_{initial} but also the seasonal swing measured by $EL_{s\text{-us}}$ and

TABLE 4 Bid-ask spread determinants

Dependent variable	Bid-ask spread			
	OLS (1)	OLS (2)	FE (3)	FE (4)
EL_{initial}	0.003* (2.02)	0.003* (1.98)		
$EL_{s\text{-us}}$	0.011*** (4.20)	0.010*** (3.76)	0.014*** (5.35)	0.016*** (5.28)
$EL_{s\text{-eu}}$	0.008+ (1.85)	0.007 (1.65)	0.002 (0.43)	0.001 (0.18)
Multi-P/L	-0.343 (-1.32)	-0.192 (-0.79)		
$EL_{s\text{-us}}$ # Multi-P/L	-0.007+ (-1.96)	-0.004 (-1.20)	-0.010** (-2.85)	-0.008* (-2.41)
Volume 1M	0.624** (2.85)	0.510* (2.42)	0.601** (3.12)	0.485* (2.53)
Market Trading Activity	-0.006*** (-4.26)		-0.007*** (-4.66)	
Maturity	0.582*** (5.56)	0.562*** (5.64)	3.099*** (5.07)	2.317 (0.98)
Constant	4.823+ (1.76)	16.497*** (5.22)	9.131** (3.25)	9.450 (1.27)
Observations	3341	3341	3341	3341
Number of bonds	229	229	229	229
$R^2/\text{within } R^2$	0.070	0.106	0.064	0.096
Adj. $R^2/\text{adj. within } R^2$	0.065	0.098	0.061	0.089
Financial market controls	Yes	Yes	Yes	Yes
Bond specific controls	Yes	Yes	Omitted	Omitted
Year-Quarter FE	No	Yes	No	Yes

Note: This table shows the determinants of bid-ask spreads. Models (1) and (2) are pooled OLS models. Models (3) and (4) apply fixed effects transformations. In Models (2) and (4), year-quarter fixed effects capture common changes in market conditions. *Volume 1M* is a dummy variable, which is 1 if the volume of a trade is larger or equal to US\$ 1 million and distinguishes between large trades and small trades. Due to limited data frequency, *Market Trading Activity* and *Reinsurance Index* are dropped in the presence of year-quarter fixed effects. All standard errors are clustered at bond level and robust to heteroscedasticity. *t* Values are shown in parentheses.

+, *, **, and *** indicate statistical significance at the 10%, 5%, 1%, and 0.1% levels, respectively.

EL_{s-eu} . Models (1) and (2) show that a 100 bps seasonal swing in EL for the US season is associated with a 1 bps change in bid-ask spreads. This effect is smaller for multi-peril bonds and larger within bonds as indicated by the FE models (3) and (4). All coefficients on EL_{s-us} are highly statistically significant at the 0.1%-level. We see no such effect for EL_{s-eu} , possibly because cat bonds in the data set have only very limited exposure to the European catastrophe season.⁶⁰ These results confirm hypothesis *H1.1*—liquidity is low if default risk is high—, which is in line with the order processing channel because search costs are higher for bonds with higher default risk, which in turn decreases liquidity.

As indicated by Huang and Stoll (1997), a large trade could have a larger bid-ask spread because brokers have disproportionately higher search costs to match larger orders. Standard TRACE provides trade volume that is capped at US\$ 1 million. Hence, we define *Volume 1M* as a dummy variable that indicates if a trade is larger or equal to the US\$ 1 million cap, and thus separates the trades into small and large trades. In this setting, we observe 1173 trades below and 2168 above the cap. We find a strong relationship between the bid-ask spread and trade size. In all four models, large trades have bid-ask spreads that are roughly 0.5 bps larger than for small trades, and the coefficients are highly statistically significant at the 0.1%-level.⁶¹ Hence, in line with Huang and Stoll (1997) we can confirm that bid-ask spreads are higher for larger trades, which is in line with hypothesis *H1.2*.

To relate a bond's liquidity to the overall market's trading activity, we define *Market Trading Activity* as the number of trades in the market for the current quarter. A one standard deviation increase in the quarterly *Market Trading Activity* is associated with a 0.12 (0.13) standard deviation decrease in bid-ask spreads in the pooled OLS model (FE model). This result is highly statistically significant at the 0.1%-level. This indicates that observed bid-ask spreads are related to the general liquidity on the cat bond market. Furthermore, the bid-ask spreads fall as bonds near their maturity. For pooled OLS in models (1) and (2), a 1-year lower time to maturity reduces the bid-ask spread by more than 0.5 bps. These results are highly statistically significant at the 0.1%-level. Within bond, this relationship increases to around three bps; however, this effect loses its statistical significance in the presence of year-quarter fixed effects, probably because year-quarter fixed effects capture most of within bond changes in maturity. Figure 6 provides further evidence: Cat bonds are more frequently traded the closer they get to their respective maturity date. In their last year of duration, cat bonds are twice as often traded as bonds with 5 years to maturity. Compared to 3 years to maturity, trading is still 25% higher in the last year to maturity. A one-way ANOVA test reveals that the differences in the mean number of trades w.r.t. the years of remaining maturity are significant at the 0.1%-level ($F = 12.67$). Overall, we accept hypothesis *H1.3* meaning that a decreasing time to maturity is related to a decreasing bid-ask spread. An additional potential liquidity factor could be the issuance volume (see Braun, 2016; Gürtler et al., 2016). However, unreported in Table 4, we do not find a relationship between issuance volume and bid-ask spread.

⁶⁰This seasonal effect is smaller for multi-peril US bond as indicated by the interaction term $EL_{s-us} \# Multi-P/L$. We do not have a similar interaction term for the European season because there are no single-peril EU wind bonds in the sample that are affected by seasonality.

⁶¹In this setting with a dummy variable for the US\$ 1 million cap, we forgo the heterogeneity below the US\$ 1 million cap. We can nevertheless use this heterogeneity by limiting the data set to a subsample where all trades have a volume below the US\$ 1 million cap. Models that use the specific trading volume in the subsample of these small trades further support *H1.2*: For small trades, the bid-ask spread increases with traded volume. The coefficients for the traded volume are significant on the 5%-level. Detailed results are available upon request.

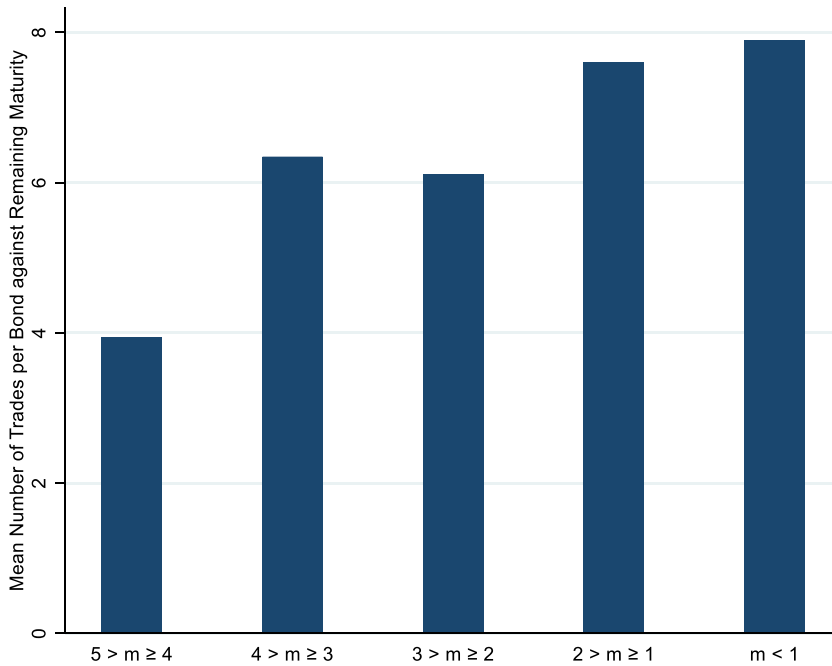


FIGURE 6 Trading frequency and maturity. This figure depicts trading activity on the secondary cat bond market against the time to maturity (m , in years). The mean number of trades per bond increases the closer a bond gets to its maturity. For bonds with 5 years to maturity there are around four trades on average. The average number of trades per bond increases to around eight trades in the last year before maturity.

4.4 | Yield spreads and liquidity

4.4.1 | Liquidity premium

We quantify the liquidity premium on the cat bond market through pooled OLS and SEM to capture differences between bonds but also FE models that quantify the liquidity effect for within bond changes and to control for unobserved constant bond properties. First, we illustrate results for pooled OLS and SEM with pooled observations (see Table 5, Model 1 and 2).⁶² All standard errors are clustered at bond level and robust to heteroscedasticity. The established literature highlights the relationship of the liquidity premium and the credit risk premium. Model (1) includes a series of variables to control for the default risk in cat bonds. $EL_{initial}$ represents the static level of EL, while EL_{s-us} and EL_{s-eu} account for seasonal fluctuations in EL induced by the US hurricane and the European winter storm season. The interaction term of EL_{s-us} and $Multi-P/L$ accounts for lower seasonal fluctuation in multi-peril and/or multi-location bonds.⁶³ As additional control variables, we include general market conditions such as the S&P500 return over the last 90

⁶²In addition to the results presented in Table 5, we implemented the effective bid-ask spread from Hong and Warga (2000) as an alternative liquidity measure. Instead of matching individual trades, we determine bid-ask spreads by subtracting the daily (volume-weighted) average price of buy transactions from the daily average price of sell transactions. We find that the overall results remain robust and the magnitude of the resulting effects is very similar. The detailed results are presented in the Appendix.

TABLE 5 Liquidity premium and other yield spread determinants

Dependent variable	Yield Spread	Yield Spread	Bid-Ask Spread	Yield Spread	Yield Spread	Bid-Ask Spread
	OLS (1)	SEM—Pooled (2a)	(2b)	FE (3)	SEM—Demeaned (4a)	(4b)
Bid-Ask Spread	10.293* (2.54)	11.638** (2.77)		8.038* (2.12)	9.254* (2.40)	
Yield Spread			-0.002 (-0.32)			-0.002 (-0.19)
EL _{initial}	1.186*** (9.03)	1.192*** (9.44)	0.004 (0.60)			
EL _{s-us}	1.202*** (4.88)	1.211*** (4.83)	0.013* (2.03)	1.252*** (5.19)	1.239*** (5.31)	0.019 (1.23)
EL _{s-eu}	0.927*** (5.16)	0.919*** (4.90)	0.009 (1.40)	0.434** (2.68)	0.438** (2.59)	0.003 (0.40)
Multi-P/L	25.791 (1.32)	30.645 ⁺ (1.69)	-0.009 (-0.03)			
EL _{s-us} # Multi-P/L	0.099 (0.35)	0.080 (0.28)	-0.004 (-0.93)	-0.527 ⁺ (-1.96)	-0.541* (-1.98)	-0.010 (-1.25)
Maturity	-0.041 (-0.01)		0.583*** (5.86)	-10.161 (-0.26)		0.910*** (5.06)
Issued Volume	-0.048 ⁺ (-1.76)		-0.000 (-0.03)			
Coupon	0.141 (1.57)	0.136 (1.58)				
Constant	-152.790 ⁺ (-1.65)	-183.345 ⁺ (-1.66)	8.549*** (7.18)	405.575* (2.16)	192.590** (2.93)	-0.128 (-0.59)

(Continues)

TABLE 5 (Continued)

Dependent variable	Yield Spread		Yield Spread		Yield Spread		Yield Spread	
	OLS (1)	SEM—Pooled (2a)	Bid-Ask Spread (2b)	FE (3)	SEM—Demeaned (4a)	Bid-Ask Spread (4b)	SEM—Demeaned (4a)	Bid-Ask Spread (4b)
Observations	3341	3341	3341	3341	3341	3341	3341	3341
Number of bonds	229	229	229	229	229	229	229	229
R ² /within R ²	0.781	0.787	0.100	0.373	0.371	0.086	0.371	0.086
Adj. R ² /adj. within R ²	0.778	0.785	0.094	0.368	0.366	0.080	0.366	0.080
Financial market controls	Yes	Yes	No	Yes	Yes	No	Yes	No
Bond specific controls	Yes	Yes	No	No	No	No	No	No
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table shows the determinants of yield spreads. Model (1) applies OLS and model (2) is a simultaneous equations model. For the yield spread (2a), *SP500 Return*, *BB Yield Index Models*, *1-Month Treasury*, *Slope Yield Curve*, *Trigger Indemnity*, *US*, *HU*, and *Coupon* are exogenous variables; for the bid-ask spread (2b), *Maturity* and *Issued Volume* are exogenous variables. Model (3) and (4) present corresponding results for an FE model and an SEM model with demeaned variables, respectively, to explain within bond variation. Explanatory variables correspond to the time-variant variables of model (1) and (2). Year-quarter fixed effects and financial market controls capture common changes in market conditions. All standard errors are clustered at bond level and robust to heteroscedasticity. *t* Values are shown in parentheses.

+, *, **, and *** indicate statistical significance at the 10%, 5%, 1%, and 0.1% levels, respectively.

days, the current yield on BB-rated corporate bonds, the 1-month treasury yield and the slope of the yield curve. Furthermore, we control for common bond properties such as the time to maturity, the issued volume and the coupon, but some control variables are also cat bond specific properties such as trigger type and peak peril regions. Year-quarter fixed effects capture unobserved heterogeneity in general market conditions. The coefficient of bid-ask spread implies that a 1 bp change of bid-ask spreads is associated with 10 bps change of yield spreads, which is statistically significant at the 5%-level.

Model (2) contains results for the SEM that pools all observations to account for possible remaining endogeneity between yield spreads and bid-ask spreads after we control for exogenous default risk. For the yield spread in column (2a), *Reinsurance Index*, *SP500 Return*, *BB Yield Index Models*, *1-Month Treasury*, *Slope Yield Curve*, *Trigger Indemnity*, *US*, *HU* and *Coupon* are exogenous variables. For the bid-ask spread in column (2b), *Maturity* and *Issued Volume* are exogenous variables. In Model (2), the coefficient for bid-ask spread remains highly statistically significant at the 1%-level. Its magnitude increases to roughly 12 bps change of yield spreads per bp change of the bid-ask spread.⁶⁴ The similar coefficients indicate that endogeneity concerns—for example dealers incorporating some yield spread information in their transaction pricing—seem to be negligible in the presence of cat bonds with exogenous default risk. We therefore find strong evidence that liquidity is priced in the secondary cat bond market and materially impacts the bonds' yield spreads. Investors demand a compensation for a cat bond if this bond is more difficult to sell.

Previously, we quantified the liquidity premium for cat bonds with pooled OLS and pooled SEM. Next, we use FE models that quantify the liquidity effect for within bond changes and control for unobserved constant bond properties. Table 5 contains the results for an FE model (Model 3) and an SEM (Model 4) with demeaned variables. The FE model (3) is in line with our results for pooled OLS. However, the slightly lower coefficient implies that the change in liquidity within bonds has a smaller effect on yield spreads. According to the FE model, a 1 bp change in bid-ask spread within bond is associated with an 8 bps change in yield-spread as opposed to 10 bps in model (1) for pooled OLS. This bid-ask spread coefficient is significant at the 5%-level.

Model (4) contains results for the SEM that uses demeaned variables to account for observed bond characteristics and explain within bond difference while accounting for possible endogeneity between yield spreads and bid-ask spreads. We consider the same exogenous variables as in model (2), except that time-invariant variables are omitted due to the within

⁶³A nonlinear relationship between yield spread and EL could more accurately explain yield spreads if, for example, investors demand a higher compensation per unit of EL when the EL is small. However, Galeotti et al. (2013) find that a nonlinear relationship only barely improves explanatory power and recommend using a linear relationship. Braun (2016) finds that predictive power is not higher for a nonlinear relationship of yield spread and EL. Nevertheless, we have also implemented a quadratic EL variable to model a nonlinear relationship of yield spread and EL. In this model, the quadratic term was not statistically significant and the coefficients of the EL and the bid-ask spread remained unchanged. Hence, a potential nonlinear relationship of yield spread and EL does not bias our results. Detailed results are available upon request.

⁶⁴For bonds with an indemnity trigger, the default event is related to the actual losses of the sponsoring insurer. However, loss assessment can take months or even years. Hence, it can take a very long time till an indemnity bond is officially declared defaulted. Investors might want to trade on potential loss information during the period of loss assessment. For parametric bonds on the other hand, a cat bond default is determined almost immediately after the specified event. Hence, being able to buy and sell a cat bond quickly can be more appealing to investors of an indemnity bond than for non-indemnity bonds. Therefore, liquidity could be more strongly priced for indemnity bonds. In undisclosed results, where we include an interaction term of bid-ask spread and a dummy variable for the indemnity trigger, we find that liquidity is more strongly priced for indemnity bonds. Detailed results are available upon request.

transformation. In model (4) the coefficient for bid-ask spread change remains highly statistically significant at the 1%-level. Its magnitude increases to roughly 9 bps change of yield spreads per bp change of bid-ask spread. In column (4b), the remaining maturity as the exogenous variable for bid-ask spreads has a highly statistically significant influence on bid-ask spread. For within bond changes, this connection is even larger than for the pooled models (1) and (2). Overall, we can identify a substantial impact of changes in liquidity on yield spreads within bonds.

It is interesting to relate the size of the pooled OLS and FE coefficients to Chen et al. (2007). In their pooled OLS setting, they find a bid-ask spread coefficient of 2.30. In their SEM setting, the bid-ask spread coefficient is 12.13—almost five times the size of the pooled OLS coefficient—highlighting the severe endogeneity problem in their OLS estimation. Our results for bonds with exogenous default risk strongly support these results because our estimated coefficients in the pooled setting are close to the SEM result from Chen et al. (2007). For their FE models, Chen et al. (2007) report a coefficient of 2.46 in the OLS setting and 12.47 in the SEM setting. Although the coefficients we find in our FE models are smaller than the SEM coefficient from Chen et al. (2007), the similar magnitude still supports the overall notion of Chen et al. (2007). In line with Braun (2016) and Gürtler et al. (2016), who used issued volume and remaining maturity as liquidity measures, we do not find these variables to be strongly related to the yield spread. For remaining maturity, there is no statistically significant relation to the yield spread. For issued volume, we find a negative coefficient, which indicates that a one standard deviation increase in issued volume dampens yield spreads by 7 bps. However, we do not further investigate this result because this coefficient is only barely significant at the 10%-level. Instead, the bid-ask spread is the dominant liquidity variable.

Overall, we can confirm *H2.1* on the general liquidity premium not only based on pooled OLS and FE regressions but also based on respective SEM models. Exploiting exogenous default risk from natural catastrophes, our results are not affected by endogeneity and therefore support the corporate bond literature on the liquidity premium. Since the estimated coefficients are relatively similar in the pooled models, we use the bid-ask spread coefficient for pooled OLS to quantify the liquidity premium on the cat bond market. Based on an average bid-ask spread in the sample of 9.5 bps and a bid-ask spread coefficient of 10.3 in model (1) of Table 5, we determine an average liquidity premium of 97.9 bps. Even if the magnitude of bid-ask spreads is mostly rather small, a large proportion of yield spreads—around 21%—can be attributed to the liquidity premium.

4.4.2 | Liquidity premium and default risk

Previous research has found the liquidity premium to be higher for bonds of low rating categories (e.g., Chen et al., 2007; Dick-Nielsen et al., 2012). To investigate liquidity effects for differing categories of riskiness, we have formed two subsamples, separated by a rating cutoff. Generally, the share of rated cat bond issues has declined substantially in the past: 70% of all cat bond issues that are contained in our TRACE subsamples have not received a rating. At the same time, the heterogeneity of ratings is very low; only BB and B ratings can be observed in the market. However, we acquired a second data set from Lane Financials and artemis.bm that contains all cat bond issues from 2002 to 2019. This data set contains 390 rated cat bond issues. We use this data set to create a naïve binary rating model that allows us to assign the rating categories “BB rating or better” or “B rating or worse” to all cat bonds from the TRACE data set.

We assign these rating categories based on a probit regression that selects a cat bond into the BB rating or better category against the B rating or worse category depending on the EL at issue, its trigger type, coupon and volume, as well as peak peril, peak region and multi-peril dummies. The most important variable in this rating model is the EL.⁶⁵ After the application of the naïve rating model, 117 bonds of our sample have a “BB rating or better” and 112 have a “B rating or worse.”

Table 6 contains liquidity effects on yield spreads for the BB rating cutoff. All models include the same explanatory variables as Table 5. For pooled OLS in models (1) and (2) and FE regressions in models (3) and (4), the coefficients for bid-ask spreads increase more than threefold when comparing rating categories “B or worse” versus “BB or better.” This indicates that the liquidity effect is much more pronounced for cat bonds of a high-risk category. In models (5)–(8) we apply an alternative cutoff of 153bps of $EL_{initial}$. This cutoff value was selected to separate the sample into two subsamples of roughly equal size.⁶⁶ Again, the coefficients for the bid-ask spreads increase more than threefold, indicating a liquidity effect that is much more pronounced for cat bonds of a high-risk category. Hence, we confirm *H2.2* on a higher liquidity premium for risky bonds.

According to the results in Table 6, we can quantify different liquidity premiums for different default risk categories. Based on an average bid-ask spread in the low-risk “BB or better” subsample of 9.4 bps and a bid-ask spread coefficient of 4.3 in model (1), we determine an average liquidity premium of 39.5 bps. For this subsample, 11.3% of yield spreads can be attributed to the liquidity premium. For the high-risk “B or worse” subsample, the premium is much larger. Slightly higher average bid-ask spreads of 9.6 bps and a coefficient of 14.8 in model (2) result in an average liquidity premium of 141.1 bps, implying that 22.5% of yield spreads can be attributed to the liquidity premium.

4.4.3 | Liquidity premium and market liquidity

In Table 7, we investigate market liquidity effects that were previously absorbed in the year-quarter fixed effects in Table 5. To better control for reinsurance market conditions in the absence of year-quarter fixed effects, we have included the Guy Carpenter Rate-On-Line index, which controls for general reinsurance market prices. Braun (2016) and Gürtler et al. (2016) have shown that the level of reinsurance prices is positively related to the yield spreads on cat bonds. As a measure for market liquidity, we use the mean bid-ask spread of the current quarter. In model (1) and (3), we present the results for OLS and FE models without the market liquidity measure, whereas this measure is included in the corresponding models (2) and (4). Model (2) for OLS and model (4) for FE regressions indicate that the average bid-ask spread across all cat bond trades in the current quarter is positively related to the yield spread of cat bonds. As suggested by model (2), a 1 bp change on average market spreads is associated with 8 bps change in yield spreads. Similarly, according to model (4) a 1 bp change on average market spreads is associated with an 11 bps change in yield spreads within bond. Both coefficients are significant at the 0.1%-level. In line with *H3*, these results confirm that market wide liquidity has a substantial impact on the yield spread of cat bonds.

⁶⁵Detailed results on the naïve rating model are available upon request.

⁶⁶As an alternative to the EL cutoff, we also implemented a spread at issue cutoff. Results remained unchanged. Detailed results are available upon request.

TABLE 6 Liquidity premium and default risk

Dependent variable	Yield Spread							
	OLS (1)	B or worse OLS (2)	BB or better FE (3)	B or worse FE (4)	EL _{initial} < 153 bps OLS (5)	EL _{initial} ≥ 153 bps OLS (6)	EL _{initial} < 153 bps FE (7)	EL _{initial} ≥ 153 bps FE (8)
Bid-Ask Spread	4.247* (2.47)	14.701* (2.34)	2.828 ⁺ (1.98)	12.447 ⁺ (1.95)	4.142* (2.20)	13.558* (2.31)	2.596 (1.64)	11.436 ⁺ (1.96)
Obs.	1943	1398	1943	1398	1666	1675	1666	1675
Number of bonds	117	112	117	112	97	132	97	132
R ² /within R ²	0.413	0.839	0.270	0.518	0.411	0.805	0.316	0.453
Adj. R ² /adj. within R ²	0.404	0.836	0.260	0.510	0.400	0.801	0.306	0.444
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table shows the liquidity premium for subsamples of different rating classes and expected loss categories. Models (1)–(4) use the imputed BB Rating as a cutoff. Models (5)–(8) use an EL_{initial} of 153 bps as a cutoff. All standard errors are clustered at bond level and robust to heteroscedasticity. *t* Values are shown in parentheses.

⁺and * indicate statistical significance at the 10% and 5% levels, respectively.

TABLE 7 Liquidity premium and market liquidity

Dependent variable	Yield Spread			
	OLS (1)	OLS (2)	FE (3)	FE (4)
Bid-Ask Spread	11.199** (2.80)	10.810** (2.73)	8.747* (2.36)	8.260* (2.25)
Bid-Ask Spread Market Quarter		8.032*** (3.76)		10.617*** (5.95)
EL _{initial}	1.191*** (9.12)	1.190*** (9.07)		
EL _{S-us}	1.195*** (5.08)	1.192*** (5.04)	1.218*** (5.15)	1.219*** (5.24)
EL _{S-eu}	0.878*** (4.70)	0.875*** (4.67)	0.347* (1.98)	0.351* (2.08)
Multi-P/L	22.767 (1.16)	22.997 (1.17)		
EL _{S-us} # Multi-P/L	0.037 (0.13)	0.053 (0.18)	-0.551 ⁺ (-1.94)	-0.526 ⁺ (-1.87)
Maturity	-1.481 (-0.23)	-1.217 (-0.19)	93.428*** (6.92)	109.873*** (7.95)
Constant	-532.424*** (-3.88)	-654.302*** (-4.74)	28.723 (0.22)	-48.318 (-0.38)
Observations	3341	3341	3341	3341
Number of bonds	229	229	229	229
R ² /within R ²	0.771	0.773	0.336	0.349
Adj. R ² /adj. within R ²	0.770	0.771	0.334	0.347
Financial market controls	Yes	Yes	Yes	Yes
Bond specific controls	Yes	Yes	No	No
Year-Quarter FE	No	No	No	No

Note: This table shows regression results for yield spreads on market liquidity. Models (1) and (2) are pooled OLS models. Models (3) and (4) apply fixed effects transformations. All standard errors are clustered at bond level and robust to heteroscedasticity. *t* Values are shown in parentheses and robust to heteroscedasticity.

⁺, *, **, and *** indicate statistical significance at the 10%, 5%, 1%, and 0.1% levels, respectively.

5 | CONCLUSION

We provide first empirical insights into trading activity and liquidity of cat bonds. The trading activity on the secondary market of cat bonds fluctuates within a calendar year. We observe that trading is less frequent during the peak of the US hurricane season from July to September; moreover, cat bonds are more often traded when they are closer to maturity. We find that reduced cat bond trading during the hurricane season can also be observed when adverse hurricane events actually occur because the seasonality-implied default risk substantially increases. On the

contrary, for the trading behavior of corporate bonds the information effect dominates, leading to elevated trading in such periods with much new information arriving in the market.

Considering that most buy and sell orders are matched within a 60-min time window, this indicates the market is dominated by brokers without a proprietary inventory. This means the bid-ask spreads on the cat bond market mostly reflect broker search and execution costs, whereas they should not contain large markups for adverse selection costs or capital costs from inventories. We find that a cat bond's liquidity is related to its current default risk, its remaining time to maturity, and the market's current liquidity: Bid-ask spreads are lower when a bond is less risky and bonds are more frequently traded when a bond approaches its maturity, which results from lower order processing cost. Additionally, we find the bid-ask spread to be smaller when there is a lot of trading in the current quarter. Regarding the liquidity premium, we find liquidity to be more strongly priced for bonds with high default risk. Moreover, we find the overall market liquidity to have an impact on the individual yield spreads.


In addition to providing novel insights into secondary market trading and liquidity for cat bonds, we contribute to the general corporate bond literature through the identification and quantification of liquidity effects based on cat bonds with strictly exogenous default risk from natural catastrophes. Overall, we find strong evidence for a substantial liquidity premium. These results are robust to endogeneity due to the exogenous nature of catastrophe events and hold after controlling for other potential sources of endogeneity between yield spreads and dealer setting of bid-ask spreads by employing simultaneous equations models. We find that a 1 bp change of bid-ask spread is associated with roughly 10 bps change of yield spread. We find that on average 97.9 bps of yield spread can be attributed to a cat bond's liquidity. Relatively speaking, 21.0% of the cat bond market's yield spread can be attributed to the liquidity premium. The magnitude of the liquidity premium varies substantially depending on the default risk of a bond: While the absolute (relative) liquidity premium accounts for 39.5 bps (11.3%) of yield spreads for bonds with low default risk ("BB or better"), this premium increases to 141.1 bps (22.5%) for bonds with high default risk ("B or worse"). Given a volume of US\$ 40 billion for outstanding cat bonds, this means that the (re-)insurance industry paid a liquidity premium of US\$ 391 million on transferred extreme event risk in 2019. If insurance companies want to take steps to reduce this substantial liquidity premium, they should work towards improving the aggregate liquidity of the market, for example, through a joint effort by setting up a central market maker or supporting existing dealers, as Eldor et al. (2006) find that market makers substantially improve the liquidity of a market. If industry-wide cooperation is infeasible, they could improve their own issuances' liquidity by offering supporting dealer services. A further possibility to reduce the liquidity premium could be to issue rather low-risk or short-term cat bonds, which generally express lower bid-ask spreads; though, the additional fixed costs for more frequent issues could eliminate the intended benefits.

ACKNOWLEDGMENTS

The authors thank the participants of the World Risk and Insurance Economics Congress 2020 for helpful comments. We are grateful for financial support from the German Insurance Science Association (DVfVW). Open Access funding enabled and organized by Projekt DEAL.

ORCID

Markus Herrmann  <http://orcid.org/0000-0001-8893-9685>

Martin Hibbeln  <http://orcid.org/0000-0003-2350-9830>

REFERENCES

- Acharya, V. V., & Pedersen, L. H. (2005). Asset pricing with liquidity risk. *Journal of Financial Economics*, 77(2), 375–410.
- Acharya, V. V., Amihud, Y., & Bharath, S. T. (2013). Liquidity risk of corporate bond returns: Conditional approach. *Journal of Financial Economics*, 110(2), 358–386.
- Amihud, Y. (2002). Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets*, 5(1), 31–56.
- Amihud, Y., & Mendelson, H. (1986). Asset pricing and the bid-ask spread. *Journal of Financial Economics*, 17(2), 223–249.
- Aon Securities. (2017). *Insurance-linked securities: Alternative capital breaks new boundaries*.
- Aon Securities. (2019). *ILS annual report 2019: Alternative capital: Strength through disruption*.
- Aon Securities. (2020). *ILS annual report 2020: Alternative capital: Growth potential and resilience*.
- Asquith, P., Covert, T., & Pathak, P. A. (2019). *The effects of mandatory transparency in financial market design: Evidence from the corporate bond market* (working paper). Available at SSRN: <http://dx.doi.org/10.2139/ssrn.2320623>
- Bai, J., Goldstein, R. S., & Yang, F. (2020). Is the credit spread puzzle a myth? *Journal of Financial Economics*, 137(2), 297–319.
- Bao, J., Pan, J., & Wang, J. (2011). The illiquidity of corporate bonds. *Journal of Finance*, 66(3), 911–946.
- BCBS. (2019). *The basel framework*. Basel Committee on Banking Supervision. Retrieved March 23, 2022, from https://www.bis.org/basel_framework
- Ben Ammar, S. (2020). Catastrophe risk and the implied volatility smile. *Journal of Risk and Insurance*, 87(2), 381–405.
- Berg, G., & Schrader, J. (2012). Access to credit, natural disasters, and relationship lending. *Journal of Financial Intermediation*, 21(4), 549–568.
- Bessembinder, H., Spatt, C., & Kumar, V. (2020). A survey of the microstructure of fixed-income markets. *Journal of Financial and Quantitative Analysis*, 55(1), 1–45.
- Black, J. R., Stock, D., & Yadav, P. K. (2016). The pricing of different dimensions of liquidity: Evidence from government guaranteed bonds. *Journal of Banking & Finance*, 71, 119–132.
- Braun, A. (2016). Pricing in the primary market for cat bonds: New empirical evidence. *Journal of Risk and Insurance*, 83(4), 811–847.
- Braun, A., Ben Ammar, S., & Eling, M. (2019). Asset pricing and extreme event risk: Common factors in ILS fund returns. *Journal of Banking & Finance*, 102, 59–78.
- Campbell, J. Y., & Taksler, G. B. (2003). Equity volatility and corporate bond yields. *Journal of Finance*, 58(6), 2321–2350.
- Chen, H., Cui, R., He, Z., & Milbradt, K. (2018). Quantifying liquidity and default risks of corporate bonds over the business cycle. *Review of Financial Studies*, 31(3), 852–897.
- Chen, L., Lesmond, D. A., & Wei, J. (2007). Corporate yield spreads and bond liquidity. *Journal of Finance*, 62(1), 119–149.
- Chordia, T., Sarkar, A., & Subrahmanyam, A. (2004). An empirical analysis of stock and bond market liquidity. *Review of Financial Studies*, 18(1), 85–129.
- Cortés, K. R., & Strahan, P. E. (2017). Tracing out capital flows: How financially integrated banks respond to natural disasters. *Journal of Financial Economics*, 125(1), 182–199.
- Corwin, S. A., & Schultz, P. (2012). A simple way to estimate bid-ask spreads from daily high and low prices. *Journal of Finance*, 67(2), 719–760.
- Dick-Nielsen, J. (2009). Liquidity biases in TRACE. *Journal of Fixed Income*, 19(2), 43–55.
- Dick-Nielsen, J. (2014). *How to clean enhanced TRACE data* (working paper). Available at SSRN: <http://dx.doi.org/10.2139/ssrn.2337908>
- Dick-Nielsen, J., Feldhütter, P., & Lando, D. (2012). Corporate bond liquidity before and after the onset of the subprime crisis. *Journal of Financial Economics*, 103(3), 471–492.
- Duffie, D., Garleanu, N., & Pedersen, L. H. (2005). Over-the-counter markets. *Econometrica*, 73(6), 1815–1847.
- Duffie, D., Garleanu, N., & Pedersen, L. H. (2007). Valuation in over-the-counter markets. *Review of Financial Studies*, 20(6), 1865–1900.

- Döhrmann, D., Gürtler, M., & Hibbeln, M. (2017). Insured loss inflation: How natural catastrophes affect reconstruction costs. *Journal of Risk and Insurance*, 84(3), 851–879.
- Edwards, A. K., Harris, L. E., & Piwowar, M. S. (2007). Corporate bond market transaction costs and transparency. *Journal of Finance*, 62(3), 1421–1451.
- Eldor, R., Hauser, S., Pilo, B., & Shurki, I. (2006). The contribution of market makers to liquidity and efficiency of options trading in electronic markets. *Journal of Banking & Finance*, 30(7), 2025–2040.
- Ericsson, J., & Renault, O. (2006). Liquidity and credit risk. *Journal of Finance*, 61(5), 2219–2250.
- Fabozzi, F. J., & Mann, S. V. (2000). *Floating-rate securities*. Frank J. Fabozzi Assoc.
- Feldhütter, P. (2012). The same bond at different prices: Identifying search frictions and selling pressures. *Review of Financial Studies*, 25(4), 1155–1206.
- Feldhütter, P., & Schaefer, S. M. (2018). The myth of the credit spread puzzle. *Review of Financial Studies*, 31(8), 2897–2942.
- Finken, S., & Laux, C. (2009). Catastrophe bonds and reinsurance. *Journal of Risk and Insurance*, 76(3), 579–605.
- Friewald, N., Jankowitsch, R., & Subrahmanyam, M. G. (2012). Illiquidity or credit deterioration: A study of liquidity in the US corporate bond market during financial crises. *Journal of Financial Economics*, 105(1), 18–36.
- Galeotti, M., Gürtler, M., & Winkelvos, C. (2013). Accuracy of premium calculation models for CAT bonds: An empirical analysis. *Journal of Risk and Insurance*, 80(2), 401–421.
- Gehde-Trapp, M., Schuster, P., & Uhrig-Homburg, M. (2018). The term structure of bond liquidity. *Journal of Financial and Quantitative Analysis*, 53(5), 2161–2197. <https://doi.org/10.1017/s0022109018000364>
- Goldstein, M. A., & Hotchkiss, E. S. (2020). Providing liquidity in an illiquid market: Dealer behavior in US corporate bonds. *Journal of Financial Economics*, 135(1), 16–40.
- Goyenko, R., Subrahmanyam, A., & Ukhov, A. (2011). The term structure of bond market liquidity and its implications for expected bond returns. *Journal of Financial and Quantitative Analysis*, 46(1), 111–139.
- Green, R. C., Hollifield, B., & Schürhoff, N. (2007). Financial intermediation and the costs of trading in an opaque market. *Review of Financial Studies*, 20(2), 275–314.
- Götze, T., & Gürtler, M. (2019). Hard markets, hard times: On the inefficiency of the CAT bond market. *Journal of Corporate Finance*, 62. <https://doi.org/10.1016/j.jcorpfin.2019.101553>
- Gürtler, M., Hibbeln, M., & Winkelvos, C. (2016). The impact of the financial crisis and natural catastrophes on CAT bonds. *Journal of Risk and Insurance*, 83(3), 579–612.
- Han, S., & Zhou, H. (2007). *Nondefault bond spread and market trading liquidity* (technical report). Federal Reserve Board.
- He, Z., & Milbradt, K. (2014). Endogenous liquidity and defaultable bonds. *Econometrica*, 82(4), 1443–1508.
- Herrmann, M., & Hibbeln, M. (2021). Seasonality in catastrophe bonds and market-implied catastrophe arrival frequencies. *Journal of Risk and Insurance*, 88(3), 785–818.
- Hong, G., & Warga, A. (2000). An empirical study of bond market transactions. *Financial Analysts Journal*, 56(2), 32–46.
- Huang, J.-Z., & Huang, M. (2012). How much of the corporate-treasury yield spread is due to credit risk? *Review of Asset Pricing Studies*, 2(2), 153–202.
- Huang, R. D., & Stoll, H. R. (1997). The components of the bid-ask spread: A general approach. *Review of Financial Studies*, 10(4), 995–1034.
- Jarrow, R. A. (2010). A simple robust model for cat bond valuation. *Finance Research Letters*, 7(2), 72–79.
- Kempf, A., Korn, O., & Uhrig-Homburg, M. (2012). The term structure of illiquidity premia. *Journal of Banking & Finance*, 36(5), 1381–1391.
- Koetter, M., Noth, F., & Rehbein, O. (2020). Borrowers under water! Rare disasters, regional banks, and recovery lending. *Journal of Financial Intermediation*, 43, 100811.
- Lane, M. (2000). Pricing risk transfer transactions. *ASTIN Bulletin: The Journal of the International Actuarial Association*, 30(2), 259–293.
- Lane, M., & Mahul, O. (2008). *Catastrophe risk pricing: An empirical analysis* (Policy Research Working Paper, 4765). The World Bank.
- Lane, M., & Roger B. (2016). *TRACE data twenty one months on—ILS trade or quote data? Annual review of four quarters, Q2 2015 to Q1 2016*. Lane Financials LLC.

- Lee, J.-P., & Yu, M.-T. (2002). Pricing default-risky CAT bonds with moral hazard and basis risk. *Journal Risk and Insurance*, 69(1), 25–44.
- Lesmond, D. A., Ogden, J. P., & Trzcinka, C. A. (1999). A new estimate of transaction costs. *Review of Financial Studies*, 12(5), 1113–1141.
- Li, D., Schürhoff, N. (2019): Dealer networks. In: *Journal of Finance*, 74(1), 91–144.
- Lin, H., Wang, J., & Wu, C. (2011). Liquidity risk and expected corporate bond returns. *Journal of Financial Economics*, 99(3), 628–650.
- Longstaff, F. A., Mithal, S., & Neis, E. (2005). Corporate yield spreads: default risk or liquidity? New evidence from the credit default swap market. *Journal of Finance*, 60(5), 2213–2253.
- Macchiavelli, M., & Xing Z. (2022). Funding liquidity and market liquidity: The broker-dealer perspective. *Management Science*, 68(5), 3379–3398.
- Major, J. A., & Kreps, R. E. (2002). Catastrophe risk pricing in the traditional market. In M. N. Lane (Ed.), *Alternative Risk Strategies* (pp. 201–222). Risk Books.
- Poliquin, B., & Lalonde, D. (2012). Role of catastrophe risk modelling in ILS. In M. Lane (Ed.), *Alternative (re) insurance strategies* (pp. 195–218). Risk Books.
- Pu, X. (2009). Liquidity commonality across the bond and CDS markets. *Journal of Fixed Income*, 19(1), 26–39.
- Risk Management Solutions. (2012). *Cat bonds demystified: RMS guide to the asset class*.
- Roll, R. (1984). A simple implicit measure of the effective bid-ask spread in an efficient market. *Journal of Finance*, 39(4), 1127–1139.
- Schestag, R., Schuster, P., & Uhrig-Homburg, M. (2016). Measuring liquidity in bond markets. *Review of Financial Studies*, 29(5), 1170–1219.
- Schultz, P. (2017). *Inventory management by corporate bond dealers* (working paper). Available at SSRN: <https://ssrn.com/abstract=2966919>
- Schuster, P., & Uhrig-Homburg, M. (2015). Limits to arbitrage and the term structure of bond illiquidity premiums. *Journal of Banking & Finance*, 57, 143–159.
- Schüwer, U., Lambert, C., & Noth, F. (2019). How do banks react to catastrophic events? Evidence from hurricane katrina. *Review of Finance*, 23(1), 75–116.
- Schwarz, K. (2019). Mind the gap: Disentangling credit and liquidity in risk spreads. *Review of Finance*, 23(3), 557–597.
- Swiss Re. (2019). *Insurance-linked securities market update* (Vol. XXXI).
- Swiss Re. (2020). *Insurance-linked securities market update* (Vol. XXXII).
- Swiss Re (2021). *Insurance-linked securities market insights* (Vol. XXXIV).
- Towers Watson (2010). Catastrophe bonds evolve to address credit risk issues.
- Towers Watson (2017). *Insurance-linked securities glossary*.
- Zhao, Y., & Yu, M.-T. (2019). Measuring the liquidity impact on catastrophe bond spreads. *Pacific-Basin Finance Journal*, 56, 197–210.

How to cite this article: Herrmann, M., & Hibbeln, M. (2023). Trading and liquidity in the catastrophe bond market. *Journal of Risk and Insurance*, 90, 283–328.
<https://doi.org/10.1111/jori.12407>

APPENDIX A: ALTERNATIVE LIQUIDITY MEASURE

We rerun our main analysis with the effective bid-ask spread from Hong and Warga (2000) to highlight the robustness of our main empirical analysis in Section 4.4.1 and Table 5. Instead of matching individual trades to compute the round-trip measure, we determine bid-ask spreads by subtracting the daily (volume-weighted) average price of buy transactions from the daily average price of sell transactions. This way, we avoid matching individual trades altogether. This condenses our data set to a strictly daily sample. Hence, we avoid potential inaccuracies

TABLE A1 Liquidity premium with effective bid-ask spreads

Dependent variable	Yield spread		Yield spread		Yield spread		Yield spread		Yield spread		Yield spread	
	OLS (1)	SEM—Pooled (2a)	SEM—Pooled (2a)	Bid-ask spread (2b)	FE (3)	SEM—Demeaned (4a)	Bid-ask spread (2b)	FE (3)	SEM—Demeaned (4a)	Bid-ask spread (2b)	Bid-ask spread (4b)	
Bid-ask spread—volume-weighted average	11.639** (2.70)	13.094** (3.14)			9.608* (2.35)	10.569* (2.56)						
Yield spread				-0.002 (-0.33)								-0.001 (-0.13)
EL _{initial}	1.171*** (8.65)	1.177*** (9.07)		0.004 (0.64)								
EL _{s-us}	1.178*** (4.73)	1.191*** (4.69)		0.013* (2.15)	1.203*** (4.92)	1.197*** (5.07)						0.018 (1.18)
EL _{s-eu}	0.907*** (4.88)	0.898*** (4.62)		0.009 (1.36)	0.390* (2.41)	0.384* (2.29)						0.002 (0.30)
Multi-P/L	27.237 (1.38)	32.224 ⁺ (1.75)		-0.045 (-0.13)								
EL _{s-us} # Multi-P/L	0.112 (0.38)	0.090 (0.31)		-0.004 (-0.96)	-0.518 ⁺ (-1.90)	-0.528 ⁺ (-1.92)						-0.010 (-1.25)
Maturity	0.317 (0.05)			0.527*** (5.48)	-2.258 (-0.06)							0.877*** (4.65)
Issued Volume	-0.050 ⁺ (-1.86)			-0.000 (-0.33)								
Coupon	0.149 (1.63)	0.145 ⁺ (1.65)										
Constant	-125.693 (-1.36)	-154.730 (-1.45)		8.895*** (7.44)	369.509 ⁺ (1.94)	198.179** (2.80)						-0.031 (-0.15)

TABLE A1 (Continued)

Dependent variable	Yield spread		Bid-ask spread		Yield spread		Bid-ask spread	
	OLS (1)	SEM—Pooled (2a)	(2b)	FE (3)	SEM—Demeaned (4a)	(4b)		
Observations	3090	3090	3090	3090	3090	3090		
Number of bonds	230	230	230	230	230	230		
R ² /within R ²	0.787	0.795	0.099	0.383	0.375	0.088		
Adj. R ² /adj. within R ²	0.785	0.793	0.092	0.378	0.370	0.081		
Financial market controls	Yes	Yes	No	Yes	Yes	No		
Bond specific controls	Yes	Yes	No	No	No	No		
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes		

Note: This table shows the determinants of yield spreads. As a liquidity measure, this table uses the effective bid-ask spread of Hong and Warga (2000) instead of the round-trip measure. Model (1) applies ordinary least squares (OLS) and model (2) a simultaneous equations model. For the yield spread (2a), *SP500 Return*, *BB Yield Index Models*, *1-Month Treasury*, *Slope Yield Curve*, *Trigger Indemnity*, *US*, *HU*, and *Coupon* are exogenous variables; for the bid-ask spread (2b), *Maturity* and *Issued Volume* are exogenous variables. Model (3) and (4) present corresponding results for a fixed effects (FE) model and a standard error of the means (SEM) model with demeaned variables, respectively, to explain within bond variation. Explanatory variables correspond to the time-variant variables of model (1) and (2). Year-quarter fixed effects and financial market controls capture common changes in market conditions. All standard errors are clustered at bond level and robust to heteroscedasticity. *t* Values are shown in parentheses.

+, *, **, and *** indicate statistical significance at the 10%, 5%, 1%, and 0.1% levels, respectively.

from matching for the cost of slightly fewer observations. Additionally, we can utilize some trades from the raw data set that were previously unmatched: In this robustness check, we use 92% of all trades, whereas previously, 86% of all trades were matched.

Table A1 contains our results for the effective bid-ask spread. Compared to our main analysis in Table 5, statistical significance remains high and the coefficients of the variables of interest are similar but slightly increased. Hence, our previous empirical results remain stable when we employ the effective bid-ask spread from Hong and Warga (2000) as an alternative methodology to measure liquidity.