JOURNAL OF FINANCIAL AND QUANTITATIVE ANALYSIS © THE AUTHOR(S), 2024. PUBLISHED BY CAMBRIDGE UNIVERSITY PRESS ON BEHALF OF THE MICHAEL G. FOSTER SCHOOL OF BUSINESS, UNIVERSITY OF WASHINGTON doi[:10.1017/S0022109024000176](https://doi.org/10.1017/S0022109024000176)

Market Liquidity in a Natural Experiment: Evidence from CDS Standard Coupons

Xinjie Wang

Department of Finance, Business School, Southern University of Science and Technology xinjie.wang@sustech.edu.cn (corresponding author)

Ge Wu Robins School of Business, University of Richmond gwu@richmond.edu

Zhaodong (Ken) Zhong Department of Finance and Economics, Rutgers Business School, Rutgers University zdzhong@business.rutgers.edu

Abstract

The credit default swap (CDS) Big Bang introduced 2 standard coupons for CDS trading. We exploit the setting of the 2 standard coupons as a natural experiment to quantify the ADSITACI
The credit default swap (CDS) Big Bang introduced 2 standard coupons for CDS trading. We
exploit the setting of the 2 standard coupons as a natural experiment to quantify the
components of the bid–ask spreads in o The credit default swap (CDS) Big Bang introduced 2 standard coupons for CDS trading. We exploit the setting of the 2 standard coupons as a natural experiment to quantify the components of the bid–ask spreads in over-the-c difference in funding costs. Furthermore, search intensity also explains the variation in the difference in bid–ask spreads in over-the-counter markets. We find that a significant portion of the difference in the bid–ask spread between the 2 coupons is explained by the difference in funding costs. Furthermore, sear coupons and can suddenly switch to the other coupon. Using the sudden switch of the primary coupon, we provide further evidence to support the predictions of search-based liquidity models.

I. Introduction

In over-the-counter (OTC) markets, buyers and sellers typically arrive in markets at different time points, and thus transactions are facilitated by market makers who provide bid and ask quotes along with a certain market size. Market In over-the-counter (OTC) markets, buyers and sellers typically arrive in markets at different time points, and thus transactions are facilitated by market makers who provide bid and ask quotes along with a certain market making incurs various costs, including order processing costs, costs related to making incurs various costs, including order processing costs, costs related to adverse selection, and funding costs (Brunnermeier and Pedersen ([2009\)](#page-25-0)). In OTC markets, market making has an additional cost component relate OTC markets, market making has an additional cost component related to search activities. When there are more buyers and sellers present in the markets, it is easier spread would be lower (Duffie, Garleanu, and Pedersen [\(2005](#page-25-1))). Despite the outstanding notional of the credit default swap (CDS) market being more than

We are grateful for the valuable comments from an anonymous referee, Raymond Fishe, Esen Onur, George Pennacchi (the editor), Julia Reynolds (discussant), Michel Robe, and Hongjun Yan as well as from conference or seminar participants of the 2022 Financial Management Association Annual Meeting and Commodity Futures Trading Commission. Wang acknowledges financial support from the National Natural Science Foundation of China (Project No. 72171107), Southern University of Science and Technology (Grant No. Y01246110), and Shenzhen Stability Support Program Project (Project No. 20231121095510002).

4 trillion USD at the end of 2020, the liquidity in this large market is not fully understood. This is partially because it is difficult to single out the effects of funding and search costs from the effects of firm fundamentals on liquidity. In this article, we exploit a natural experiment comprised of CDS standard coupons to fill this important gap in the literature.

A CDS contract was traditionally traded at a coupon rate that set the contract value to 0 on the inception day. This practice requires no upfront payments from CDS traders. However, it creates CDS contracts with a wide range of coupon rates, and offsetting CDS positions on the same underlying firm becomes difficult. To facilitate trade compression and central clearing, the International Swaps and Derivatives Association (ISDA) introduced a couple of contract and trading convention changes in the CDS market on Apr. 8, 2009, known as the CDS Big Bang.^{[1](#page-1-0)} Since this trading convention change, CDS contracts trade with 2 standardized coupons of 100 and 500 bps. It induces an upfront payment, which depends both on the CDS spread level and the fixed coupon rate. Investors make discretionary choices on which standard coupon to use. Quite often, CDS contracts with both standard coupons are traded on the same day. The coupon on which the largest number of unique dealers are quoting prices is called the "primary coupon" in our data, and the other coupon is called the "secondary coupon." The primary coupon can switch between 100 and 500 over time. We show that the switch occurs in order to minimize upfront payments, which depend on the level of CDS spreads. Bid and ask quotes on the 2 standard coupons are typically different, and sometimes the differences are quite large. Since the payoff of the protection bought is identical no matter which coupon is used, why are bid and ask quotes different between the 2 coupons? The differences in bid and ask quotes are related to the funding cost of upfront payments and the intensity of trading activities. When more buyers and sellers trade a contra quotes are related to the funding cost of upfront payments and the intensity of trading activities. When more buyers and sellers trade a contract with a particular the theory in Duffie et al. ([2005](#page-25-1)). Why would trading activities concentrate on one coupon instead of the other? The answer is mainly because investors prefer smaller upfront payments and trading activities would concentrate on the coupon that minimizes upfront payments.

The CDS standard coupons provide a unique setting to study the funding and search components of CDS liquidity with the effects of firm characteristics disentangled, since the effects of firm characteristics are identical for CDS contracts on the same underlying firms. Therefore, the coexistence of the standard coupons can help us eliminate the effects of order processing and adverse selection. This allows neip us chinnate the effects of order processing and adverse selection. This anows
us to focus on factors of interest (i.e., funding cost and search friction) that affect
liquidity without worrying about the effects of fir liquidity without worrying about the effects of firm characteristics. Using daily CDS data on 748 North American firms from Apr. 2010 to Sept. 2020, we examine cross-sectional variations in the difference in bid–ask spread CDS data on 748 North American firms from Apr. 2010 to Sept. 2020, we examine coupons are driven by funding costs and search frictions.

¹The purposes of standardizing CDS contracts are to improve operational efficiency, facilitate central clearing, and increase transparency. See Markit Research Paper "The CDS Big Bang: Understanding the Changes to the Global CDS Contract and North American Conventions" Mar. 13, 2009.

We first show that the difference in bid–ask spreads between the 2 standard coupons is positively associated with the difference in the cost of upfront payments. Upfront payments are an impediment to trading for both dealers and investors. We first show that the difference in bid–ask spreads between the 2 standard coupons is positively associated with the difference in the cost of upfront payments. Upfront payments are an impediment to trading for both deale ask spreads. In addition, when upfront payments are large, financially constrained investors find it either impossible or not economic to take on positions, which also Dealers compensate for their funding costs of upfront payments by widening bid-ask spreads. In addition, when upfront payments are large, financially constrained investors find it either impossible or not economic to take upfront payments between the standard coupons is larger, the difference in the bid– ask spread is also larger. This result provides support for the prediction in Brun-nermeier and Pedersen ([2009\)](#page-25-0) and is consistent with the empirical findings in Wang, Wu, Yan, and Zhong (2021). The economic magnitude of the funding effect is sizable. A 1-standard-deviation increase in upfront funding cos Wu, Yan, and Zhong [\(2021](#page-26-0)). The economic magnitude of the funding effect is sizable. A 1-standard-deviation increase in upfront funding cost leads to an increase of 0.66 bps in bid–ask spreads.
To further identify the relation between upfront funding costs and bid–ask

For factory are relation between upfront randing costs and ord-ask spreads, we exploit CDS contracts with different maturities. CDS contracts on the same entity with different maturities have identical firm characteristics same entity with different maturities have identical firm characteristics but different upfront payments. Typically, the longer the CDS maturity, the larger the upfront variation across maturities within firms. Specifically, our regression model includes firm and day fixed effects to control for all firm-specific effects. The estimated effect of upfront costs on bid–ask spreads using o
payment. We identify the effect of upfront costs on bid–ask spreads using o
variation across maturities within firms. Specifically, our regression model in
firm and day fi

Since the CDS Big Bang, single-name CDS trades may voluntarily be cleared through a central counterparty clearinghouse. CDS traders (especially dealers) having multiple positions with the same central counterparty can effectively net their positions and reduce upfront payments. Therefore, central clearing can partially alleviate funding effects. Consistent with this expectation, we provide evidence that the funding effects. Consistent with the same central counterparty can effectively net
their positions and reduce upfront payments. Therefore, central clearing can par-
tially alleviate funding effects. Consiste for centrally cleared CDS contracts. dence that the funding effect on the difference in bid–ask spreads is 0.83 bps smaller
for centrally cleared CDS contracts.
It is possible that a dealer would incorporate upfront funding costs into the
midpoint of the bid–

It is possible that a dealer would incorporate upfront funding costs into the the midpoint, we regress the difference in the midpoint between the 2 coupons on the difference in upfront funding costs between the 2 coupons and other relevant control variables. The results indicate that contracts with higher upfront costs are associated with a correspondingly higher midpoint of the spread. Furthermore, the difference in upfront funding costs between the 2 coupons on the difference in upfront funding costs between the 2 coupons and other relevant control variables. The results indicate that contracts with higher upfront c up, we investigate whether the funding effect on one side of the market is stronger than the other. As expected, the results show higher upfront funding costs have a greater impact on ask prices relative to bid prices. Finally, we show that there are assumed the old ask spread whether the funding effect on one side of the market is stronger than the other. As expected, the results show higher upfront funding costs have a greater impact on ask prices relative to bid pri than the other. As expected, the results show higher upfront funding costs have a greater impact on ask prices relative to bid prices. Finally, we show that there are asymmetric effects of the upfront funding cost on the b spread is about 0.47 bps higher when the dealer provides upfront payments. asymmetric effects of the upfront funding cost on the bid–ask spread depending on whether the dealer provides or receives funds for upfront payments. The bid–ask spread is about 0.47 bps higher when the dealer provides upf whether the dealer provides or receives funds for upfront payments. The bid–ask spread is about 0.47 bps higher when the dealer provides upfront payments.
Having examined the funding effect on bid–ask spreads, we next turn

a search-based market in which investors trade CDS contracts through dealers (Duffie et al. ([2005\)](#page-25-1)). When there are more investors trading CDS contracts, it is easier for dealers to find counterparties and keep their inventory of CDS contracts a search-based market in which investors trade CDS contracts through dealers
a search-based market in which investors trade CDS contracts through dealers
(Duffie et al. (2005)). When there are more investors trading CDS co

primary to secondary, the number of investors trading this coupon significantly decreases, making it difficult for dealers to find counterparties to balance their ⁴ Journal of Financial and Quantitative Arialysis
primary to secondary, the number of investors trading t
decreases, making it difficult for dealers to find counte
inventory. Therefore, the bid–ask spread would increase. ary to secondary, the number of investors trading this coupon significantly asses, making it difficult for dealers to find counterparties to balance their thory. Therefore, the bid–ask spread would increase. To establish a

spread, we exploit the event of the primary coupon switch as a natural experiment. Since the effect of the switch of the primary coupon occurs in 1 day, the changes in To establish a causal relationship between search intensity and the bid–ask spread, we exploit the event of the primary coupon switch as a natural experiment.
Since the effect of the switch of the primary coupon occurs in trading from one standard coupon to another, while all other factors are kept 100 coupon widens by 58% and the bid–ask spread on the 500 coupon narrows unchanged, including upfront payments. We find that when a primary coupon since the effect of the switch of the primary coupon occurs in 1 day, the enanges in
bid–ask spreads around the switch dates are driven purely by coordinating CDS
trading from one standard coupon to another, while all othe by 11%. There is no immediate and significant change in the midpoint of the CDS spreads on both coupons. The aggregate trading activities also decrease on the switch days and then increase in the following days. When a primary coupon 100 coupon widens by 58% and the bid–ask spread on the 500 coupon narrows by 11%. There is no immediate and significant change in the midpoint of the CDS spreads on both coupons. The aggregate trading activities also decre the 100 coupon by 33% and widens on the 500 coupon by 13%. There is also no immediate and significant change in the midpoint of the CDS spreads. The aggregate trading activities increase on the switch day and then decrease in the following days.

Our article contributes to the literature on the effects of funding liquidity. Important theoretical contributions include Grossman and Miller [\(1988](#page-25-2)), Shleifer and Vishny ([1997](#page-26-1)), Basak and Croitoru [\(2000](#page-25-3)), Kyle and Xiong ([2001\)](#page-26-2), Xiong [\(2001\)](#page-26-3), Gromb and Vayanos ([2002\)](#page-25-4), Brunnermeier and Pedersen ([2009\)](#page-25-0), Mitchell, Pedersen, and Pulvino ([2007](#page-26-4)), Mitchell and Pulvino [\(2012\)](#page-26-5), He and Krishnamurthy [\(2013\)](#page-25-5), and Brunnermeier and Sannikov [\(2014](#page-25-6)). On the empirical side, most evidence has been indirect. For example, some studies use major market events as exogenous shocks to the funding condition of financial intermediaries to examine their effects on market liquidity (e.g., Aragon and Strahan [\(2012](#page-25-7)), Acharya, Schaefer, and Zhang [\(2015](#page-25-8))).

Wang et al. ([2021\)](#page-26-0) employ the CDS Big Bang as a natural experiment to wang et al. (2021) employ the CDS Dig Dang as a hadden experiment to
provide direct evidence of the effect of funding liquidity on market liquidity. They
find that an increase in funding requirements of CDS trading leads t find that an increase in funding requirements of CDS trading leads to a decrease in market liquidity. Our article differs significantly from Wang et al. ([2021\)](#page-26-0) in several spread between the 2 standard coupons on the same CDS contracts after the CDS Big Bang, whereas Wang et al. [\(2021](#page-26-0)) use the sudden change in funding requirements of CDS trading around the event of the CDS Big Bang to identify funding effects. To the best of our knowledge, our article is the first empirical study of the Big Bang, whereas Wang et al. (2021) use the sudden change in funding requirements of CDS trading around the event of the CDS Big Bang to identify funding effects. To the best of our knowledge, our article is the first emp a comprehensive study of both funding cost and search cost components of market liquidity, whereas Wang et al. (2021) focus only on the effects of funding cost on market liquidity. Third, we study the search effects on mar liquidity, whereas Wang et al. ([2021](#page-26-0)) focus only on the effects of funding cost on market liquidity. Third, we study the search effects on market liquidity and establish adds to this literature by using the CDS standard coupons as a natural experiment to provide direct evidence of the effect of funding liquidity on market liquidity. markets. Duffie et al. ([2005\)](#page-25-1) show that bid–ask spreads are lower when investors are lower and the direct evidence of the effect of funding liquidity on market liquidity.
Our article also contributes to the strand of liter

Our article also contributes to the strand of literature on search-based OTC

can find other investors more easily. Vayanos and Weill ([2008\)](#page-26-6) show that positivenet-supply assets with identical cash flows can have different liquidity and prices in a search-based market. Our results show that zero-net-supply assets with identical payoffs can have different liquidity but similar prices in a search-based market. not sumply assets with identical cash flows can have different liquidity and prices in
a search-based market. Our results show that zero-net-supply assets with identical
payoffs can have different liquidity but similar pri that search based market. Our results show that zero-net-supply assets with ide-
a search-based market. Our results show that zero-net-supply assets with ide-
payoffs can have different liquidity but similar prices in a se Fig. can have different liquidity but similar prices in a search-based market.
If is can have different liquidity but similar prices in a search-based market.
If ically, the bid–ask spread is lower when search intensity is Specifically, the bid–ask spread is lower when search intensity is higher, indicating that search friction contributes to a significant portion of the bid–ask spread.
Our article is related to the literature on the determi

nents, including asymmetric information, inventory risk, and order processing costs hending asymmetric information, inventory risk, and other processing costs
(Amihud and Mendelson ([1980\)](#page-25-9), Ho and Stoll [\(1981\)](#page-25-10), Glosten and Milgrom
(1985), Glosten and Harris (1988), and Huang and Stoll (1997)). Our setting ([1985\)](#page-25-11), Glosten and Harris ([1988\)](#page-25-12), and Huang and Stoll ([1997\)](#page-25-13)). Our setting provides a clean way to separate and quantify the funding cost and search components

Finally, our article is also related to the literature on the liquidity of the CDS market. Important contributions in this area include Longstaff et al. [\(2005](#page-26-7)), Tang and Yan [\(2007](#page-26-8)), Chen, Fabozzi, and Sverdlove ([2010\)](#page-25-14), Bongaerts, De Jong, and Driessen ([2011](#page-25-15)), Qiu and Yu [\(2012](#page-26-9)), Kitwiwattanachai and Pearson [\(2014](#page-26-10)), Junge and Trolle [\(2015](#page-26-11)), and Siriwardane [\(2019](#page-26-12)). Our results shed light on the determinants of the liquidity in the CDS market.

The rest of the article is organized as follows: [Section II](#page-4-0) describes the institutional background and our data. [Section III](#page-8-0) presents the analysis of the impact of funding costs on bid–ask spreads. [Section IV](#page-16-0) studies the search effects on market liquidity. [Section V](#page-22-0) concludes the article.

II. Institutional Background and Data

A. Institutional Background

The CDS Big Bang represents an important step to standardize the CDS market. The primary purpose for standardizing the CDS market is to facilitate central clearing. Before the CDS Big Bang, the common practice had been to set the CDS coupon to be equal to the CDS spread so that the present value of the fee leg was equal to the present value of the contingent leg. After a trade was executed, the coupon was fixed for the life of the contract. As the CDS spread fluctuated with the market, the CDS coupon for new contracts also changed daily. While this practice allowed CDS traders to pay 0 upfront to enter into trades, it made it difficult to eliminate a position exactly by taking an offsetting position on the same underlying firm. This was because the fee legs had different cash flows. Since the CDS Big Bang, the CDS coupon has been fixed to either 100 bps or 500 bps regardless of the level of CDS spreads. The side effect of using fixed coupons is that traders need to make upfront payments to ensure the fair value of a contract equals 0 at the inception of the trade.

Which coupon do traders choose? The rule of thumb is that traders choose the coupon that minimizes the upfront payment. The coupon for a CDS contract on an investment-grade reference entity is normally 100 bps, whereas the coupon for a CDS contract on a speculative-grade reference entity is normally 500 bps. Typically, both coupons are quoted on the same trading date. The reason why both coupons are traded is likely that traders need to unwind existing positions by taking offsetting positions with the same coupon. Traders can also take advantage of trading the secondary coupon. For example, suppose the CDS spread on a firm is 100 bps. If a CDS buyer wants to trade the 5-year CDS with a notional of 10 million USD and chooses the 100 coupon, the upfront payment for this transaction will be 0. Alternatively, the buyer can choose the 500 coupon and receive an upfront fee of around 2 million USD (400 bps \times 5 \times 10 million) from the CDS seller. This is equivalent to obtaining a loan of 2 million USD from the CDS seller (typically CDS dealers).

To fix ideas, take the example of CDS contracts with a CDS spread of 200 bps. If the coupon is set to be 100 bps, which is less than the breakeven rate (200 bps), the CDS buyer needs to pay an upfront fee that is equal to the present value of 100 bps per year until the maturity of the CDS contract. On the other hand, if the coupon is set to be 500 bps, which is more than the breakeven rate (200 bps), the CDS seller needs to pay an upfront fee that is equal to the present value of 300 bps per year until the maturity of the CDS contract. In this case, the 100 bps coupon will be chosen as the primary contract and most of the trading activities will be concentrated on this coupon since it minimizes the upfront payments. However, the secondary coupon may still be traded at the same time because traders might want to unwind existing positions with the same coupon or they might want to use the secondary coupon to obtain loans from their counterparties.

In this study, we first use this cross-sectional variation to examine the explanatory power of funding costs (i.e., upfront payments) and searching costs (i.e., trading activities) on our liquidity measure. When there is a significant change in market-wide or firm-level credit risk, we might observe a switch of the primary coupon. In other words, the majority of the trading activities move from one coupon to the other. Taking the same CDS contracts as in our previous example, if the CDS spread moves up from 200 bps to 400 bps, the upfront fee for the 500 bps coupon will be significantly less than the upfront fee for the 100 bps coupon. Therefore, we will observe a switch of the primary coupon from 100 bps to 500 bps and this will happen in 1 trading day. In the second part of our article, we use this type of primary coupon switch as a natural experiment to document the causal impact of search costs (i.e., trading activities) on our liquidity measure.

B. Data

Our primary data set for this study comes from Markit end-of-day (EOD) CDS data. To gauge liquidity risk in the CDS market, Markit provides a set of CDS B. Data
Our primary data set for this study comes from Markit end-of-day (EOD) CDS
data. To gauge liquidity risk in the CDS market, Markit provides a set of CDS
liquidity metrics. The data set provides daily EOD quotes for midpoints expressed in both upfront payments and conventional spreads.² The data include important information on the CDS coupon and whether a coupon is a primary coupon. When a CDS contract trades with both coupons on t include important information on the CDS coupon and whether a coupon is a primary coupon. When a CDS contract trades with both coupons on the same date, bid–ask spreads and midpoints are also provided for the secondary coupon. The data also provide information on bid–ask spreads and coupons for CDS contracts

²Conventional spreads are calculated from the upfront payment using the ISDA CDS Standard model. For more details about the ISDA CDS standard model, see <https://www.cdsmodel.com/>.

with different maturities. We use observed 5Y quotes on senior unsecured debts in USD for most of our analyses since they are the most liquid contracts. We also utilize contracts with maturities of 1Y, 3Y, 7Y, and 10Y. Since the CDS Big Bang took effect on Apr. 8, 2009, our sample begins after this date and consists of 748 North American firms spanning the period from Apr. 8, 2010, through Sept. 10, 2020.

We utilize the primary coupon flag provided by Markit, which acts as a key variable in our analysis and identification. Markit collects CDS quotes from various CDS dealers. Typically, each CDS dealer provides a quote based on a single running coupon for a specific CDS reference entity. For investment grade entities, it is generally expected that trading will occur with a coupon of 100 basis points, while high yield credits tend to employ a coupon of 500 basis points. Markit takes these coupon values into account and designates the primary coupon accordingly. However, it is worth noting that dealers have the flexibility to make markets for either coupon for a given entity. In cases where multiple dealers provide quotes with different coupons for a particular CDS entity, Markit determines the primary coupon by considering the coupon value that has the largest number of unique dealers quoting it. By employing this approach, Markit ensures that the primary coupon assigned to each CDS entity reflects the consensus among a significant number of dealers, thus enhancing the reliability and accuracy of the information we rely on for our study.

The Markit EOD data provide bid–ask spreads and midpoint information for each coupon. However, when it comes to the trading activity variables (the number of quotes and the number of dealers), the EOD data only offer aggregate numbers for the 100 and 500 coupons combined. This limitation prevents us from observing the individual counts for each coupon. To overcome this challenge, we have incorporated the Markit intraday quote data in the second part of our analysis, which provides more detailed information.

The Markit intraday quote data include time-stamped bid and ask quotes for CDS contracts of firms in the Markit EOD data. By leveraging this data set, we are able to derive the number of quotes and dealers for each specific coupon. To achieve this, we aggregate the bid and ask quotes based on the coupon, maturity, firm, and date, allowing us to obtain the precise counts for each coupon.

From Datastream, we obtain the daily close values of the CBOE volatility index (VIX), the daily 3 M Libor rate, and the 3 M Overnight-Indexed Swap (OIS) rate. The VIX is used to proxy for overall market uncertainty, and the difference between the 3 M Libor rate and the 3 M OIS rate (LOIS) is used to proxy for the funding cost. LOIS is the typical 3-month credit spread for large dealer banks, that is, a measure of bank default risk. Making the upfront payment is more difficult when the bank is less credit worthy because the bank will have a harder time raising C. Decomposing the Bid–Ask Spread the capital to pay this amount.

Decomposing the Bid–Ask Spread
The bid–ask spread is the most popular measure of market liquidity. In classical theory (e.g., Amihud and Mendelson [\(1980](#page-25-9)), Ho and Stoll [\(1981](#page-25-10)), Glosten C. Decomposing the Bid-Ask Spread
The bid-ask spread is the most popular measure of market liquidity. In
classical theory (e.g., Amihud and Mendelson (1980), Ho and Stoll (1981), Glosten
and Milgrom [\(1985](#page-26-13)), Kyle (1985), an spread in equity markets is classified into order processing cost, adverse selection, and inventory cost. In OTC markets, dealers have to find customers to offset their positions. Therefore, the bid–ask spread in OTC markets is classified into order processing cost, adverse selection, and inventory cost. In OTC markets, dealers have to find customers to offset their positions. Therefore, (Brunnermeier and Pedersen ([2009\)](#page-25-0), Andersen, Duffie, and Song ([2019](#page-25-16))) and search costs (Duffie et al. ([2005\)](#page-25-1)). We follow the same method to decompose the and inventory cost. In OTC markets, dealers have to find eastoniers to onset their positions. Therefore, the bid–ask spread in OTC markets includes funding costs (Brunnermeier and Pedersen (2009), Andersen, Duffie, and Son follows:

$$
(1) \qquad \qquad \text{BAS}_{c,i,t} = \text{BAS}_{i,t}^O + \text{BAS}_{i,t}^{\text{AI}} + \text{BAS}_{c,i,t}^F + \text{BAS}_{c,i,t}^S + \epsilon_{c,i,t},
$$

where c is the index for coupon, i is the index for firm, and t is the index for date. BAS is the bid–ask spread on CDS contracts, BAS^O is the order processing cost, BAS^{AI} is the adverse selection cost and inventory cost, BAS^F is the funding cost, and BAS^S is the search cost. It is worth noting that BAS^F and BAS^S are coupon specific. In [Sections III](#page-8-0) and [IV,](#page-16-0) we exploit the setting of the dual coupons to estimate BAS^O , BAS^{AI} , BAS^F , and BAS^S .

D. Summary Statistics

In this section, we conduct a univariate analysis of our sample to estimate D. Summary Statistics
In this section, we conduct a univariate analysis of our sample to estimate
components of the bid–ask spread related to order processing and adverse selection. In this section, we conduct a univariate analysis of our sample to estimate components of the bid–ask spread related to order processing and adverse selection.
Panel A of Table 1 reports the summary statistics of variables

Panel A of [Table 1](#page-8-1) reports the summary statistics of variables in our sample. 18.24 bps for the secondary coupon, suggesting that the liquidity of the primary components of the ota-ask spical related to order processing and adverse selection.

Panel A of Table 1 reports the summary statistics of variables in our sample.

The mean value of the bid–ask spread is 14.09 bps for the ask spread at the 1st percentile is 4.00 bps. Since the order processing cost is roughly constant for different contracts, this suggests that the upper bound for the order processing cost of CDS contracts, BAS^O , is around 4.00 bps (28% of the average bid–ask spreads). The average difference in bid–ask spreads between the primary books as a bid–ask spreads). The average difference in bid–ask spreads between the primary bid–ask spreads). The average difference in bid–as bid—ask spreads). The average unference in ord—ask spreads between the primary
and secondary coupons is 4.15 bps. Since the CDS contracts on the 2 coupons have
the same order processing cost and adverse selection cost, as the same order processing cost and adverse selection cost, as shown in [equation \(1\)](#page-7-0), the difference of 4.15 bps represents the difference in the funding cost and search funding and search costs cannot be identified. As a rough estimate, the adverse the same offer processing cost and adverse selection cost, as shown in equation (1), the difference of 4.15 bps represents the difference in the funding cost and search cost (29% of the average bid–ask spread). It is wort (14.09 – 4.00 – 4.15 = 5.94 bps, 42% of the average bid–ask spread). It is worth noting that the level of the funding and search costs cannot be identified. As a rough estimate, the adverse selection and inventory cost of and [IV,](#page-16-0) we further estimate the portions of the funding cost (BAS^F) and search cost exactle costs can
selection and inventory cost of $(14.09 - 4.00 - 4.15 = 5.94$ bps
and IV, we further estimate the
 (BAS^S) in the bid–ask spread.

The mean value of the upfront fee as a fraction of the notional is 0.05 for the primary coupon and 0.17 for the secondary coupon, which indicates that the primary coupon tends to be the coupon that minimizes the upfront payment. The average firm has about 6 dealers and about 92 quotes per day. We employ VIX (the closing value of the CBOE volatility index) and the LIBOR-OIS_SPREAD (the spread between the 3-month Libor rate and the 3-month OIS rate) to measure macroeconomic uncertainty and funding cost. The average values for VIX and LIBOR-OIS_SPREAD are 17.23% and 0.24%, respectively. The 2-week rolling standard deviation of CDS spread has an average value of 61.73 bps.

Summary Statistics

[Table 1](#page-8-1) presents summary statistics of the variables in our sample of 5Y CDS contracts from Apr. 2010 to Sept. 2020. BID– ASK_SPREAD (P/S) is the bid–ask spread on the CDS spread with the primary/secondary coupon, expressed in bps. UPFRONT (P/S) is defined as the present value of the difference between the CDS spread and the fixed coupon during the life of a CDS contract in terms of the notional value of the CDS contract. DIFF_IN_UPFRONTCOST is the difference in the funding costs of upfront payment between the secondary and primary coupons, expressed in bps. MIDPOINT (P/S) is the midpoint of the bid and ask prices of the primary/secondary coupons, expressed in bps. DEALERS_COUNT is the number of dealers. QUOTES_COUNT is the number of quotes. CDS_VOLATILITY is the 2-week rolling standard deviations of CDS spread, expressed in bps. VIX is the daily close values of the CBOE volatility index, expressed in percentage. LIBOR-OIS_SPREAD is the spread between 3 M Libor rate and 3 M OIS rate, expressed in percentage.

We then split the sample into 2 subsamples by standard coupons. Panel B of [Table 1](#page-8-1) shows that the average CDS spread is 94.33 bps when the primary coupon is 100 and 294.07 bps when the primary coupon is 500. This pattern indicates that the 100 coupon is mainly used for investment-grade CDSs and the 500 coupon is mainly used for high-yield CDSs. We also find that the bid–ask spreads for the mainly used for high-yield CDSs. We also find that the bid–ask spreads for the mainly used for high-yield CDSs. We also find that the bid–ask s primary contracts (i.e., 10.53 bps and 23.24 bps) are lower than the ones for the secondary contracts (11.60 bps and 35.35 bps) in the 2 subsamples. III. Funding Effects on Bid–Ask Spreads
III. Funding Effects on Bid–Ask Spreads

Funding Effects on Bid–Ask Spreads
In this section, we estimate the effect of funding costs on the bid–ask spreads. III. Funding Effects on Bid–Ask Spreads
In this section, we estimate the effect of funding costs on the bid–ask spreads.
We first regress the difference in bid–ask spread between 2 coupons on the difference in upfront costs. Then, we utilize variations across maturities to further identify funding costs, and use central clearing to check the robustness of our results. Finally, we investigate the effects of upfront funding costs on the midpoint of spreads and the asymmetric effects of upfront funding costs depending on whether the dealer pays or receives upfront fees.

A. Effect of Upfront Costs on Bid–Ask Spreads

We define the funding costs of upfront payment for CDS contract i with coupon C on day t in our sample as

(2) UPFRONT_COST_{C,i,t} = |UPFRONT_{C,i,t}| \times LOIS_{t,}

where UPFRONT_{C,*i,t*} is the upfront payment of CDS contract *i* with coupon C on day t and $LOIS_t$ is the 3-month LIBOR-OIS SPREAD on day t. When a dealer bank is less creditworthy, it is harder to raise funds to make upfront payments in CDS trading, which occurs when LOIS is high.^{[3](#page-9-0)} A positive UPFRONT_{C,it} means that buyers pay the upfront and vice versa. In our sample, many contracts have bid and ask quotes on the same trading day for both coupons. The primary coupon is the coupon on which the largest number of dealers quote prices. We then examine the effects of the difference in upfront funding costs between the primary and the bayers pay the upfront and vice versa. In our sample, many contracts have out and ask quotes on the same trading day for both coupons. The primary coupon is the coupon on which the largest number of dealers quote prices. W sext quotes on the same trading day for both coupons. The primary coupon is the coupon on which the largest number of dealers quote prices. We then examine the effects of the difference in upfront funding costs between the coupons eliminates the effect of order processing and adverse selection on the secondary coupons on the difference in their bid–ask spreads. Exploring the cross-
sectional variations in the difference in the bid–ask spreads between the dual
coupons eliminates the effect of order processing and advers sectional variations in the difference in the bid–ask spreads between the dual First, upfront payments, which can be viewed as funding costs, directly affect the bid–ask spreads because the dual coupon contracts are issued by the same firm.
Upfront payments can affect the bid–ask spreads through the following 2 channels.
First, upfront payments, which can be viewed as funding costs Second, upfront payments can affect the bid–ask spreads through the following 2 channels.
First, upfront payments, which can be viewed as funding costs, directly affect the bid–ask spreads. The larger the upfront payment, choice of the primary coupon. The primary coupon attracts more buyers and sellers bid–ask spreads. The larger the upfront payment, the larger the bid–ask spread. Second, upfront payments indirectly determine the bid–ask spread by affecting the

To test our hypothesis that the difference in upfront cost should be positively and thus has significantly lower bid–ask spreads than the secondary coupon.
To test our hypothesis that the difference in upfront cost should be positively associated with the difference in bid–ask spreads, we estimate the sion model:

(3) $\triangle BAS_{i,t} = \beta_1 * \triangle UPFRONT_COSTS_{i,t} + \beta_2 * X_{i,t} + u_i + \varepsilon_{i,t}$

where Δ BAS_{it} is defined as

$$
(4) \qquad \qquad \Delta BAS_{i,t} = BAS_{S,i,t} - BAS_{P,i,t}.
$$

e $\triangle BAS_{i,t}$ is defined as
 $\triangle BAS_{i,t} = BAS_{S,i,t} - BAS_{P,i,t}.$
 $BAS_{P,i,t}$ is the bid–ask spread for the primary CDS contract *i* on day *t*, and (4) $\triangle BAS_{i,t} = BAS_{S,i,t} - BAS_{P,i,t}.$
BAS_{P,*i,t*} is the bid–ask spread for the primary CDS contract *i* on day *t*, and $BAS_{S,i,t}$ is the bid–ask spread for the secondary CDS contract *i* on day *t*. \triangle UPFRONT_COSTS_{*i,t*} is defined as

(5) \triangle UPFRONT_COST_{i,t} = UPFRONT_COST_{S,i,t} - UPFRONT_COST_{P,i,t,}

where UPFRONT_COST_{P,i,t} is the funding cost of upfront payment for the primary CDS contract *i* on day *t*, UPFRONT_COST_{S,i,t} is the funding cost for the secondary CDS contract *i* on day *t*, $X_{i,t}$ is the set of co CDS contract *i* on day *t*, UPFRONT_COST_{S,i,t} is the funding cost for the secondary CDS contract *i* on day t , $X_{i,t}$ is the set of control variables which might affect the for any unobserved heterogeneity across firms.

³It is worth noting that this holds mainly for the dealer bank. The trader who is the counterparty to the dealer bank may have a different credit spread that makes it harder to raise the funds.

Effects of Funding Costs on CDS Bid–Ask Spread

Effects of Funding Costs on CDS Bid–Ask Spread
[Table 2](#page-10-0) reports the effects of upfront funding costs on CDS bid–ask spread. The regressions are based on the sample of 5Y
CDS contracts from Apr. 2010 to Sept. 2020. The depen secondary and primary coupons, expressed in bps. ΔUPFRONT_COST is the difference in the funding costs of upfront payment between the secondary and primary coupons, expressed in bps. CDS_VOLATILITY is the 2-week rolling standard deviations of CDS spread. VIX is the daily close values of the CBOE volatility index, expressed in percentage. LOIS is the spread between 3 M Libor rate and 3 M OIS rate, expressed in percentage. The t-statistics are given in parentheses. Standard errors are clustered by firm and time. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

[Table 2](#page-10-0) reports the regression results. The coefficient of ΔUPFRONT_COST $\frac{724}{724}$
Table 2 reports the regression results. The coefficient of $\triangle UPFRONT_COST$
identifies the effects of funding costs on the bid–ask spreads. To control for potential confounding factors, we include CDS volatility, the CBOE volatility index, and LOIS.^{[4](#page-10-1)} We find that the coefficients of \triangle UPFRONT COST are both statistically and economically significant across these specifications. In column 3, we find that a 1-standard-deviation increase in ΔUPFRONT_COST leads to an increase of 0.66 bps in $\Delta BAS_{i,t}$, 4.7% (6.6%) relative to the sample mean (median). These results suggest that higher funding costs have a negative impact on market liquidity measures.

B. Analysis Using Variation Across Maturities

To establish the robustness of our results, we collect additional quotes on 1Y, 3Y, 7Y, and 10Y CDS contracts. We first reestimate our baseline regression model with firm fixed effects (the same as column 3 of [Table 2](#page-10-0)) using CDS contracts with different maturities. Columns 1 to 5 of [Table 3](#page-11-0) report the regression results. The coefficient of ^ΔUPFRONT_COST identifies the effects of funding costs on the bid– ask spreads. We find that this funding effect remains statistically significant and economically meaningful across all maturities. It is interesting to note that the funding effect exhibits a U-shaped pattern. It is stronger for less liquid maturities (e.g., 1Y and 10Y). We note that the size of the upfront payment is equal to the difference between the present values of the CDS spread and the fixed coupon during the life of a CDS contract. Therefore, the upfront payment is proportional to

⁴As a robustness check, we conduct separate regressions incorporating the 3 M Libor rate and 3 M OIS rate. The results are robust to this change.

Effects of Funding Costs on CDS Bid–Ask Spread with Different Maturities

Effects of Funding Costs on CDS Bid–Ask Spread with Different Maturities.
[Table 3](#page-11-0) reports the effects of upfront funding costs on CDS bid–ask spread for contracts with different maturities. The regressions are based on the sample of CDS contracts with different maturities from Apr. 2010 to Sept. 2020. The —
Table 3 reports the effects of upfront funding costs on CDS bid–ask spread for contracts with different maturities. The
dependent variable ΔBAS is the difference in bid–ask spread between the primary and secondary coupo bps. ΔUPFRONT_COST is the difference in the funding costs of upfront payment between the secondary and primary coupons, expressed in bps. The t-statistics are given in parentheses. Standard errors are clustered by firm and time. *, * and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

the maturity of the CDS contract. We then use the full sample to estimate the following regression model:

(6)
$$
\Delta \text{BAS}_{i,m,t} = \beta_1 * \Delta \text{UPFRONT_COST}_{i,m,t} + \beta_2 * X_{i,t} + u_{i,t} + \varepsilon_{i,t},
$$

where *m* indexes a particular CDS maturity, $\Delta BAS_{i,mt}$ is similarly defined in [equation \(4\)](#page-9-1), and \triangle UPFRONT_COSTS_{i,m,t} is similarly defined in [equation \(5\)](#page-9-2). We add the firm by date fixed effect to control for any unobserved heterogeneity across firms at any given point of time. In this regression model, we identify the funding effect using variations across maturities but within the same firms and dates.

Column 6 of [Table 3](#page-11-0) reports the regression results. We find that this funding effect is positive and statistically significant and also economically significant. A 1-standard-deviation increase in ΔUPFRONT_COST leads to an increase of 3.31 bps in $\Delta BAS_{i,t}$, 14.3% (19.4%) relative to the sample mean (median). The estimated economic magnitude is larger than our estimate in [Section III.A](#page-9-3). This is because the funding effect is stronger for less liquid CDS contracts with maturities shorter or longer than 5 years.

C. Central Clearing

Following the CDS Big Bang event, an important development took place when the United States Congress approved the Dodd-Frank Wall Street Reform and Consumer Protection Act. This act included a provision that requires central counterparty (CCP) clearing for eligible OTC derivatives. Consequently, ICE Clear Credit (ICECC) emerged as the inaugural CCP for North American CDS contracts

and initiated the clearing process for selected individual CDS names beginning from Dec. 2009.

Our sample consists of 748 reference entities. Among them, 45 initiated central clearing before Apr. 8, 2010 (the beginning of our sample period), while 205 underwent central clearing during our sample period from Apr. 2010 to Sept. 2020. The remaining 498 entities did not transition to central clearing by the end of our sample. The list of the 250 cleared reference entities is reported in the [Appendix](#page-24-0). As illustrated in the [Appendix,](#page-24-0) initially, the CDS contracts were not centrally cleared, but they were subsequently rolled out in batches to central clearing at different dates. Therefore, there is cross-sectional variation in terms of which CDS contracts are cleared.
For centrally cleared trades, all CDS traders, including dealers, face a sole counterparty—a central counterparty contracts are cleared.

For centrally cleared trades, all CDS traders, including dealers, face a sole trader can be netted with a CCP across different trades. For CDS end users, netting benefit from central clearing may not be significant since end users typically do not have many offsetting positions. For CDS dealers, the netting benefit from central clearing could be significant since they have a large number of offsetting positions and thus a significant portion of upfront payments can be netted across trades. Therefore, we expect that the effect of upfront payments is weaker for centrally cleared trades.
To test our hypothesis that central clearing mitigates the effects of upfront funding costs on the bid–ask spreads, we estima cleared trades.

To test our hypothesis that central clearing mitigates the effects of upfront model:

(7)
$$
\Delta BAS_{i,t} = \beta_1 * \Delta UP \text{FRONT}_\text{COST}_{i,t} + \beta_2 * \text{CLEAREN}_{i,t} + \beta_3 * \Delta UP \text{FRONT}_\text{COST}_{i,t} \times \text{CLEAREN}_{i,t} + \beta_2 * X_{i,t} + u_i + \varepsilon_{i,t},
$$

where CLEARED_{i,t} is a dummy variable that is equal to 1 if the CDS contract i on day t is centrally cleared; and 0 otherwise, and u_i is the firm fixed effect. We add the firm fixed effect to control for any unobserved heterogeneity across firms.

As shown in [Table 4](#page-13-0), the interaction term ΔUPFRONT_COST × CLEARED captures the impact of central clearing on the funding effect. The coefficient of ΔUPFRONT_COST × CLEARED is negative and statistically significant, which is As shown in Table 4, the interaction term $\triangle UPFRONT_COST \times CLEAREN$
captures the impact of central clearing on the funding effect. The coefficient of
 $\triangle UPFRONT_COST \times CLEARENED$ is negative and statistically significant, which is
consistent ask spread of cleared CDS contracts is 0.83 bps lower than that of uncleared contracts.

D. Effects of Upfront Funding Costs on the Midpoint of the Spread

In this section, we explore whether dealers incorporate upfront costs into D. Effects of Upfront Funding Costs on the Midpoint of the Spread
In this section, we explore whether dealers incorporate upfront costs into
the midpoint of the bid–ask spread. It is plausible that by having to fund upfron D. Effects of Upfront Funding Costs on the Midpoint of the Spread
In this section, we explore whether dealers incorporate upfront costs into
the midpoint of the bid–ask spread. It is plausible that by having to fund upfron of the spread. Our prediction is as follows: for contracts with higher upfront costs, the midpoint of the bid–ask spread should be higher as well. This is because dealers are typically CDS sellers (credit protection seller In this section, we explore whether dealers incorporate upfront costs into
the midpoint of the bid–ask spread. It is plausible that by having to fund upfront
costs, dealers can not only widen the bid–ask spread but also ad because dealers are typically CDS sellers (credit protection sellers) and they

Effects of Central Clearing on CDS Bid–Ask Spread

Effects of Central Clearing on CDS Bid-Ask Spread
[Table 4](#page-13-0) reports the effects of central clearing on CDS bid-ask spread. The regressions are based on the sample of 5Y CDS
contracts from Apr. 2010 to Sept. 2020. The depende and secondary coupons, expressed in bps. ΔUPFRONT_COST is the difference in the funding costs of upfront payment between the secondary and primary coupons, expressed in bps. CLEARED is a dummy variable that is equal to 1 if the CDS contract is centrally cleared on a specific date; and 0 otherwise. The t-statistics are given in parentheses. Standard errors are clustered by firm and time. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Dependent Variable = ΔBAS 1 2 ΔUPFRONT_COST 20.0143*** 33.7179***

compensate for the higher upfront cost. To test this prediction, we estimate the following regression model:

(8) $\Delta \text{MIDPOINT}_{i,t} = \beta_1 * \Delta \text{UPFRONT_COST}_{i,t} + \beta_2 * X_{i,t} + u_i + \varepsilon_{i,t},$

where \triangle MIDPOINT_{*i,t*} is defined as

(9) $\triangle MIDPOINT_{i,t} = MIDPOINT_{S,i,t} - MIDPOINT_{P,i,t}.$

MIDPOINT $_{P,i,t}$ is the midpoint of the bid–ask spread for the primary CDS (9) $\triangle MIDPOINT_{i,t} = MIDPOINT_{S,i,t} - MIDPOINT_{P,i,t}.$
MIDPOINT_{P,i,t} is the midpoint of the bid–ask spread for the primary CDS contract *i* on day *t*, and MIDPOINT_{S,i,t} is the midpoint of the bid–ask spread for the secondary CDS contract i on day t .

We report the regression results in Panel A of [Table 5](#page-14-0). The coefficient of ΔUPFRONT_COST identifies the effect of upfront costs on the midpoint secondary CDS contract *i* on day *t*.
Secondary CDS contract *i* on day *t*.
We report the regression results in Panel A of Table 5. The coefficient
of $\triangle UPFRONT_COST$ identifies the effect of upfront costs on the midpoint
o ΔUPFRONT_COST is positive and highly statistically significant in all 3 columns. In column 3 that incorporates the full sets of controls, we find that an increase of 1-standard-deviation in $ΔUPFRONT_COST$ leads to a 3.55 bps increase in $ΔMDPONT_{i,t}$, which represents a 2.4% (3.8%) increase relative to the sample mean (median).
Since both the bid–ask spread widens and the midpoint of the b Δ MIDPOINT_{it}, which represents a 2.4% (3.8%) increase relative to the sample mean (median).

increases as the upfront funding cost goes up, it is interesting to investigate whether the funding effect on one side of the market is stronger than the other. To do this, we estimate the regression model in [equation \(8\)](#page-13-1) with the dependent variable replaced by the difference in the ask prices or bid prices. The regression results are presented in Panels B and C of [Table 5](#page-14-0). The coefficient of ΔUPFRONT_COST is positive and

Effects of Funding Costs on the Midpoint of Bid and Ask Prices

ETIECTS OF FUNDING USSIS ON THE MIDDOINT OF BIO AND ASK PRCES
[Table 5](#page-14-0) reports the effects of funding costs on the midpoint of bid and ask prices. The regressions are based on the sample of
SY CDS contracts from Apr. 2010 t spread. The dependent variable ΔMIDPOINT is the difference in the midpoint of the bid and ask prices between the primary and secondary coupons, expressed in bps. Panel B reports the effects of funding costs on CDS ask price. The dependent variable ΔASK is the difference in the ask price between the primary and secondary coupons, expressed in bps. Panel C reports the effects of funding costs on CDS bid price. The dependent variable ΔBID is the difference in the bid price between the primary and secondary coupons, expressed in bps. ΔUPFRONT_COST is the difference in the funding costs of upfront payment between the secondary and primary coupons, expressed in bps. CDS_VOLATILITY is the 2-week rolling standard deviations of CDS spread. VIX is the daily close values of the CBOE volatility index, expressed in percentage. LOIS is the spread between 3 M Libor rate and 3 M OIS rate, expressed in percentage. The t-statistics are given in parentheses. Standard errors are clustered by firm and time. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. spread between 3 M Libor rate and 3 M O
errors are clustered by firm and time.
respectively.
Panel A. Midpoint of the Bid–Ask Spread

statistically significant in all specifications, indicating that both bid and ask prices increase as upfront funding costs become greater. However, the coefficient of \triangle UPFRONT COST for ask prices is about 50% larger than that for bid prices, SUT ROIVI_COST for ask prices is about 50% larger than that for old prices, suggesting that the ask price increases more than the bid price when the upfront cost increases. This is expected because a higher ask price can c increases. This is expected because a higher ask price can compensate dealers for the upfront funding cost. These findings demonstrate that as upfront costs increase, prices to compensate for the upfront funding cost.

E. Asymmetric Effects of the Upfront Funding Costs

In this section, we investigate whether there are asymmetric effects of the upfront funding cost depending on whether the dealer is long or short in terms of providing or receiving funds for upfront payments. Since the information on whether the dealer is long or short for a particular CDS contract is not disclosed to the public, we consider whether the dealers are on average net protection buyers or sellers. When protection sellers pay upfront, we expect a higher funding effect if the dealers are on average net protection sellers. Similarly, when protection buyers pay upfront, we expect a higher funding effect if the dealers are on average net protection buyers. To test these predictions, we obtain dealers' aggregate net position against customers from the trade information warehouse (TIW) reports of the Depository Trust and Clearing Corporation (DTCC),⁵ and construct a dummy variable, DEALER_PAY_{it}, as follows:

(10) DEALER_PAY_{i,t} =
\n
$$
\begin{cases}\n1, \text{ if (DEALER_POS}_t < 0 \text{ and UPFRONT}_{S,i,t} < 0) \text{ or} \\
(\text{DEALER_POS}_t > 0 \text{ and UPFRONT}_{S,i,t} > 0), \\
0, \text{ otherwise,} \n\end{cases}
$$

where DEALER_POS_t is dealers' aggregate net position against customers at day t. A negative (positive) DEALER_POS_t indicates that dealers are the net protection seller (buyer). A negative (positive) UPFRONT $_{S,i,t}$ indicates that the CDS seller (buyer) pays an upfront fee. We run the following regression:

(11)
$$
\Delta BAS_{i,t} = \beta_1 * \Delta UP \text{FRONT}_\text{COST}_{i,t} \times \text{DEALER}_\text{PAY}_{i,t} + \beta_2 * \Delta UP \text{FRONT}_\text{COST}_{i,t} + \text{DEALER}_\text{PAY}_{i,t} + \beta_2 * X_{i,t} + u_i + \varepsilon_{i,t},
$$

The interaction term, \triangle UPFRONT COST × DEALER PAY, captures the asymmetric effect of upfront funding costs depending on whether the dealer pays or receives upfront fees.

The regression results are presented in [Table 6](#page-16-1). In column 1, we incorporate firm fixed effects to examine the asymmetric impact of funding costs. We find that the coefficient of the interaction term ΔUPFRONT_COST × DEALER_PAY is positive

⁵TIW of DTCC is a centralized and electronic database providing weekly position information for virtually all cleared and bilateral CDS contracts outstanding in the global marketplace. The TIW data were provided to the public via their website before Oct. 2018. Therefore, our data on dealers' aggregate net position are up to Oct. 2018. We extrapolate the rest of the sample using the last available data.

Asymmetric Effects of Funding Costs on CDS Bid–Ask Spread

Asymmetric Effects of Funding Costs on CDS Bid–Ask Spread
[Table 6](#page-16-1) reports the asymmetric effects of upfront funding costs on CDS bid–ask spread. The dependent variable ABAS is the
difference in bid–ask spread between the difference in the funding costs of upfront payment between the secondary and primary coupons, expressed in bps. DEALER_PAY is dummy variable that is equal to 1 if the dealers' aggregate net position is short credit protection and the short side pays an upfront fee or if the dealers' aggregate net position is long credit protection and the long side pays an upfront fee; and 0 otherwise. The regressions are based on the sample of 5Y CDS contracts from Apr. 2010 to Sept. 2020. The t-statistics are given in parentheses. Standard errors are clustered by firm and time. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

and is statistically significant. In columns 2 and 3, by introducing additional control $\frac{724}{724}$ $\frac{724}{724}$ $\frac{724}{724}$ $\frac{724}{724}$ $\frac{724}{724}$ and is statistically significant. In columns 2 and 3, by introducing additional control variables that could influence CDS bid–ask spread, we find qual regarding the asymmetric effect of funding costs. Given that the average of \triangle UPFRONT COST is 0.03, as observed in our sample, this outcome suggests an experiment of approximately 0.47 bps for the asymmetric effect. The bid–ask Superintendomic magnitude of approximately 0.47 bps for the asymmetric effect. The bid–ask speed and Δ UPFRONT_COST is 0.03, as observed in our spread is about 0.47 bps higher when the dealer provides funds for upfront payments. IV. Search Effects on Bid–Ask Spreads
IV. Search Effects on Bid–Ask Spreads
IV. Search Effects on Bid–Ask Spreads

CDS contracts are traded in a search-based OTC market, where investors trade IV. Search Effects on Bid-Ask Spreads
CDS contracts are traded in a search-based OTC market, where investors trade
through dealers. Duffie et al. ([2005](#page-25-1)) predict that dealers will tighten their bid-ask spreads when the search intensity between dealers and investors is high and they can easily find counterparties to keep low levels of inventory. In this section, we first examine the effects of search intensity on bid–ask spreads using panel regressions.
We then exploit a natural experiment of primary coup examine the search intensity between dealers will tighten their bid–ask spreads when the search intensity between dealers and investors is high and they can easily find counterparties to keep low levels of inventory. In th We then exploit a natural experiment of primary coupon switch to further identify
the effect of search intensity on bid–ask spreads.
A. Effect of Search Intensity on Bid–Ask Spreads

The liquidity in the CDS market is provided by multiple dealers.^{[6](#page-16-2)} In a typical CDS transaction, investors send requests for pricing quotes to a few dealers, who

⁶Major dealers in the CDS market include Bank of America, BNP Paribas, Citigroup, Credit Suisse, Goldman Sachs, HSBC, J.P. Morgan, Morgan Stanley, Nomura, and UBS.

respond to investors' requests by sending back bid and ask quotes. Therefore, the search intensity between dealers and investors $(\rho$ in Duffie et al. (2005)) can be proxied by the daily number of dealers' quotes. Inste Expond to investors requests by sending back of the difference in search intensity between dealers and investors ($ρ$ in Duffie et al. ([2005\)](#page-25-1)) can be proxied by the daily number of dealers' quotes. Instead of directly re proxied by the daily number of dealers' quotes. Instead of directly regressing the focusing on the difference, we can effectively control for the effects of firm bid–ask spread on search intensity, we test the relationship between the difference in bid–ask spreads and the difference in search intensity between the 2 coupons. By focusing on the difference, we can effectively control of quotes or dealers between the 2 coupons as a proxy for the difference in search intensity. However, we do not have separate data on the number of quotes or dealers for the primary coupon and the number of quotes or dealers for the secondary coupon. For most CDS contracts, quotes concentrate on the primary coupon and thus search intensity for the secondary coupon is close to 0. Therefore, we assume that the number of quotes or dealers for the secondary coupon is 0. The difference in search intensity between the 2 coupons is then proxied by the total number of quotes or dealers. Following Duffie et al. ([2005\)](#page-25-1), we take the natural logarithm of the search intensity and estimate the following regression model:

(12)
$$
\Delta BAS_{i,t} = \beta_1 * \log(\text{SEARCH_INTERSITY}_{i,t}) + \beta_2 * \Delta \text{UPFRONT_COST}_{i,t} + \beta_3 * \text{CDS_VOLATILITY}_{i,t} + u_i + g_{i,t} + \varepsilon_{i,t},
$$

where SEARCH_INTENSITY_{it} is the natural logarithm of the number of quotes or the number of dealers for the CDS contract i on day t , and $g_{i,t}$ is the group fixed $+p_3 * CDS_V OLA11111_{i,t} + u_i + g_{i,t}$
where SEARCH_INTENSITY_{i,t} is the natural logarithm of the number of quotes
or the number of dealers for the CDS contract *i* on day *t*, and $g_{i,t}$ is the group fixed
effect. We also add t spread for the secondary CDS contract. The purpose of the group fixed effect is to ally or the number of dealers for the CDS contract *i* on day *t*, and $g_{i,t}$ is the group file of the bid–spread for the secondary CDS contract. The purpose of the group fixed effect is align the bid–ask spread for diff effect. We also add the group fixed effect based on the 20 quantiles of the bid–ask spread for the secondary CDS contract. The purpose of the group fixed effect is to align the bid–ask spread for different firms when searc

between the 2 coupons, we expect β_1 to be positive. We add the firm fixed effect to control for any unobserved heterogeneity across firms. To remove outliers of If larger search intensity leads to a greater difference in bid–ask spreads
between the 2 coupons, we expect β_1 to be positive. We add the firm fixed effect
to control for any unobserved heterogeneity across firms. To regression.

[Table 7](#page-18-0) reports the regression results. In column 1, the coefficient of log(QUOTES_COUNT) is positive and highly significant after controlling for upfront cost, CDS volatility, and fixed effects. This effect is also economically relevant. For example, a 1-standard-deviation increase in the number of quotes counter and the regression results. In column 1, the coefficient of log(QUOTES_COUNT) is positive and highly significant after controlling for upfront cost, CDS volatility, and fixed effects. This effect is also economical 1.9% (2.[7](#page-17-0)%) relative to the sample mean (median).⁷ In column 2, we use $log(DEALERS_COUNT)$ as our alternative search intensity measure and obtain similar results to our previous regression specification. In sum, these results p log(DEALERS_COUNT) as our alternative search intensity measure and obtain similar results to our previous regression specification. In sum, these results provide intensity in competing dealer markets.

B. Primary Coupon Switch Events

As the systemic or idiosyncratic credit risk of a firm moves up and down, the primary coupon can switch between 100 and 500 bps as a result of minimizing As the systemic or idiosyncratic credit risk of a firm moves up and down, the hary coupon can switch between 100 and 500 bps as a result of minimizing

Larger quotes count leads to a greater difference in bid–ask spreads

 7 Larger quotes count leads to a greater difference in bid-ask spreads between the 2 coupons. This primary coupon can switch betwe

Targer quotes count leads to a greater

translates to a decrease in bid–ask spreads.

Effect of Search Intensity on CDS Bid–Ask Spread

Effect of Search Intensity on CDS Bid–Ask Spread
[Table 7](#page-18-0) reports the effects of trading activities on CDS bid–ask spread. The regressions are based on the sample of 5Y CDS
contracts from Apr. 2010 to Sept. 2020. The depend and secondary coupons, expressed in bps. log(DEALERS_COUNT) is the natural logarithm of the number of dealers. log(QUOTES_COUNT) is the natural logarithm of the number of quotes. CDS_VOLATILITY is the 2-week rolling standard
deviations of CDS spread. The t-statistics are given in parentheses. Standard errors are clustered by firm a deviations of CDS spread. The *t*-statistics are given in parentheses. Standard errors are clustered by firm and time. $*$, denote statistical significance at the 10%, 5%, and 1% levels, respectively.

upfront payments.[8](#page-18-1) For instance, suppose that the CDS spread on a reference entity is quoted as 125 bps. The primary coupon is 100 bps as the quoted CDS spread is close to 100 bps. If the credit condition of the reference entity worsens, the quoted CDS spread increases significantly to, say, 400 bps. The primary coupon can then switch to the 500 bps. From Apr. 2010 to Sept. 2020, our sample includes about 176 switch events. The switches from 100 to 500 concentrate around the middle of 2010 and early 2012 when the LIBOR-OIS_SPREAD spikes. During these periods, the credit condition deteriorates and CDS spreads widen quickly. After Jan. 2013, the credit market is relatively stable and thus switch events are rare. Thus, high funding costs and large moves in CDS spreads are driving forces for coupon 1. Bid–Ask Spreads Around Switch Events switches.

The switch of the primary coupon allows us to observe some interesting aspects of liquidity. We first conduct an event study of switches of the primary 1. Bid–Ask Spreads Around Switch Events
The switch of the primary coupon allows us to observe some interesting
aspects of liquidity. We first conduct an event study of switches of the primary
coupon between 100 and 500 by The switch of the primary coupon allows us to observe some interesting
aspects of liquidity. We first conduct an event study of switches of the primary
coupon between 100 and 500 by comparing bid–ask spreads immediately be spreads of the 2 coupons on the first day of the switches since the number of investors trading with the primary coupon or the secondary coupon changes dramatically.

⁸The primary coupon tends to be sticky and typically it does not switch immediately when the CDS spread moves across 300 bps. When a major CDS dealer switches the primary coupon, traders and other dealers would follow.

FIGURE 1

Change in Average CDS Bid–Ask Spread Around Coupon Switches

Craph A of [Figure 1](#page-19-0) shows the change CDS Bid–Ask Spread Around Coupon Switches
Graph A of Figure 1 shows the change in the average CDS bid–ask spread on the primary and secondary coupons
respectively when the primary coupo spread on the primary and secondary coupons, respectively, when the primary coupon switches from 500 to 100. The sample period is from Apr. 2010 to Sept. 2020. Day 0 is the date on which the primary coupon switches. The total number of switches from 500 to 100 is 63, and that from 100 to 500 is 113.

Graph A of [Figure 1](#page-19-0) shows the differences in bid–ask spreads between the 500 and 100 coupons (S500–S100) around the switch of the primary coupon from Graph A of Figure 1 shows the differences in bid–ask spreads between the 500 and 100 coupons (S500–S100) around the switch of the primary coupon from 100 to 500. There is indeed a sudden drop of about 20 bps in the differe ask spreads from day -1 to day 0. Graph B of Figure 1 shows the differences in bid—
ask spreads between the 500 and 100 coupons (S500–S100) around the primary 1 shows the differences in bid–ask spreads between the S500–S100) around the switch of the primary coupon from deed a sudden drop of about 20 bps in the difference in bid–1 to day 0. Graph B of [Figure 1](#page-19-0) shows the differenc 500 and 100 coupons (S500–S100) around the switch of the primary coupon from 100 to 500. There is indeed a sudden drop of about 20 bps in the difference in bidask spreads from day -1 to day 0. Graph B of Figure 1 show coupon switch from 500 to 100. There is a similar jump of 13 bps in the difference From Bid–ask spreads from day -1 to day 0. Graph B of Figure 1 shows the differences in bid-ask spreads between the 500 and 100 coupons (S500–S100) around the primary coupon switch from 500 to 100. There is a similar ju ask spreads hold ay $\frac{1}{10}$ to day 0. Staph B of Figure 1 shows the differences in bid-ask spreads between the 500 and 100 coupons (S500–S100) around the primary coupon switch from 500 to 100. There is a similar jump o α spreads between the 500 and 100 codpoils (5500 5100) around the primary
coupon switch from 500 to 100. There is a similar jump of 13 bps in the difference
in bid–ask spreads from day -1 to day 0. It is interesting on 100. However, when the primary coupon is 500, the difference is around -14 bps. This suggests that in general investors prefer the 500 coupon to the 100 coupon. not bid–ask spread on 500 is only around 5 ops larger than the ord–ask spread
00. However, when the primary coupon is 500, the difference is around
bps. This suggests that in general investors prefer the 500 coupon increas -14 bps. This suggests that in general investors prefer the 500 coupon to the 100 coupon.

Panel A of Table 8 shows that the bid–ask spread on the 100 coupon increases by 58% and the bid–ask spread on the 500 coupon dec

primary coupon.

Panel A of Table 8 shows that the bid–ask spread on the 100 coupon increases

by 58% and the bid–ask spread on the 500 coupon decreases by 11% when the

primary coupon switches from 100 to 500. As shown in Framel A of Table 8 shows that the bid–ask spread on the 100 coupon increases
by 58% and the bid–ask spread on the 500 coupon decreases by 11% when the
primary coupon switches from 100 to 500. As shown in Panel B of Table 500 coupon increases by 13% when the primary coupon switches from 500 to 100. by 36% and the bid–ask spread on the 360 coupon decreases by 11% when the primary coupon switches from 100 to 500. As shown in Panel B of Table 8, the bid–ask spread on the 100 coupon decreases by 33% and the bid–ask spre are not significantly different from 0.

2. Placebo Tests on Matched Firms

In this section, we conduct placebo tests on matched firms to investigate whether the bid–ask spread of firms without primary coupon switching experiences similar changes as firms with primary coupon switching. We expect that the bid–ask spread of firms without primary coupon switching should not experience significant changes around the actual switch dates. To select matched firms, we use propensity

Event Study Using Primary Coupon Switches

[Table 8](#page-20-0) reports the changes in the bid–ask spread, quotes count, and CDS spread around the switch dates of the primary coupon. The switch dates are in the period from Apr. 2010 to Sept. 2020. Three event windows are considered: from days -5 coupon. The switch dates are in the period from Apr. 2010 to Sept. 2020. Three event windows are considered: from days -5

to -1, from days -1 to 0, and from days 0 to 5. Day 0 represents the date on which the actual prima occurs.

scores derived from a probit model that estimates the probability of primary coupon switching. The dependent variable is a dummy variable that equals 1 if the primary coupon of a firm switches during our sample period; and 0 otherwise. The independent variables consist of 3 categories: credit risk, market condition, and liquidity. The credit risk category includes CDS_SPREAD and CDS_VOLATILITY. The market condition includes VIX and LIBOR-OIS_SPREAD. The liquidity category includes DEALERS_COUNT, QUOTES_COUNT, and a dummy variable that equals 1 if the firm is centrally cleared; and 0 otherwise.

Panel A of [Table 9](#page-21-0) reports the estimation results from fitting 2 probit models to this sample. After controlling for credit risk, the overall market condition appears not to be significantly related to switching. DEALERS_COUNT is positively associated with the probability of switching. A greater number of dealers means a greater depth of liquidity, which leads to a higher probability of switching.
Using the estimated probit models, we repeat the ev dealers means a greater depth of liquidity, which leads to a higher probability of switching.

spread around the actual switching dates in the prior section. Specifically, we examine the changes in the bid–ask spreads of the matched firms around the actual switching dates in the prior section. Specifically, we examine the changes in the bid–ask spreads of the matched firms around the actual switching dates. The results are reported in Panels B and C of [Table 9.](#page-21-0) Consistent sing the estimated proof modes, we repeat the event stady of the ord ask spread around the actual switching dates in the prior section. Specifically, we examine the changes in the bid–ask spreads of the matched firms aroun primary coupon switch) does not experience significant changes around the actual switching dates.

3. Revisiting the Effect of Search Intensity Using Switch Events

In this section, we quantify the search component of the bid–ask spread using only switch events. Around the primary coupon switch events, the funding costs of

Event Study Using Pseudo-Coupon Switches

[Table 9](#page-21-0) reports the relative changes in bid–ask spread of the propensity score matched firms around the actual switching dates of the primary coupon. Panel A presents probit models examining primary coupon switching in our sample firms of 5Y CDS contracts from Apr. 2010 to Sept. 2020. The dependent variable in column 1 is a dummy variable that equals 1 if the primary coupon of a firm switches from 100 to 500 during our sample period; and 0 otherwise. The dependent variable in column 2 is a dummy variable that equals 1 if the primary coupon of a firm switches from 500 to 100 during our sample period; and 0 otherwise. CDS_SPREAD is the midpoint of the CDS bid and ask prices. CDS_VOLATILITY is the 2-week rolling standard deviations of CDS spread. VIX is the daily close values of the CBOE volatility index, expressed in percentage. LOIS is the spread between 3 M Libor rate and 3 M OIS rate, expressed in percentage. DEALERS_COUNT is the number of dealers. and bound wise. UDS spread. WX is the daily close values of the CBOE volatility index, expressed in percentage. LOIS is the
deviations of CDS spread. WX is the daily close values of the CBOE volatility index, expressed in spread of the matched firms around the actual switching dates. We select matched firms based on propensity scores derived from the previous probit models. Three event windows are considered: from days -5 to -1 , from days -1 to 0, and from days 0 to 5. Day 0 represents the date on which the actual primary coupon switch occurs.

Panel A. Probability of Coupon Switches

both primary and secondary CDS contracts stay at the same levels. Therefore, the both primary and secondary CDS contracts stay at the same levels. Therefore, the changes in bid–ask spreads around these events are only driven by the inventory risk or searching costs, which could be proxied by our trading activity measures. We then use the primary coupon switch events as natural experiments to identify the both primary and secondary CDS contracts stay a
changes in bid–ask spreads around these events a
risk or searching costs, which could be proxied by a
then use the primary coupon switch events as nateffects of search intens

We estimate the following regression model to identify the effects of search We estimate the following intensity on the bid–ask spreads:

(13) CHANGE_{IN}_{BAS_i} =
$$
\beta_1 * \log(\text{CHANGE_IN_SEARCH_INTENSITY}_i)
$$

+ $g_i + \varepsilon_i$,

where CHANGE IN BAS_i is defined as

(14)
$$
\text{CHANGE_IN_BAS}_{i} = \text{BAS}_{100(500),0} - \text{BAS}_{100(500),-1}.
$$

e CHANGE_IN_BAS_i is defined as

CHANGE_IN_BAS_i = BAS_{100(500),0} – BAS_{100(500),–1}.

BAS_{100(500),–1} is the bid–ask spreads on the 100 (500) coupon on the previous trading date before the coupon switch, and $BAS₁₀₀₍₅₀₀₎₀$ is the bid–ask spread on the 100 (500) coupon on the date of the coupon switch. CHANGE_IN_SEARCH_ INTENSITY $_i$ is defined as

CHANGE_IN_SEARCH_INTENSITY_i = $log(QUOTES_COUNT_{100(500),-5})$ $+$ QUOTES_COUNT_{100(500),-1} $-$ QUOTES_COUNT_{100(500),1} $+$ QUOTES_COUNT_{100(500).5}),

where $QUOTES_COUNT_{100(500), -5(-1)}$ is the number of quotes for the 100 (500) coupon contract 5 (1) days before the primary coupon switch date and QUOTES_COUNT₁₀₀₍₅₀₀₎, $5(1)$ is the number of quotes for the 100 (500) coupon contract 5 (1) days after the primary coupon switch date. g_i is the group fixed effect based on the quartile of the bid-ask spread before the switch 100 (500) coupon contract 5 (1) days before the primary coupon switch date
and QUOTES_COUNT_{100(500),5(1)} is the number of quotes for the 100 (500)
coupon contract 5 (1) days after the primary coupon switch date. g_i is events.

We report the regression results in [Table 10](#page-23-0). In column 1, we find that CHANGE_IN_BAS is positively associated with search intensity measures when the primary coupon switches from 100 to 500. Given the small size of the sample, the high t-statistics, such as 2.79 in specification 1, are quite impressive. The economic magnitude is also significant. A 1-standard-deviation increase in the number of quotes count (from 0 to 131) leads to a decrease of 4.36 bps in the high *t*-statistics, such as 2.79 in specification 1, are quite impressive. The economic magnitude is also significant. A 1-standard-deviation increase in the number of quotes count (from 0 to 131) leads to a decrease nitude of this estimation is in line with the estimation using panel regression in [Section IV.A](#page-16-3). In column 2, we find similar results when the primary coupon switches from 500 to 100. These results confirm that search intensity has a signifin The bid–ask spreads, 30.276 (45.076) removed in the Section IV.A. In column 2, we fissure the bid–ask spreads.

V. Conclusion

CDS standard coupons were introduced as part of the CDS Big Bang. We exploit the CDS standard coupons as a natural experiment to quantify the determinants of CDS market liquidity. Our estimation shows that the order processing CDS standard coupons were introduced as part of the CDS Big Bang. We
exploit the CDS standard coupons as a natural experiment to quantify the deter-
minants of CDS market liquidity. Our estimation shows that the order proc exploit the CDS standard coupons were intoduced as part of the CDS Dig Dang. We
exploit the CDS standard coupons as a natural experiment to quantify the deter-
minants of CDS market liquidity. Our estimation shows that the

Estimating Search Effects on CDS Bid–Ask Spread Using Switch Events

[Table 10](#page-23-0) reports the effects of trading activities on the change in CDS bid–ask spread around primary coupon switches. The regressions are based on the sample of 5Y CDS contracts from Apr. 2010 to Sept. 2020. Column 1 shows the results Table 10 reports the effects of trading activities on the change in CDS bid-ask spread around primary coupon switches.
The regressions are based on the sample of 5Y CDS contracts from Apr. 2010 to Sept. 2020. Column 1 show as $BAS_{100,0} - BAS_{100,-1}$, where $BAS_{100,-1}$ log(CHANGE_IN_QUOTES_COUNT (100)) is defined as log(QUOTES_COUNT_{100,-5} + QUOTES_COUNT_{100,-1} - QUOTES_ $10Q$ (CHANGE IN QUOTES COUNT (100)) is defined as $log(QUO)$ i.e. $COMN_{100, -5} + QUO$ i.e. $COMN_{100, -1} - QUO$ i.e. $COMN_{100, -5} + QUO$ is the number of quotes for the 100 coupon contract $5(1)$ days before the primary coupon switch date. QUOTES_COUNT_{100.5(1)} is the number of quotes for the 100 coupon contract 5
(1) days before the primary coupon switch date. QUOTES_COUNT_{100.5(1}) is the number of quote (1) days after the primary coupon switch date. Column 2 shows the results of the regressions using primary coupon switches from 100 to 500. The dependent variable CHANGE_IN_BAS (500) is defined as BAS_{500,0} - BAS_{500,-1}, where BAS_{500,-1} is spread on the 500 coupon on the date of the coupon switch. log(CHANGE_IN_QUOTES_COUNT (500)) is defined
as log(QUOTES_COUNT_{500,-5}+QUOTES_COUNT_{500,-1} -QUOTES_COUNT_{500,1}+QUOTES_COUNT_{500,5}), where QUOTES_ $\text{COUNT}_{500,-5(-1)}$ is the number of quotes for the 500 coupon contract 5 (1) days before the primary coupon switch date and QUOTES_COUNT_{500,5(1)} is the number of quotes for the 500 coupon contract 5 (1) days after the primary coupon switch date.

upfront payments explains a sizable portion of the variations in the difference in upfront payments explains a sizable portion of the variations in the difference in
bid–ask spreads between the standard coupons (about 5% on average, but can be several times larger). The funding effect is weaker after central clearing is intro-
duced. Consistent with the search theories, the bid–ask spread is lower when
search intensity is higher. The search cost accounts for abo upfront payments explains a sizable portion of the variations in the difference in
bid–ask spreads between the standard coupons (about 5% on average, but can be
several times larger). The funding effect is weaker after cen search intensity is higher. The search cost accounts for about 24% of the difference in bid–ask spreads between the standard coupons. When most trading activities switch between the standard coupons, there are significant activities switch between the standard coupons, there are significant changes in Our results are not unique to the CDS market and can be extended to liquidity in other OTC markets.

Appendix. List of Centrally Cleared Entities

This table lists the central clearing initiation dates, the number of reference entities cleared on each date, and the names of reference entities cleared on each date from Dec. 21, 2009 to Sept. 10, 2020. Panel A lists reference entities centrally cleared before Apr. 8, 2010 (the beginning of our sample period). Panel B lists reference entities centrally cleared during our sample period between Apr. 8, 2010 and Sept. 10, 2020.

References

- Acharya, V. V.; S. M. Schaefer; and Y. Zhang. "Liquidity Risk and Correlation Risk: A Clinical Study of **eferences**
narya, V. V.; S. M. Schaefer; and Y. Zhang. "Liquidity Risk and Correlation Risk: A Clinical Study of
the General Motors and Ford Downgrade of 2005." *Quarterly Journal of Finance, 5 (2015), 1–51*.
- Amihud, Y., and H. Mendelson. "Dealership Market: Market-Making with Inventory." Journal of narya, V. V.; S. M. Schaefer; and Y. Zhan
the General Motors and Ford Downgrai
ihud, Y., and H. Mendelson. "Dealer:
Financial Economics, 8 (1980), 31–53. the Gener

ihud, Y.,
 Financial

dersen, L.

145–192.
- Andersen, L.; D. Duffie; and Y. Song. "Funding Value Adjustments." Journal of Finance, 74 (2019), *Financial Economics*, 8 (1980), 31–53.
dersen, L.; D. Duffie; and Y. Song. "Funding Value Adjustments." Ja
145–192.
Igon, G. O., and P. E. Strahan. "Hedge Funds as Liquidity Providers
Bankruptcy." Journal of Financial Eco
- 145–192.
Aragon, G. O., and P. E. Strahan. "Hedge Funds as Liquidity Providers: Evidence from the Lehman
Bankruptcy." Journal of Financial Economics, 103 (2012), 570–587.
Basak, S., and B. Croitoru. "Equilibrium Mispricing
- Basak, S., and B. Croitoru. "Equilibrium Mispricing in a Capital Market with Portfolio Constraints."
 Review of Financial Studies, 13 (2000), 715–748. Bankruptcy." Journal of Financial Economics, 103 (2012), 570–587.
Review of Financial Studies, 13 (2000), 715–748.
Review of Financial Studies, 13 (2000), 715–748.
In equents, D.; F. De Jong; and J. Driessen. "Derivative P
- Bongaerts, D.; F. De Jong; and J. Driessen. "Derivative Pricing with Liquidity Risk: Theory and *Review of Financial Studies, 13 (2000), 1* gaerts, D.; F. De Jong; and J. Driessen
Evidence from the Credit Default Swap N
mnermeier, M. K., and L. H. Pedersen.
Financial Studies, 22 (2009), 2201–2238.
- Evidence from the Credit Default Swap Market." Journal of Finance, 66 (2011), 203–240.
Brunnermeier, M. K., and L. H. Pedersen. "Market Liquidity and Funding Liquidity." *Review of*
Financial Studies, 22 (2009), 2201–2238.
- Brunnermeier, M. K., and Y. Sannikov. "A Macroeconomic Model with a Financial Sector." American *Financial Studies, 22* (2009), 2201–2238.

Impermeire, M. K., and Y. Sannikov. "A Macroeconomic Model with a Financial Sector."
 Economic Review, 104 (2014), 379–421.

En, R. R.; F. J. Fabozzi; and R. Sverdlove. "Corpor
- Chen, R. R.; F. J. Fabozzi; and R. Sverdlove. "Corporate Credit Default Swap Liquidity and its Economic R
en, R. R.; I
Implications
ffie, D.; N. (
1815–1847.
-
- Implications for Corporate Bond Spreads." Journal of Fixed Income, 20 (2010), 31–57.

Duffie, D.; N. Garleanu; and L. H. Pedersen. "Over-the-Counter Markets." *Econometrica* 73 (2005), 1815–1847.

Glosten, L. R., and L. E. 1815–1847.
Glosten, L. R., and L. E. Harris. "Estimating the Components of the Bid/Ask Spread." Journal of Financial Economics, 21 (1988), 123–142.
Glosten, L. R., and P. R. Milgrom. "Bid, Ask and Transaction Prices in a S
- Financial Economics, 21 (1988), 123–142.

Glosten, L. R., and P. R. Milgrom. "Bid, Ask and Transaction Prices in a Specialist Market with

Heterogeneously Informed Traders: *Journal of financial Economics*, 14 (1985), 71–1
- Gromb, D., and D. Vayanos. "Equilibrium and Welfare in Markets with Financially Constrained Heteroger
9mb, D.,
Arbitrage
9ssman, S
617–633.
- Grossman, S. J., and M. H. Miller. "Liquidity and Market Structure." Journal of Finance, 43 (1988), Arbitrage

17–633.
 *S*_{17–633}.
 *Z*_., and *A*

732–770.
- He, Z., and A. Krishnamurthy. "Intermediary Asset Pricing." American Economic Review, 103 (2013),
- Ho, T., and H. R. Stoll. "Optimal Dealer Pricing Under Transaction and Return Uncertainty." Journal of 61 /-633.

Z., and A. Krishnamurthy. "Intermedia

732–770.

T., and H. R. Stoll. "Optimal Dealer Pri

Financial Economics, 9 (1981), 47–73. He, Z., and A. Krishnamurthy. "Intermediary Asset Pricing." *American Economic Review*, 105 (2013),
1732–770.
Ho, T., and H. R. Stoll. "Optimal Dealer Pricing Under Transaction and Return Uncertainty." *Journal of*
Financi *(32–1/0)*

T., and H. R. Stoll. "Optimal Dealer Pricing

Financial Economics, 9 (1981), 47–73.

ang, R. D., and H. R. Stoll. "The Component

of Financial Studies, 10 (1997), 995–1034.
-
- Junge, B., and A. Trolle. "Liquidity Risk in Credit Default Swap Markets." Swiss Finance Institute Research Paper No. 13-65 (2015).
- Kitwiwattanachai, C., and N. D. Pearson. "The Illiquidity of CDS Market: Evidence from Index Inclusion." Working Paper, University of Connecticut (2014). Junge, B., and A. Trolle. "Liquidity Kisk in Credit Default Swap Markets." Swiss Finance

Research Paper No. 13-65 (2015).

Kitwiwattanachai, C., and N. D. Pearson. "The Illiquidity of CDS Market: Evidence free Inclusion." Kitwiwattanachai, C., and N. D. Pearson. "The Illiquidity of CDS Market: Evidence from Index
Inclusion." Working Paper, University of Connecticut (2014).
Kyle, A. S. "Continuous Auctions and Insider Trading." *Econometrica*

Longstaff, F. A.; S. Mithal; and E. Neis. "Corporate Yield Spreads: Default Risk or Liquidity? New Inclusion." Working Paper, University of Connecticut (2014).

Le, A. S. "Continuous Auctions and Insider Trading." *Econometrica*, 53 (1985), 1315–35.

Le, A. S., and W. Xiong. "Contagion as a Wealth Effect." *Journal of F*

- Evidence from the Credit Default Swap Market." Journal of Finance, 60 (2005), 2213–2253.
Mitchell, M.; L. H. Pedersen; and T. Pulvino. "Slow Moving Capital." *American Economic Review*, 97
(2007), 215–220.
Mitchell, M., an (e, A. S., and W. X

19 passaff, F. A.; S.

Evidence from th

chell, M.; L. H. P

(2007), 215–220.
- Mitchell, M., and T. Pulvino. "Arbitrage Crashes and the Speed of Capital." Journal of Financial (2007), 215–220.
chell, M., and T.
Economics, 104 (
, J., and F. Yu. "E
(2012), 611–631.
- Qiu, J., and F. Yu. "Endogenous Liquidity in Credit Derivatives." Journal of Financial Economics, 103 Mitchell, M., and 1. Pulvino. "Arbitrage Crashes and the Speed of Capital." Journal of Finance, 104 (2012), 469–490.
Comomics, 104 (2012), 469–490.
Qiu, J., and F. Yu. "Endogenous Liquidity in Credit Derivatives." Journal
-
- Siriwardane, E. N. "Limited Investment Capital and Credit Spreads." Journal of Finance, 74 (2019), (2012), 611–631.

Shleifer, A., and R. W. Vishny. "The Limits of Arbitrage." *Journal of Finance*, 52 (1997), 35–55.

Siriwardane, E. N. "Limited Investment Capital and Credit Spreads." *Journal of Finance*, 74 (20
 2303
- Hong Kong (2007).
- 2503–2547.
Tang, D. Y., and H. Yan. "Liquidity and Credit Default Swap Spreads." Working Paper, University of Hong Kong (2007).
Vayanos, D., and P. O. Weill. "A Search-Based Theory of the On-the-Run Phenomenon." Journal of Vayanos, D., and P. O. Weill. "A Search-Based Theory of the On-the-Run Phenomenon." Journal of Hong Kong (2007).

France, G. and P. O. Weill. "A Search-Based Theory of the On-the-Run Phenomenon." Jou.

France, 63 (2008), 1361–1398.

Evidence from the CDS Big Bang." Journal of Financial Economics, 139 (2021), 545–560
- Wang, X.; Y. Wu; H. Yan; and Z. K. Zhong. "Funding Liquidity Shocks in a Quasi-Experiment:
- Xiong, W. "Convergence Trading with Wealth Effects: An Amplification Mechanism in Financial *Finance*, 63 (2008), 1361–1398.
ng, X.; Y. Wu; H. Yan; and Z. K. Zhong. "Funding Liquidity
Evidence from the CDS Big Bang." *Journal of Financial Economics*, W. "Convergence Trading with Wealth Effects: An Ampli
Markets."