Endogenous Liquidity in Credit Derivatives

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Abstract

We study the determination of liquidity provision in the single-name credit default swap (CDS) market as measured by the number of distinct dealers providing quotes. We find that liquidity is concentrated among large obligors and those near the investment-grade/speculative-grade cutoff. Consistent with endogenous liquidity provision by informed financial institutions, more liquidity is associated with obligors for which there is a greater information flow from the CDS market to the stock market ahead of major credit events. Furthermore, the level of information heterogeneity plays an important role in how liquidity provision responds to transaction demand and how liquidity is priced into the CDS premium.

1 Introduction

The infrastructure of the credit default swap (CDS) market has undergone significant transformations in recent years, such as the standardization of documentation and settlement, more streamlined trade processing and confirmation, the mitigation of counterparty risk with central clearing, and improved transparency through the reporting of transaction statistics (ICE, 2010a; Duffie, Li, and Lubke, 2010). While these developments make it natural to consider a migration toward exchange trading, the CDS market has so far remained an over-the-counter structure dominated by major banks.[1] Through direct or electronic communications, often with the assistance of inter-dealer brokers, these banks disseminate bids and offers to potential clients seeking to trade credit protection.[2] Consequently, they play a crucial role in providing liquidity to the market. Despite its clear academic and practical relevance, not much is known about the behavior of liquidity provision in the credit derivatives market. In this paper, we offer insights into liquidity determination in the single-name CDS market by exploiting available data on an important dimension of liquidity—the number of distinct dealers providing quotes about a given obligor on any given day, which can be considered as an empirical proxy for market depth.

Operating primarily as a quote-driven dealership market, the CDS market nonetheless shares a few characteristics with limit order markets. First, although major banks play a significant role in this market, the barrier to entry is likely to be low because the total number of entities providing quotes can be quite large.[3] This blurs the traditional boundary

[1] The recently formed clearing facility for credit default swaps, ICE Trust, counts these prominent financial institutions as its members: Bank of America, Barclays Bank, BNP Paribas, Citibank, Credit Suisse, Deutsche Bank, Goldman Sachs, HSBC, JPMorgan Chase, Merrill Lynch, Morgan Stanley, Nomura, Royal Bank of Scotland, and UBS (ICE, 2010b).

[2] The process of trading in the CDS market usually begins with clients receiving indicative quotes from dealers through information providers such as Bloomberg. They then initiate an RFQ (request-for-quote) with a single dealer or multiple dealers by phone, email, or through an electronic trading platform. Dealers can respond with competitive binding quotes that often result in actual transactions. They can also respond with non-competitive quotes with wide bid-ask spreads or choose not to provide quotes if they do not wish to trade.

[3] According to the Markit.com User Guide (2008), 74 global banks and two brokers contribute data to Markit's credit derivatives database as of December 2006.

between dealers and non-dealers; rather, it is the decision to supply or take liquidity that distinguishes the participants. Second, electronic trading systems have been developed to facilitate access to dealer quotations. To the extent that investors can obtain quotes from multiple dealers in these trading systems, they may have access to what resembles a small portion of a limit order book. These features suggest that we can think of CDS liquidity from the perspective of the recent literature on endogenous liquidity provision in limit order markets.

One potentially important consideration in the decision to supply or demand liquidity is the nature of information possessed by traders. The dominant players in the CDS market, i.e., major banks, may have access to non-public information on CDS obligors through their lending and investment banking activities, and can potentially trade on this information. In an important recent study, Acharya and Johnson (2007, AJ hereafter) analyze the lead-lag relation between the CDS market and the stock market. They show that the information flow from the CDS market to the stock market becomes stronger when a CDS obligor's credit condition deteriorates, and that this information flow is positively related to the number of the obligor's relationship banks.[4] This looks, then, like evidence of insider trading or at least informed quote revision by the banks.

In classical market microstructure models such as Kyle (1985) and Glosten and Milgrom (1985), an uninformed market maker provides liquidity to other uninformed traders and an informed insider who submit market orders. When the information advantage of the insider increases, the market maker widens the bid-ask spread or decreases the market depth to protect herself against the risk of being exploited by the insider. In other words, an increased presence of information asymmetry is associated with a reduction in liquidity provision by an uninformed market maker.

The more recent literature on limit order markets recognizes the decision to provide liquidity as endogenously shaped by the strategic competition among trading agents who

[4] This measure is constructed by counting the number of a firm's active lead lenders in the bank loan market at any point in time. For details, refer to Section 2.

might be differentially informed. In this setting, informed traders emerge as natural liquidity providers because their superior information mitigates the adverse selection risk associated with the use of limit orders. In an experimental setting, Bloomfield, O'Hara, and Saar (2005) find that informed traders initially use market orders to exploit the value of their information, but switch to limit orders as this value starts to dissipate. Kaniel and Liu (2006) argue that long-lived private information increases the execution probability of limit orders and makes them more appealing to informed traders. Empirically, they show that limit orders are more informative than market orders on the NYSE. Goettler, Parlour, and Rajan (2009) numerically solve the equilibrium of a dynamic limit order market in which traders decide whether to acquire information about the fundamental value of the traded asset before placing market or limit orders. They show that traders with no inherent motive to trade have the most incentive to acquire information and that they submit most of the limit orders. Overall, these papers confirm that informed traders play an important role in providing liquidity to the market.

Much of this literature assumes the sequential arrival of traders and focuses on the resulting dynamics of the limit order book. Meanwhile, the nature of private information is greatly simplified, typically, by assuming common information about the value of the asset among informed traders. In the credit derivatives market, however, major dealers' information about credit risk could be diverse. For instance, the differential information major banks had about the state of the U.S. housing market likely resulted in different exposures to subprime mortgages during the recent credit crisis (e.g., Lehman Brothers vs. Goldman Sachs).

A model of endogenous liquidity provision that incorporates heterogeneously informed traders is provided by Boulatov and George (2010). In an extension of the Kyle model, they assume that informed traders can submit price-contingent supply schedules (which are essentially a collection of limit orders) or market orders. In their model, diverse private information results in imperfect competition among informed traders, who want to earn additional rents by providing liquidity. However, the limit orders that they place can partially reveal their information to the rest of the market. Boulatov and George show that, when the market is "dark" (the consolidated supply schedule is not made known), all informed traders will act as liquidity providers; when the market is "open," only some of the informed traders will provide liquidity, but the number of liquidity providers is still proportional to the total number of heterogeneously informed traders.[5] Given the intuition of "more insiders, more insider trading" in the lightly regulated CDS market (Acharya and Johnson, 2010), one would expect a positive association between the amount of informed trading and the number of quote providers.[6]

Besides information heterogeneity, liquidity provision in the CDS market is also expected to depend on the frequency of uninformed trading and the riskiness of the CDS obligor. A larger uninformed trading volume, perhaps as a result of higher hedging demand by bond market investors, implies a higher level of profits to be shared among the dealers. Riskier obligors, on the other hand, may be associated with more mispriced dealer quotes that are susceptible to being picked off by market participants (Goettler, Parlour, and Rajan, 2009). Since these determinants of CDS liquidity—information heterogeneity, the frequency of uninformed trading, and the riskiness of the CDS obligor—are potentially correlated with each other as well as common firm attributes, we begin our empirical analysis by simply documenting the relation between the quarterly average number of CDS quote providers and lagged quarterly firm characteristics.

Using comprehensive CDS market data spanning 2001-08 and 732 North American obligors, we identify robust cross-sectional relations between CDS liquidity and several important

[5] Since, in the CDS market, buy-side firms may have access to quotes from multiple dealers and can partially infer dealers' information from these quotes, one could arguably make the case that the CDS market is closer in spirit to the open market described by Boulatov and George.

[6] In the Boulatov and George model, liquidity is solely provided by informed agents. To the extent that CDS market liquidity can be provided by both informed and uninformed agents, the relation between informed trading and liquidity will remain an empirical issue. It does seem, though, that the dominant role played by potentially informed dealers is what sets the CDS market apart from the equity market. This may explain why informed trading is associated with reduced liquidity in the equity market (see references in Acharya and Johnson, 2007), but increased liquidity in the CDS market, as we show later in this paper.

firm characteristics. First, larger firms and firms with more stock trading volume have more CDS quote providers. Intuitively, such firms are associated with a greater demand for CDS trading from uninformed investors. Second, when conditioning on firm size, we uncover an inverse U-shaped relation between liquidity provision and credit rating, with the peak of liquidity centered around the investment-grade/speculative-grade cutoff. This interesting nonlinear relation could reflect investors' hedging demand and/or dealers' risk of supplying limit orders. Third, the number of CDS quote providers increases with the number of banking relationships of the CDS obligor, which suggests that endogenous liquidity provision in the CDS market is increasing in the level of information heterogeneity.

With regard to the connection between liquidity provision and informed trading, we also attempt to estimate a direct link. Specifically, we follow AJ's methodology to measure informed trading by the amount of information flow from the CDS market to the stock market under adverse credit conditions (up to 90 days before a one-day increase in the CDS premium greater than 50 basis points, among others). We find that this conditional information flow is indeed increasing in the number of CDS quote providers, and moreover, our result is robust to controlling for firm characteristics that might be correlated with hedging activities. While such a finding goes against the intuition of classical market microstructure models, it is consistent with the endogenous provision of liquidity by informed traders.

We further explore the marginal dealer's decision to start or stop supplying liquidity by analyzing the time-series behavior of the number of quote providers. Using the lagged CDS premium change to proxy for transaction demand, we find that a higher demand leads to more liquidity provision when the market is relatively calm. During the period preceding an abrupt increase of the CDS premium, however, the positive link between transaction demand and liquidity provision is weakened, and can even turn negative among obligors with a large number of quote providers. Since the number of liquidity providers is positively related to the amount of informed trading in the CDS market, especially prior to major credit events, this result suggests that a given increase in demand matters less for the marginal dealer when the existing level of information heterogeneity is high.

If CDS liquidity is provided by potentially informed dealers, then it is not clear how the number of quote providers will impact the level of the CDS premium. On one hand, more dealers would bring greater competition, which can lower the premiums customers have to pay, particularly in light of the fact that dealers are net-sellers of CDS to customers. On the other hand, more dealers could also indicate greater informed trading (protection buying) ahead of negative credit news, and this can increase the CDS premium. To explore these distinct possibilities, we examine how lagged changes in liquidity provision predict changes in the CDS premium. Generally, we find that an increase in liquidity provision leads to a reduction of the CDS premium. However, this effect can go the other way when the existing number of dealers is large. Therefore, it appears that the degree of information heterogeneity also plays an important role in how liquidity is reflected in the CDS premium.

To the best of our knowledge, our paper is the first to explore the determinants and implications of endogenous liquidity provision in the CDS market. The prior literature has mainly focused on estimating the liquidity component of CDS premiums or expected CDS returns by exploiting the relation between the CDS premium and various liquidity proxies, such as the bid-ask spread (Tang and Yan, 2007; Bühler and Trapp, 2010; Bongaerts, de Jong, and Driessen, 2010). Our paper also complements the empirical literature on the determinants of the number of NASDAQ market makers. For instance, Wahal (1997) finds that both the level and change of the number of market makers are explained by trading activities and the riskiness of the stock, and Ellis, Michaely, and O'Hara (2002) further show that exiting market makers have low volume and profit rankings relative to other market makers. Our paper extends this literature by identifying information heterogeneity as a determinant of the level and change of CDS market liquidity.

Currently, new regulations regarding over-the-counter (OTC) derivatives market transparency have been proposed by both the CFTC and the SEC in an effort to implement the

Dodd-Frank Act.[7] The proposed changes would put CDS trading on so-called "swap execution facilities" (SEFs), with real-time trade reporting and dealer quotes disseminated to a wider set of investors. These changes are meant to increase market liquidity by intensifying competition among dealers and encouraging participation among non-dealers. However, to the extent that increased transparency reduces information heterogeneity, the results of our paper suggest that this could lead to a reduction of liquidity provision in the CDS market.

The rest of the paper proceeds as follows. Section 2 describes the data used in our analysis as well as related summary statistics. Section 3 presents our empirical results. We first analyze the cross-sectional determinants of CDS liquidity, then focus on establishing a direct connection between liquidity and informed trading, and finally explore the time-series determinants of liquidity as well as the pricing of liquidity. Section 4 concludes.

2 Data

2.1 Variables

We obtain the variables used in our study from several different databases. Our CDS data comes from the Markit Group, a financial information service provider created by major CDS dealers in 2001. This data is commonly used by CDS market participants for daily marking-to-market purposes, and has also been widely used in recent academic research related to credit derivatives. While there is no trade reporting or quote-level information (such as bids, offers, and bid-ask spreads) in this dataset, Markit gathers daily closing prices from dealers' books of records and feeds to automated trading systems. After filtering out stale prices and outliers, Markit uses pricing information from all data contributors to compute a daily composite term structure of CDS premiums (CDS curve) for each obligor. Since five-year contracts are usually the most liquid among points on the CDS curve, we use five-year CDS premiums on senior unsecured obligations of North American reference entities for our study. Besides the five-year CDS premium, the Markit dataset also provides information on

[7] For an excellent discussion of the benefit and cost of transparency in the OTC market and how transparency impacts market quality, see the survey article by Avellaneda and Cont (2010).

the number of data contributors for the five-year contract on a daily basis. In the absence of intradaily trade and quote information or summary statistics such as the daily trading volume, we rely on the number of quote providers as a proxy for the depth of the CDS market.

Besides the CDS pricing and liquidity information, we obtain the following variables from the Compustat quarterly and annual files: firm size, defined as the logarithm of total assets; S&P's long-term issuer credit rating, converted into a numerical scale;[8] firm leverage, defined as long-term debt plus debt in current liabilities, divided by the sum of these variables and the market value of equity. From CRSP, we obtain the daily stock trading volume as well as the annualized average and standard deviation of daily stock returns from the previous 252 trading days. From I/B/E/S, we obtain the number of analysts covering a given stock. Lastly, we construct the number of banking relationships following the methodology described by Bharath, Dahiya, Saunders, and Srinivasan (2007). Specifically, for each reference entity in our CDS database on any given day, we search the Loan Pricing Corporation (LPC) DealScan database for all active syndicated loan facilities for which the reference entity happens to be the borrower. We compute the number of unique lead lenders and define this measure as the number of banking relationships for the reference entity.[9] The purpose for obtaining these variables is so that we can analyze the cross-sectional determinants of CDS liquidity, such as the frequency of uninformed trading (proxied by firm size, stock trading volume, and analyst coverage), the level of credit risk (proxied by credit rating, firm leverage, and equity volatility), and the amount of information heterogeneity (proxied by the number of banking relationships that a CDS obligor has), later in our paper.

[8]The mapping is as follows: 1-AAA, 2-AA+, 3-AA, 4-AA-, 5-A+, 6-A, 7-A-, 8-BBB+, 9-BBB, 10-BBB-, 11-BB+, 12-BB, 13-BB-, 14-B+, 15-B, 16-B-, 17-CCC+, 18-CCC, 19-CCC-, 20-CC, 21-C, and 22-D.

[9]Following Bharath, Dahiya, Saunders, and Srinivasan (2007) and Sufi (2007), we adjust the LPC data for merger and acquisition activities of the lender and the borrower. Our subsequent results are robust to computing the number of banking relationships in slightly different ways such as including the bank loans of affiliated companies, including non-lead lenders, or searching for active loan facilities originated in a trailing five-year window.

2.2 Summary Statistics

Our sample period spans 2001-08 and includes 732 firms with at least 252 daily CDS premium observations.[10] The total number of observations with both daily CDS premium and daily stock return data is just under one million. Table 1 presents the summary statistics of the variables used in this study. The average firm in our sample has a CDS premium of 157 basis points, annualized stock return of 13 percent, annualized stock return volatility of 36 percent, market leverage of 32 percent, and credit rating around BBB. Furthermore, the average firm is covered by 12 analysts, has seven dealers providing quotes on its CDS contracts, and is related to six lead lenders through its syndicated loan facilities. The median firm size is $6.7 billion, which is significantly less than the average firm size of $16.6 billion, suggesting that the distribution of firm size is positively skewed. This is why we use the logarithm of total assets in the subsequent analysis. We also use the logarithm of the stock trading volume because of a similar positive skewness.

Table 2 presents pairwise correlations among the variables. Not surprisingly, we note that the CDS premium is strongly correlated with variables that proxy for the level of credit risk, such as leverage (+), stock return volatility (+), average stock return (-), and the numerical credit rating (+). Moreover, the CDS premium is negatively correlated with variables that proxy for firm size, such as total assets and the number of analysts. These results are consistent with what we know from theoretical and empirical studies of credit spreads.

Table 2 also shows that the number of quote providers is positively correlated with the number of banking relationships, confirming AJ's conjecture that firms with more banking relationships have better liquidity in the CDS market. One possibility is that firms with more banking relationships might naturally have more uninformed trading due to the portfolio

[10] In Section 3.2, we exploit the lead-lag relation between stock returns and CDS premium changes to estimate the amount of informed trading in the CDS market. Implicitly assumed in this methodology is the negative correlation between stock returns and CDS premium changes. This need not be the case, however, as buyout activities such as LBOs can cause stock prices and CDS premiums to move in the same direction. To mitigate this concern, we use the SDC Platinum database to identify and remove 74 firms that would otherwise be included in our analysis, but were subject to takeover bids during our sample period.

rebalancing by the banks. Alternatively, these relationship banks might emerge endogenously as liquidity providers in the CDS market because of their information advantage. What separates these explanations seems to be whether better liquidity in the CDS market is accompanied by a higher level of informed trading. This is one of the questions that we will turn to in Section 3.

We further observe a positive correlation between the number of quote providers and total assets, the daily stock trading volume, and the number of analysts, as well as a negative correlation between the number of quote providers and leverage, stock return volatility, the numerical credit rating, and the level of the CDS premium. These observations suggest that safer and larger firms tend to have superior CDS market liquidity.

Figure 1 presents the time-series of the cross-sectional average CDS premium, number of quote providers, and number of banking relationships. Panel A shows that the average CDS premium of our sample firms exceeded 600 basis points towards the end of 2008, which corresponds to the height of the recent financial crisis. Panel B plots the average number of CDS quote providers. Evident in this graph are the rapid growth of the market during 2001-05, the effort by the Federal Reserve Bank of New York to clean up the CDS trading backlog around 2005-06,[11] and the trade compression implemented during the financial crisis to reduce counterparty risk.[12] While the average number of quote providers varies substantially over time, starting from about three in 2001, peaking at around 11 in 2005, and dropping to about five at the end of 2008, the average number of banking relationships has remained in a narrow range between 5.5 and 6.5 (see Panel C). A variance decomposition shows that more

[11] Credit default swap contracts used to be recorded on paper and trades could go unconfirmed for 90 days or longer. In 2005, the Federal Reserve Bank of New York forced banks to improve their back office operations with respect to credit derivatives. As a result, the number of trades unconfirmed for over 30 days fell by 50 percent in 2006 (Wessel, 2006). The required cost and effort to streamline operations likely caused some smaller CDS dealers to exit the market around 2005-06. Interestingly, the significant one-day drop in the number of quote providers in 2006, visible from Panel B of Figure 1, occurred on March 13, the day after 14 major dealers responded to the Fed with specific targets for reducing the amount of trading backlog (http://newyorkfed.org/newsevents/news_archive/markets/2006/industryletter2.pdf).

[12] Trade compression refers to the practice by which new credit derivatives contracts are proposed to reduce the total number of contracts outstanding, while keeping the net positions of participating dealers unchanged. This practice likely contributed to a further reduction in the number of quote providers in 2008.

than half of the variance of the CDS premium and the number of quote providers is within firms, while less than a quarter of the variance of the number of banking relationships is within firms. This suggests that an examination of the determinants of CDS liquidity should make use of both cross-sectional and time-series variation of the number of quote providers.

3 Empirical Findings

3.1 Cross-Sectional Behavior of CDS Liquidity

To shed light on the determinants of CDS liquidity, such as the frequency of uninformed trading, the level of information heterogeneity, and firm risk, we start our empirical analysis by examining the cross-sectional relation between CDS liquidity and various firm characteristics.

To the extent that larger firms have more publicly traded debt and hence more demand for CDS contracts as a hedging vehicle, they will have better CDS liquidity. In Panel A of Figure 2, we plot the number of CDS quote providers for each firm size decile. Clearly, this graph shows that larger firms tend to have a higher number of quote providers, and that the relation appears to be monotonic. On average, the largest firms have more than nine quote providers, while the smallest firms have only four.

The relation between CDS liquidity and the level of credit risk is less straightforward. Top-quality credits may have little hedging demand because investors consider it unnecessary to insure them. As credit quality declines, investors begin to pay attention to credit deterioration by purchasing credit protection. However, by the time that these bonds fall below investment-grade, credit protection may become too expensive, portfolio managers may have been forced to sell them because of rating-based investment mandates, and people who do hold these bonds could in fact prefer to bear the risk of further deterioration.[13] This suggests that the maximum of the hedging demand is reached near the investment-grade/speculative-grade boundary. Additionally, what we observe as the number of CDS quote providers is

[13] See Kisgen and Strahan (2009) for examples of rating-based regulation that restricts institutional investors from holding bonds below investment-grade or below a rating of B.

an equilibrium outcome that reflects not only investors' hedging demand, but also dealers' propensity to supply quotes. When the risk of the CDS obligor increases, dealers may be more reluctant to provide firm quotes, which are essentially open limit orders.

In Panel B of Figure 2, we plot the number of CDS quote providers for each credit rating category. It appears that, unconditionally, CDS liquidity is lower for riskier firms. On average, AAA-rated firms have over nine quote providers, while firms rated CC or below have fewer than three quote providers. In particular, there is a rather steep drop-off in liquidity between BBB and BB and also between B and CCC. It is possible, however, that higher rated firms have more CDS liquidity not because they are safer, but because they happen to be larger (Table 2 shows that the correlation between firm size and the numerical credit rating is -0.463). Hence, we re-examine the relation between CDS liquidity and credit rating, holding fixed firm size. Panel C of Figure 2 shows that, conditional on firm size (large, medium, or small), there is an inverse U-shaped relation between the number of quote providers and credit rating. For all three firm size terciles, the peak of CDS liquidity is reached at the credit rating of BBB.[14]

These descriptive results are largely confirmed when we regress the number of quote providers on various firm characteristics. Since many of the firm characteristics are only available at the quarterly frequency, we conduct pooled cross-sectional regressions of the quarterly average number of quote providers on lagged firm characteristics. We control for industry-level differences by including two-digit SIC dummies, and we allow for correlated residuals among observations of the same firm by adjusting the standard errors for clustering at the firm level.

Table 3 presents the results of the estimations. In Column (1), we regress the number of quote providers on the two key variables, firm size and credit rating. This regression

[14] It would be interesting to see if hedging demand itself peaks at the BBB level. However, unlike the futures market, in which hedgers are clearly identified as such and their aggregate positions are reported periodically, information on the trading volume and open interest for single-name CDS contracts became publicly available from the Depository Trust & Clearing Corporation only after June 2009, and the data offers no information on the positions of those who can be considered as hedgers in the CDS market.

shows that larger firms and safer firms have higher CDS liquidity. Notably, firms that are 2.7 times larger in terms of total assets are expected to have about two more CDS quote providers. While both coefficients are statistically significant, the effect of firm size appears to be much stronger than that of credit rating. When we allow for the nonlinear effect of credit rating by incorporating a quadratic term in Column (2), it turns out that the previous linear specification on credit rating is misspecified—CDS liquidity depends on credit rating in an inverse U-shaped relation, reaching its peak when the numerical credit rating is equal to $0.752/(2 \times 0.047) = 8.0$, or BBB+. This is in line with the earlier evidence from Figure 2. Moreover, this nonlinear relation is robust to the inclusion of other firm characteristics in the regression, as shown in Columns (3)-(5).

In Column (3), we include leverage, stock return volatility, stock trading volume, and the number of analysts as additional explanatory variables. It turns out that even when controlling for credit rating and firm size, the relation between the number of quote providers and leverage is nonlinear. Fixing firm size, leverage essentially captures the amount of publicly traded bonds issued by the firm, and is therefore directly related to the demand for hedging through credit derivatives. This might explain the positive relation between CDS liquidity and leverage when the leverage ratio is low. However, when the leverage ratio is high, the elevated level of firm risk could force CDS dealers to reduce their supply of liquidity. This is the same reasoning that might account for the lower CDS liquidity among speculative-grade obligors. For the other included variables, we find that the coefficient on stock return volatility is negative and significant, and the coefficient on stock trading volume is positive and significant.[15] These results are consistent with the stock return volatility as a measure of firm risk and the stock trading volume as a measure of the amount of uninformed trading in the CDS market.

To further demonstrate the robustness of the nonlinear dependence of CDS liquidity on

[15] We do not detect any nonlinear effect of the stock return volatility on CDS liquidity. It is possible that, when we control for firm size, credit rating, and firm leverage, there is not enough variation in the stock return volatility to permit an accurate inference of potential nonlinear effects.

credit rating, we employ categorical dummies rather than linear and quadratic terms of the numerical credit rating. We group the S&P credit ratings into three categories: AAA and AA (High), A and BBB (Medium), and BB and below (Low), with the Low rating group acting as the baseline. As shown in Column (4), the High (Medium) rating group has 2.4 (3.1) more quote providers than the Low rating group. This fits well with the pattern depicted in Panel C of Figure 2.

Lastly, we include the number of banking relationships in Column (5). We find significant result (at the one-percent significance level) that firms with more banking relationships tend to have more CDS quote providers. While the evidence presented by AJ points to the number of banking relationships as a proxy for the degree of asymmetric information in the CDS market, a more rigorous result that directly relates CDS liquidity to the amount of informed trading awaits in the next subsection.

Summarizing the cross-sectional evidence, we find that CDS liquidity is strongly related to firm size, with larger firms commanding superior liquidity. CDS liquidity is also strongly related to the level of credit risk, albeit the relation appears to be driven by competing forces such as the demand for hedging from bond market investors and the willingness of dealers to supply quotes. These forces may depend on the level of credit risk in different ways, creating an interesting nonlinear relation between CDS liquidity and credit rating. We also uncover a positive relation between CDS liquidity and the number of banking relationships, indicating that liquidity provision may be related to the presence of informed trading in the CDS market.

3.2 The Role of Informed Trading

3.2.1 Measuring Informed Trading

As we have discussed in the introduction of our paper, the recent literature on limit order markets shows that informed traders play an important role in providing liquidity to the market. Since the CDS market is dominated by large banks/major dealers that might trade on their private information or use this information to make markets, it presents an ideal setting to study the effect of informed trading on endogenous liquidity. However, the first question that we need to address is how one should measure the amount of informed trading in the CDS market.

Given the limited data from the CDS market, one approach offered by AJ is to exploit the lead-lag relation between the CDS market and the stock market. Their method is based on the assumption that the stock market is efficient with respect to publicly available information, and that informed dealers will either trade on their superior information by purchasing credit protection or post updated quotes that reflect this information before major credit events materialize. This assumption prompts AJ to focus on the information flow from the CDS market to the stock market before credit events. The purpose of this subsection is to present evidence of such information flow in our significantly larger sample (our sample is about ten times the size of AJ's sample in terms of the number of firms covered). We also modify AJ's definition of credit condition dummies to make it more suitable for a significantly longer sample period (our sample period is more than twice as long as AJ's sample period).

Following AJ, we extract information unique to the CDS market at time t by running the following time-series regression for each firm in our sample:

$$\begin{aligned} & (\text{CDS return})_{it} \\ = \; & \alpha_i + \sum_{k=0}^{5} \left(\beta_{ik} + \gamma_{ik} / \left(\text{CDS premium}\right)_{it}\right) (\text{Stock return})_{i,t-k} \\ & + \sum_{k=1}^{5} \delta_{ik} \left(\text{CDS return}\right)_{i,t-k} + u_{it}, \end{aligned} \tag{1}$$

In this specification, the CDS return is defined as the difference in the logarithm of the CDS premium, and the interaction between the stock return and the inverse of the CDS premium is included to account for the nonlinear dependence between the CDS return and the stock return (see an illustration in AJ using the Merton model). In essence, the above specification removes the influence of past shocks in the stock market and the CDS market up to five lags, as well as the contemporaneous shock in the stock market, leaving the regression residual u_{it} as news unique to the CDS market for firm i at time t, or what we call "CDS innovations."

As in AJ, we use the following panel regression to measure the amount of informed trading in the CDS market:

$$\begin{aligned} & (\text{Stock return})_{it} \\ = \; & a + \sum_{k=1}^{5} \left(b_k + b_k^D \, (\text{Credit condition dummy})_{it} \right) (\text{CDS innovation})_{i,t-k} \\ & + \sum_{k=1}^{5} \left(c_k + c_k^D \, (\text{Credit condition dummy})_{it} \right) (\text{Stock return})_{i,t-k} + \epsilon_{it}. \end{aligned} \tag{2}$$

Of key importance in this regression equation is the interpretation of the coefficient $\sum_{k=1}^{5} \left(b_k + b_k^D \right)$, which measures the flow of information from the CDS market to the stock market conditional on there being some type of credit event just ahead.

For the credit condition dummies, we use two different specifications. In Specification A, we adopt AJ's definition of a credit event as a one-day increase in the CDS premium greater than 50 basis points. However, instead of defining the credit condition dummy to be one for all days in the sample period prior to each credit event, we limit its scope to up to five, 30, or 90 days before each credit event. Since the sample period can be up to eight years long for many firms in our sample, it would be more appropriate to focus on a shorter period before each credit event if we are to uncover evidence of informed trading before the event.

In Specification B, we follow Berndt and Ostrovnaya (2008) in defining a credit event as a one-day increase in the CDS premium that satisfies the following condition:

$$\Delta CDS_{it} \geq \text{average} \left(\Delta CDS_i \right) + 4 \cdot \text{stdev} \left(\Delta CDS_i \right). \tag{3}$$

What is different about this definition is that it accounts for the scale of variation of each firm's CDS premium.[16] As before, the credit condition dummy takes the value of one up to five, 30, or 90 days before each credit event.

[16] We choose four standard deviations above the mean for this condition because it yields approximately the same number of credit events as our first definition.

For Specification A, 456 out of the 732 sample firms have at least one episode in which the CDS premium rose by at least 50 basis points in a single day. Among these firms, the average length of the sample period is 1,938 days, out of which 139 days have the credit condition dummy being "on" (equal to one) when using the 30-day definition. The summary statistics for Specification B are similar. These observations show that the so-called "credit events" are actually quite common and that the credit condition dummy is activated during a substantial part of the sample period. Hence, it seems unlikely that our subsequent results are driven by a small number of firms or a small portion of the sample period.

Our results are summarized in Table 4 for both specifications of the credit condition dummy. We find strong evidence that CDS innovations affect future stock returns for firms about to experience credit events. Specifically, $\sum_{k=1}^{5} b_k$ represents the unconditional flow of information from the CDS market to the stock market. Although this coefficient is positive and significant, it is an order of magnitude smaller than the size of $\sum_{k=1}^{5} b_k^D$, which is negative and significant at the one percent level in all cases. Using Specification A and a 30-day pre-event period as the benchmark case, we find that $\sum_{k=1}^{5} \left(b_k + b_k^D\right) = -0.043$, which represents a 4.3 percent transmission of information in the CDS innovation to future stock returns during the 30 days prior to the credit event. This estimate suggests that a positive CDS innovation on day t is followed by an overall negative response in the stock market during the subsequent five days. The magnitude of this response is comparable to the findings documented by AJ.

Intuitively, since the likelihood of informed trading probably increases as one approaches the credit event, the amount of information transmitted from the CDS market to the stock market should be greater when we condition on a shorter pre-event window. Our results are consistent with this intuition, namely, the magnitude of the coefficient $\sum_{k=1}^{5} \left(b_k + b_k^D\right)$ decreases with the length of the pre-event window. For example, for Specification A, we find that $\sum_{k=1}^{5} \left(b_k + b_k^D\right)$ is equal to -0.065, -0.043, and -0.030 for a pre-event window of five, 30, and 90 days, respectively. Similarly, for Specification B, $\sum_{k=1}^{5} \left(b_k + b_k^D\right)$ is equal to

-0.080, -0.033, and -0.021, respectively.

Turning to the lagged stock returns, Table 4 shows that the unconditional coefficient $\sum_{k=1}^{5} c_k$ is around -15 to -10 percent. This is consistent with Lo and MacKinlay (1988), who find a daily autocorrelation of about -3 percent for individual stock returns, and attribute it to infrequent trading (Scholes and Williams, 1977) and the bid-ask bounce (Roll, 1984). Interestingly, when conditioning on the credit dummies, the coefficient $\sum_{k=1}^{5}\left(c_k + c_k^D\right)$ becomes less negative compared to $\sum_{k=1}^{5} c_k$. Intuitively, there may be a sequence of bad news preceding the credit event, which implies more frequent trading and perhaps a negative trend in the stock price, both of which would help to mitigate the negative autocorrelation in daily stock returns. Indeed, to the extent that there is more trading as the credit event becomes more imminent, the coefficient $\sum_{k=1}^{5}\left(c_k + c_k^D\right)$ should be the least negative using the shortest pre-event window definition. This is precisely what we find based on the five-day pre-event window.

In results not presented here, we also separate our sample period into a first half that corresponds to AJ's sample period (January 2001 to October 2004) and a remaining second half (October 2004 to December 2008). We find that the conditional information flow from the CDS market to the stock market appears stronger in the second half of the sample period. One possible explanation is that the second half includes the recent financial crisis, which has been an exceptionally volatile period.[17] The higher volatility implies that there are more credit events according to our definition, and this can help increase the power of our estimation in detecting conditional information flow from the CDS market to the stock market. Indeed, about two thirds of the credit events (of Specification A) occurred during the second half of our sample period.

Also in results not presented here, we consider two other definitions of the credit condition dummy. In the first definition, we let the dummy be equal to one on day t if the CDS premium stays above 100 basis points for a certain number of days afterwards. In the second definition,

[17] In fact, when we further restrict the second sub-period to January 2007 to December 2008, the conditional information flow from the CDS market to the stock market strengthens even more.

we require the credit rating on day t to be lower than a certain threshold (this is identical to one used by AJ). We find weaker, and in some cases insignificant, conditional information flow coefficients using these two alternative definitions. Collectively, these findings suggest that it is important to condition the information flow on abrupt changes in credit risk and not on persistently high credit spreads and low credit ratings per se, as the latter typically do not impart a "surprise" to the market and are less relevant in terms of detecting the presence of asymmetric information.

To sum up the evidence gathered in this subsection, we find that CDS innovations lead stock returns prior to significant changes in the credit spread. The coefficient measuring the lead-lag relation is greater as the credit event gets closer. These findings are consistent with informed trading taking place in the CDS market before the identified credit events, confirming the results obtained by AJ using earlier data.[18]

3.2.2 CDS Liquidity and Informed Trading

Having confirmed AJ's methodology for detecting informed trading in the CDS market using our substantially larger sample, we now focus on estimating the relation between informed trading and CDS liquidity provision.[19]

Our first approach is to create liquidity terciles and then estimate the conditional information flow as before for each group separately. Specifically, the liquidity terciles are defined as Low: $N \leq 5$, Medium: $5 < N \leq 10$, and High: $N > 10$, where N denotes the number of CDS quote providers. Table 5 shows that the coefficient measuring conditional information flow, $\sum_{k=1}^{5} \left(b_k + b_k^D\right)$, indeed behaves as expected: it is equal to -0.024, -0.062, and -0.178 for the low to high liquidity terciles, respectively. Hence, firms that tend to be the

[18] AJ raise an interesting possibility that if the information flow from the CDS market to the stock market occurs within a day, their methodology of detecting informed trading in the CDS market (which relies on daily data) might miss out on the pattern. This will certainly become a more serious criticism as the CDS market liquidity improves. However, it is not clear whether the market has reached that stage of maturity. Judging solely on the basis of the number of quote providers, the latter part of the sample period, such as 2007-08, does not appear to be substantially different from earlier sub-periods. Moreover, the market continues to trade no more than ten times per day even among the more liquid obligors.

[19] To conserve space, we only present results using Specification A of the credit condition dummies below. The results using Specification B are similar and omitted.

most liquid in the CDS market are associated with the highest level of informed trading as measured by the incremental price discovery relative to the stock market.

Next, we follow an alternative approach by including interaction terms with the number of quote providers. Specifically, we estimate variants of the following basic specification, in which we condition the flow of information from the CDS market to the stock market on the number of quote providers:

$$(\text{Stock return})_{it} = a + (b_1 + b_2 N_{it})\,(\text{CDS innovation})_{i,t-1} + \sum_{k=1}^{5} c_k\,(\text{Stock return})_{i,t-k} + \epsilon_{it}. \quad (4)$$

In Column (1) of Table 6, we first estimate the above equation without the liquidity provision interaction term. This is basically Eq. (2) with one lag of the CDS innovation and without the credit condition dummies. The coefficient b_1 captures the unconditional spillover from the previous day's CDS innovation to today's stock return. The result shows a b_1 of -0.001 that is not statistically significant. In Column (2), we allow positive and negative CDS innovations to make distinct contributions to future stock returns. We find that it is information embedded in positive CDS innovations that makes a significant impact on stock returns over the next day; in contrast, the spillover from negative CDS innovations to future stock returns is not significant. This suggests that informed trading in the CDS market is manifested primarily through purchasing credit protection ahead of impending bad news about an obligor.

The rest of Table 6 turns to the role of liquidity provision. Column (3) presents the estimation of Eq. (4). Specifically, we find that $b_1 = 0.004$ and $b_2 = -0.001$, and the latter is significant at the one percent level. When the number of quote providers is set to its sample mean of 7.2, the overall coefficient measuring information flow is only $0.004 - 0.001 \times 7.2 \approx -0.003$. Given an average within-firm standard deviation of 3.67, a one-standard-deviation increase in the number of quote providers will increase this coefficient in magnitude to -0.007. In Column (4), we expand Eq. (4) to allow for the positive and negative parts of the CDS innovation, as well as their interactions with the number of quote providers. While the results on positive CDS innovations are similar to Column (3), there is weak evidence here that negative CDS innovations could lead to positive stock returns (which are more positive when the number of quote providers is larger). This suggests that informed trading/quote updating might also be going on when there is good news in the CDS market.

In Column (5), we bring credit condition dummies into Eq. (4). Since we have already shown that the amount of information flow is concentrated in periods leading up to credit events, it would be of interest to examine the effect of liquidity provision conditional on having impending credit events. What we find is that the dependence of information flow on liquidity provision is much stronger during these periods in the same way that the overall level of information flow is stronger. For example, without these credit events, we find that $b_0 = 0.004$ and $b_1 = -0.0006$. Conditional on the credit condition dummies, these coefficients become $b_0 + b_0^D = 0.013$ and $b_1 + b_1^D = -0.0056$.

While these results are certainly consistent with dealers themselves being informed agents who supply liquidity, it is also possible that dealers are uninformed agents who merely respond to hedging activities, providing more liquidity when more is needed, which coincides with a higher level of informed trading because informed agents can more easily go undetected when there is greater uninformed trading. To address this issue, we expand Eq. (4) to include interactions between the CDS innovation and various firm characteristics that might be correlated with the hedging demand, such as firm size, leverage, stock return volatility, average stock return, and credit rating. Column (6) shows that the coefficients pertaining to liquidity provision are similar to those in Column (5) without the firm-level controls. Furthermore, among the additional control variables, only the interaction between the average stock return and the CDS innovation is statistically significant.[20] Since the hedging demand may be related to credit quality in a nonlinear manner, potentially reaching its maximum near the BBB rating, Column (6) also includes the square of credit rating. However, neither the linear nor quadratic credit rating term is significant. We further remove all BBB-rated

[20]The sign of the coefficient suggests that a greater average stock return over the past 252 trading days, likely corresponding to a sequence of good news, tends to weaken the information flow from the CDS market to the stock market, which is consistent with the asymmetric response of future stock returns to positive and negative CDS innovations uncovered earlier.

firms from our sample and re-estimate the specifications in Tables 5 and 6. Results remain qualitatively the same (available upon request). Therefore, the relation between CDS liquidity and informed trading does not appear to be driven by a common dependence on hedging activities.

The last set of results in this subsection examine the robustness of the relation between CDS liquidity and informed trading to the number of banking relationships. AJ demonstrate that firms with more banking relationships are associated with more informed trading in the CDS market. Since the number of banking relationships is positively correlated with the number of quote providers (Table 2 shows a correlation of 0.212), one might naturally question the robustness of our results. At a deeper level, the number of banking relationships might capture only one set of players in the market (i.e., lenders in the bank loan market) that have access to non-public information about CDS obligors. In comparison, if all or a proportional number of all informed agents end up providing liquidity (as, say, predicted by the Boulatov and George model), then the number of quote providers would be a better proxy for the amount of informed trading in the CDS market.

We examine this interesting issue in Table 7. Specifically, we augment Eq. (4) with the interaction between the number of banking relationships and the CDS innovation, as well as distinct effects involving the positive and negative parts of the CDS innovation. To better compare with AJ's findings, we use AJ's sample period (with additional firms from our data) for Columns (1)-(4). For Columns (5)-(8), we use the remaining sample period up to December 2008.

First, we focus on AJ's sample period. In Column (1), we seek to replicate their basic results related to the number of banking relationships. We find that the coefficient on the interaction between the number of banking relationships and the CDS innovation is -0.0008, which is significant at the one percent level. For a firm with an average number of banking relationships, which stands at 6.0, the coefficient of interest is $0.003 - 0.0008 \times 6.0 = -0.0018$. These results are qualitatively consistent with AJ's findings. In Column (2), we also include the interaction between liquidity provision and the CDS innovation. While the coefficient related to the number of banking relationships remains unchanged, the coefficient related to the number of quote providers is -0.0011 and significant at the five percent level. This suggests that the two effects are independent and distinct. In Columns (3) and (4), we analyze the differential information flow when the CDS innovation is either positive or negative. Consistent with earlier results, we find that the effects of banking relationships and liquidity provision are both exclusively driven by negative news (or positive CDS innovations), and they are both statistically significant.

We then look to the second half of the sample period in Columns (5)-(8). We find that the coefficient related to the number of quote providers continues to be significant, now at the one percent level, and its magnitude is very similar to that of the earlier sub-period. However, the coefficient related to the number of banking relationships is no longer significant, either on a stand-alone basis or when jointly included with the number of quote providers. To better understand this result, note that the number of banking relationships measure focuses exclusively on lending relationships established through bank loans. It does not account for any non-public information obtained from investment banking activities, such as mergers and acquisitions, and the issuance of debt and equity. It also does not consider the possibility that loans may be sold to third parties or hedged with credit derivatives, both of which tend to weaken lenders' incentive to monitor and obtain non-public information about borrowers. These considerations suggest that the number of banking relationships is a noisy measure of the number of informed traders in the CDS market. The presence of measurement noise may account for the lack of significance of the number of banking relationships in the second half of the sample period.

In summary, we find strong evidence that liquidity provision in the CDS market is positively related to the amount of informed trading, and it does not appear that this relation is driven by a common dependence on the hedging demand. On the other hand, this result is consistent with the recent literature on endogenous liquidity in limit order markets, which predicts that informed traders are the natural liquidity providers. Furthermore, this finding is robust to controlling for the number of banking relationships, which was used by AJ as a measure of information asymmetry in the CDS market.

3.3 Time-Series Behavior of CDS Liquidity

In Section 3.1, we have examined the relation between CDS liquidity and firm characteristics using quarterly data, drawing inferences mainly from the cross-sectional variation of these variables. Nevertheless, about half of the variation in the number of CDS quote providers actually comes from time-series fluctuations at the daily frequency. Therefore, we examine the time-series behavior of CDS liquidity in this subsection, paying particular attention to the marginal dealer's decision to start or stop supplying liquidity as reflected in the daily change in the number of quote providers.

Our preliminary analysis shows that the number of quote providers is a highly persistent variable with a half life on the order of about one month. In nearly 60 percent of the observations, the daily change in the number of quote providers is zero. This is to be expected given the potential fixed cost of making a market for credit derivatives.[21] Intriguingly, the first-order serial correlation of the daily change is strongly negative (-0.35), suggesting that whenever the number of quote providers does change, a significant part of the change is only temporary and will be reversed in a matter of days. Therefore, while the number of quote providers is well-explained in the cross-section, it seems to contain a significant amount of noise in the time-series.

Without being able to ascertain the identity of the entering and exiting dealers, we can only speculate as to the source of this noise. For example, it is mentioned in the Markit.com

[21] The fixed cost of market-making might include the cost of setting up hardware (electronic trading platforms), accessing historical data, and hiring dedicated credit analysts and traders. In line with earlier discussions, dealers' decision to start or stop providing liquidity could be influenced by the following considerations: 1) anticipated changes in hedging demand; 2) whether the CDS obligor has become too risky for binding quotes to be offered to the market; 3) whether they have an information advantage about the obligor relative to other market participants. For example, consistent with the last scenario, a dealer could stop providing liquidity for an obligor if she no longer has a material position in its debt, and therefore has less incentive to "research" the underlying credit risk.

User Guide (2008) that a dealer might occasionally miss a data feed to Markit. The result of that would be a reduction in the number of quote providers by one, followed by an increase of one the next day when the data feed is restored. This creates a negative serial correlation in the daily change of the number of quote providers. A similar data-related explanation might have to do with Markit's statistical data cleaning procedure, which might flag a contributor's data as stale or outliers one day (hence dropped) and acceptable a few days later. This could be caused, for example, by dealers not updating their quotes diligently when there is no request for quotes over several days. Of course, this situation would be corrected as soon as transaction demand picks up and dealers start to respond to customer requests. In other words, even the "noisy" part of the daily change of the number of quote providers could reflect meaningful fluctuations in the demand for credit protection.

For explanatory variables, we note that the firm characteristics that have been shown to explain CDS liquidity in the cross-section are largely constant at the daily frequency. Instead, we use changes in the CDS premium as an empirical proxy for shocks to the transaction demand. From an equilibrium perspective, the supply of liquidity is driven by the number of CDS dealers, which tends to be fairly sticky as we have seen. Thus, the daily change in the CDS premium largely reflects short-run fluctuations in the transaction demand for CDS contracts.

We analyze the response of CDS liquidity to transaction demand using the following regression specification:

$$\begin{aligned} \Delta N_{it} \;=\;& a_0 + a_1 N_{i,t-1} + a_2 \Delta N_{i,t-1} + (a_3 + a_4 N_{i,t-1})\,(\text{CDS return})_{i,t-1} \\ & + (\text{Credit condition dummy})_{it} \\ & \times \left[b_0 + b_1 N_{i,t-1} + b_2 \Delta N_{i,t-1} + (b_3 + b_4 N_{i,t-1})\,(\text{CDS return})_{i,t-1} \right] + \epsilon_{it}. \qquad (5) \end{aligned}$$

In Eq. (5), the coefficient a_1 captures the speed of mean reversion of the number of quote providers, while a_2 accommodates potential serial correlation of the dependent variable, as described above. The CDS return, defined earlier as the difference in the logarithm of the

CDS premium, is included as an empirical proxy for transaction demand. Further, we allow for an interaction between the CDS return and the number of quote providers. Together, a_3 and a_4 describe how CDS liquidity responds to past shocks to the transaction demand conditional on the existing number of CDS dealers. If, as shown in the previous subsection, that the number of quote providers is closely related to the level of information heterogeneity in the CDS market, we would expect the number of quote providers to play a crucial role in how liquidity provision responds to transaction demand. Specifically, when the level of information heterogeneity is low, we expect dealers to respond positively to an increase in transaction demand. However, when the level of information heterogeneity is high, dealers may be reluctant to provide more liquidity because the increasing CDS premium could be a signal of informed trading in the market. Given earlier evidence suggesting that informed trading tends to take place during a short window before adverse credit events, we also interact all of the aforementioned terms with a credit condition dummy (using Specification A in Section 3.2.1 with a 30-day window), yielding the second set of terms in Eq. (5) with the coefficients b_0 to b_4.

Table 8 presents the results of this analysis. In Column (1), we estimate a nested version of Eq. (5) that includes only the intercepts a_0 and b_0. Outside the 30-day window before credit events, we find that the daily change in the number of quote providers is on average positive ($a_0 = 0.003$). This probably reflects the overall growth of the CDS market and the improvement to liquidity during our sample period. Within the 30-day pre-event window, however, the average daily change is negative ($a_0 + b_0 = -0.005$). This suggests that CDS dealers are exiting the market prior to significant credit events.

To see why dealers are exiting the market prior to bad credit news, we plot the average number of CDS dealers, equity trading volume, and CDS premium within the 60-day window straddling credit events. Panel A of Figure 3 shows that the number of CDS dealers decreases steadily before the credit events, jumps up on the event day, drops back down over the following day, and begins a gradual increase thereafter. Panel B shows that the jumps in

CDS liquidity and equity trading volume in the vicinity of the event day are quite similar, and are likely driven by increasing transaction demand in response to public news announcements (Kim and Verrecchia, 1991). Panel C shows that the CDS premium rises slowly before the credit events, spikes on the event day, and then gradually declines toward the pre-event level. The behavior of the CDS premium and the number of CDS dealers pre- and post-event suggests a negative correlation between the two, which is consistent with the hump-shaped relation between CDS liquidity and credit quality documented in Section 3.1.[22] We also notice in Panel A that CDS liquidity is higher pre-event than post-event. While this difference may be partly related to the difference in CDS premiums, it is also consistent with there being greater information heterogeneity before the credit events.

In Column (2) of Table 8, we estimate another nested version of Eq. (5) that excludes the interactions between transaction demand and the number of quote providers. Outside the 30-day window before credit events, the coefficients a_0 and a_1 together indicate a long-run mean value of N around 7 (0.268/0.036) and a half life of about one month ($\ln 2/0.036 \approx 19$ trading days). Consistent with our preliminary analysis, a_2 shows that 33 percent of the shock to N is reversed over the following day. We also identify a positive and significant response of CDS liquidity to transaction demand as reflected in the coefficient $a_3 = 0.459$. Within the 30-day pre-event window, the long-run mean of N is smaller ($(0.268 + 0.012) / (0.036 + 0.016) \approx 5$), perhaps reflecting a higher level of risk for firms about to experience a sharp increase in their CDS premiums, and the half life is shorter ($\ln 2/ (0.036 + 0.016) \approx 13$ trading days). More interestingly, we find that b_3 is negative and significant (-0.335), which suggests a muted response of CDS liquidity to transaction demand ($a_3 + b_3 = 0.124$) when major credit events lie ahead. This muted response could be due to a higher level of credit risk making dealers more cautious in supplying liquidity to the market.

In Column (3), we condition the response coefficient on the number of quote providers. Interestingly, we do not find any significant dependence on the number of quote providers

[22] The average level of the CDS premium before and after credit events is well above 300 basis points. This suggests that we have moved beyond the hump into the region where CDS liquidity is lower on worse credits.

outside the pre-event window ($a_4 = 0.013$ and not significant). This suggests that informed trading is of lesser concern when major credit events are not imminent. However, there is a significantly negative dependence on the number of quote providers inside the pre-event window. To see this, we combine the coefficients a_3, a_4, b_3, and b_4 to yield an overall response to past transaction demand of $0.671 - 0.140N_{t-1}$. Therefore, the positive response of CDS liquidity to transaction demand is tempered by the existing number of dealers. This is consistent with the existing number of dealers acting as a proxy for the amount of information asymmetry in the market—dealers will be reluctant to respond to transaction demand if they think others in the market possess superior information. In results not reported here, we further note that the magnitude of $a_4 + b_4$ is larger when the pre-event window is shorter. This is also consistent with there being more informed trading or quote revision in the CDS market closer to a major credit event.

It is plausible that an increase in transaction demand may be fully absorbed by a large number of existing dealers without triggering a further increase in the number of market makers. Stated somewhat differently, "inactive" dealers are more likely to receive a request-for-quote (and respond to it) when the number of dealers who already offer quotes is small. This alternative view can also explain why the response of CDS liquidity to transaction demand is decreasing in the number of existing dealers. However, it cannot explain why the response depends differently on the number of existing dealers in and out of the pre-event window.

To accommodate the possibly nonlinear relation between ΔN and the lagged CDS return, we allow the slope coefficient to depend on the overall risk of the obligor. In Column (4), we include the interactions of various firm characteristics with the lagged CDS return both in and out of the 30-day pre-event window.[23] Among the included controls, we find that the CDS liquidity change of larger firms and firms with lower leverage responds more positively to the lagged CDS return. Also, firms with a higher CDS premium tend to have a more

[23] To conserve space, we report only the interactions outside the 30-day pre-event window in Table 8. The interaction terms inside the 30-day pre-event window are omitted because none of them is significant.

negative relation between CDS liquidity changes and lagged CDS returns, although the coefficient is not statistically significant. These results are consistent with the inverse U-shaped relation between CDS liquidity and credit quality identified in Section 3.1. Meanwhile, the dependence of the response on the existing number of dealers remains virtually unchanged from Column (3). Specifically, we have $a_4 = 0.001$ (not significant) and $b_4 = -0.153$ (significant at the one-percent level), relative to $a_4 = 0.013$ (not significant) and $b_4 = -0.153$ (significant at the one-percent level) without controlling for the firm characteristics.

Hence, using time-series information, we find that CDS liquidity provision responds significantly to changes in transaction demand (proxied by lagged CDS returns). The response depends on the level of credit risk, consistent with earlier evidence on the inverse U-shaped relation between CDS liquidity and credit quality. More importantly, the response is modulated by N in a way that is consistent with our earlier interpretation of N as a measure of information heterogeneity in the CDS market.

3.4 The Pricing of CDS Liquidity

In the last part of our paper, we examine the effect of liquidity for the pricing of credit default swaps. Although CDS premiums and corporate bond yield spreads are related by the absence of arbitrage, we do not expect to see liquidity effects in the CDS premium to the same extent that liquidity is reflected in corporate bond yield spreads. As argued in Longstaff, Mithal, and Neis (2005), while corporate bonds are in limited supply, credit default swaps are financial contracts that can be more readily created and offsetting positions are more easily taken. This means that CDS pricing is less affected by supply and demand pressures that play a greater role in the bond market. Nevertheless, the weekly Trade Information Warehouse data provided by the Depository Trust & Clearing Corporation shows that dealers are slightly more likely to sell CDS to non-dealers/customers than to purchase CDS from them (dealers are net-sellers of about \$150 billion of credit protection on single-name CDS as of February 2011). With more dealers competing to sell CDS in the market, customers should benefit from a lower CDS premium (the "competitiveness" effect). On the other hand, more dealers could mean more information asymmetry, which may result in a higher CDS premium because of the one-sided nature of private information in this market (the "asymmetric information" effect).

To sort out these different channels, we estimate the effect of lagged changes of N on the CDS return, controlling for five lags of the CDS return as well as the stock return. As in Section 3.3, we use differenced and lagged explanatory variables to mitigate concerns about endogeneity, in particular the effect of time-invariant heterogeneities and the joint determination of CDS pricing and liquidity.[24] The regression specification is as follows:

$$\begin{aligned}
(\text{CDS return})_{it} &= a_0 + \sum_{k=1}^{5} a_{1k} (\text{CDS return})_{i,t-k} \\
&+ \sum_{k=1}^{5} a_{2k} (\text{Stock return})_{i,t-k} + (a_3 + a_4 N_{i,t-1}) \Delta N_{i,t-1} \\
&+ (\text{Credit condition dummy})_{it} \times \left[b_0 + \sum_{k=1}^{5} b_{1k} (\text{CDS return})_{i,t-k} \right. \\
&\left. + \sum_{k=1}^{5} b_{2k} (\text{Stock return})_{i,t-k} + (b_3 + b_4 N_{i,t-1}) \Delta N_{i,t-1} \right]. \qquad (6)
\end{aligned}$$

Of key interest in this regression is the coefficient of $\Delta N_{i,t-1}$ with and without the interaction with the credit condition dummy, and with and without the interaction with the existing number of CDS dealers.

We report the estimation results in Table 9. In Column (1), we estimate a nested version of Eq.(6) without the interactions between $\Delta N_{i,t-1}$ and $N_{i,t-1}$. Overall, the result shows a negative and statistical significant effect both in and out of the 30-day pre-event period ($a_3 = -0.0002$ and $a_3 + b_3 = -0.0005$).[25] This suggests that the competitiveness effect generally dominates the asymmetric information effect.

[24] The tradeoff is that our estimates of the effect of liquidity on the CDS premium tend to be much smaller compared to other studies that examine the *contemporaneous* relation between CDS liquidity and CDS premium *levels*.

[25] The economic significance of these estimates is very small. With $a_3 = -0.0002$, the effect of one more quote provider would be to increase the CDS premium from, say, 100 basis points to 100.02 basis points.

With the competitiveness effect, the marginal benefit of competitive market-making on the CDS premium likely declines with N (with a large number of existing dealers, the market could already be quite competitive). In contrast, with the asymmetric information effect, the likelihood that the marginal dealer is informed may actually increase with N. This is because a large N may indicate a high level of information heterogeneity already in the market, and this could discourage uninformed agents from providing liquidity. Thus, it seems that one could distinguish these two channels by examining the effect of one more quote provider on the CDS premium when the existing number of quote providers is large.

We do this in two ways. In Column (2), we incorporate interactions between $\Delta N_{i,t-1}$ and $N_{i,t-1}$. We find that $a_3 = -0.0006$ and $a_4 = 0.00004$ outside the 30-day pre-event window, both of which are statistically significant at the one percent level. Inside the 30-day pre-event window, we find that $a_3 + b_3 = -0.0026$ and $a_4 + b_4 = 0.00024$. These coefficients are an order of magnitude larger than outside the pre-event window and are also statistically significant at the one percent level. The fact that both a_4 and b_4 are positive means that the marginal reduction in the CDS premium caused by one more dealer is declining in N. Specifically, we can infer from the estimates that the marginal effect of one more dealer on the CDS premium could be zero when N reaches 11.

In Column (3), we interact ΔN with the liquidity provision tercile dummies (Low: $N \leq 5$, Medium: $5 < N \leq 10$, and High: $N > 10$), using the Low liquidity group as the baseline. While there is virtually no difference in the effect of liquidity between the Low and Medium liquidity groups (the coefficients for the interaction between ΔN and the Medium liquidity group are not significant), the effect for the High liquidity group is significantly different. Specifically, the effects for the three groups outside the pre-event period are -0.0004, -0.0004, and 0, respectively. Inside the pre-event period, they are -0.0014, -0.0014, and 0.0007, respectively.[26] Based on these estimates, the asymmetric information effect appears

[26] Specifically, outside the pre-event period, the effects are $a_3 = -0.0004$ for the Low liquidity group, $a_3 + a_5 = -0.0004$ for the Medium liquidity group, and $a_3 + a_6 = 0$ for the High liquidity group. Within the pre-event period, they are $a_3 + b_3 = -0.0014$ for the Low liquidity group, $a_3 + b_3 + a_5 + b_5 = -0.0014$ for the Medium liquidity group, and $a_3 + b_3 + a_6 + b_6 = 0.0007$ for the High liquidity group.

to play a role when the existing number of dealers is large, say, when $N > 10$.

4 Concluding Remarks

In this paper, we examine the determinants of liquidity provision in the over-the-counter market for credit default swaps. As highlighted by Acharya and Johnson (2007), this is a market dominated by major dealers, in which informed trading or quote updating plays an important role. The recent literature on limit order markets has shown that, when given a choice, informed traders will often choose to act as liquidity providers. Therefore, we treat the CDS market as a laboratory for studying the general properties of endogenous liquidity in dealership markets, in particular how it relates to the level of information heterogeneity.

Using the number of quote providers as a measure of CDS market depth, we explore the behavior of CDS liquidity across 732 firms over 2001-08. Cross-sectionally, we find that large firms and firms near the investment-grade/speculative-grade boundary tend to be the most liquid. This is generally consistent with these firms having the largest amount of hedging demand from investors. We also demonstrate that the amount of information flow from the CDS market to the stock market is increasing in the number of CDS quote providers. This shows that the total amount of CDS liquidity is positively related to the level of informed trading/quote updating in the CDS market.

In the time-series, we examine the marginal dealer's decision to start or stop providing liquidity as a function of transaction demand. We find that CDS liquidity normally responds positively to transaction demand, but this response is weakened significantly during a short window prior to major credit events, particularly when the existing number of dealers is large. We interpret this as evidence of dealers turning away from supplying liquidity when they are concerned about other dealers having superior information.

Given the endogenous nature of CDS liquidity and especially its close relation with information heterogeneity, we also study the effect of CDS liquidity on CDS pricing. We find that the effect is normally negative, suggesting that better liquidity generally leads to a lower CDS premium. However, this effect could become positive when the existing number of dealers is large, consistent with the latter proxying for the level of information asymmetry in the CDS market.

Overall, our findings underscore the important role of information heterogeneity in the determination of CDS market liquidity. In particular, they imply a potential downside to the current regulatory reform calling for increasing transparency in the dealer-dominated CDS market. While this reform may result in greater participation by uninformed investors, it could also reduce the incentive for privately informed dealers to act as liquidity providers, leading to lower CDS market liquidity.

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Figure 1: CDS premium, number of quote providers, and number of banking relationships. CDS premium is the daily composite five-year CDS premium in basis points. Number of quote providers is the daily number of dealers providing CDS quotes for each reference entity. Number of banking relationships is the number of unique lead lenders in the LPC DealScan database that have an ongoing lending relationship with the reference entity. The cross-sectional averages across 732 CDS reference entities are presented. The sample period is from 2001 to 2008.

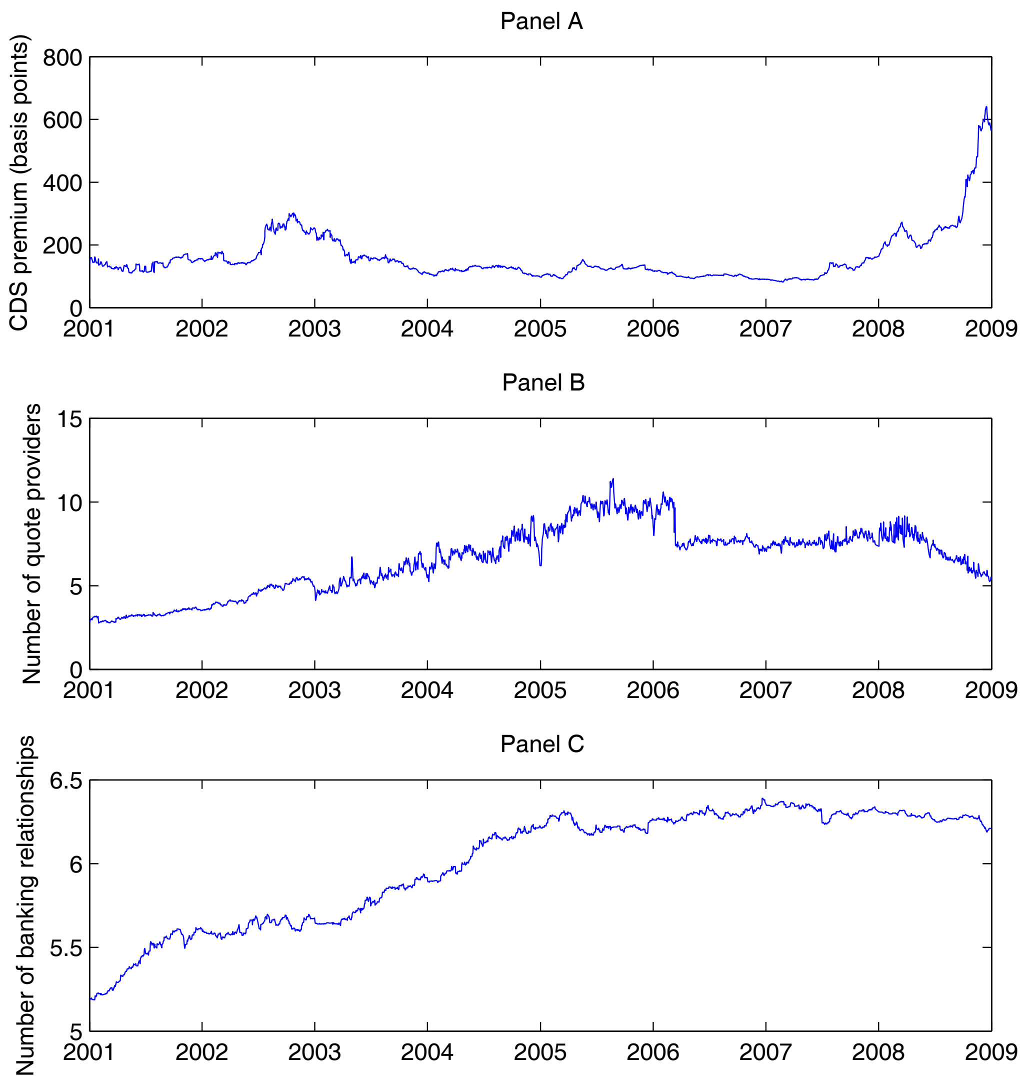

Figure 2: Firm size, credit rating, and the number of quote providers.
Panel A presents the average number of quote providers for each firm size decile. Panel B presents the average number of quote providers for each rating category. Panel C presents the average number of quote providers for each rating category conditional on firm size (large, medium, or small).

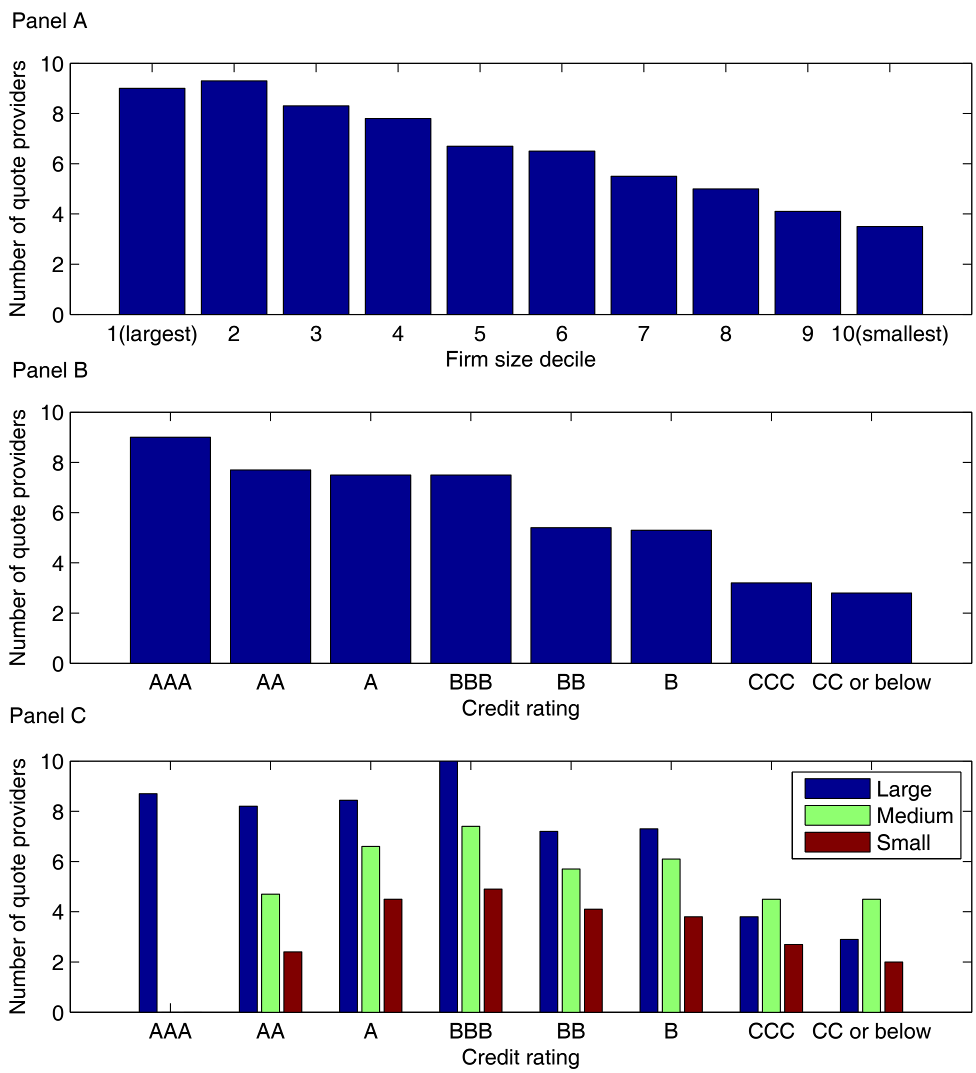

Figure 3: Number of quote providers, stock trading volume, and CDS premium in a 60-day window surrounding credit events.

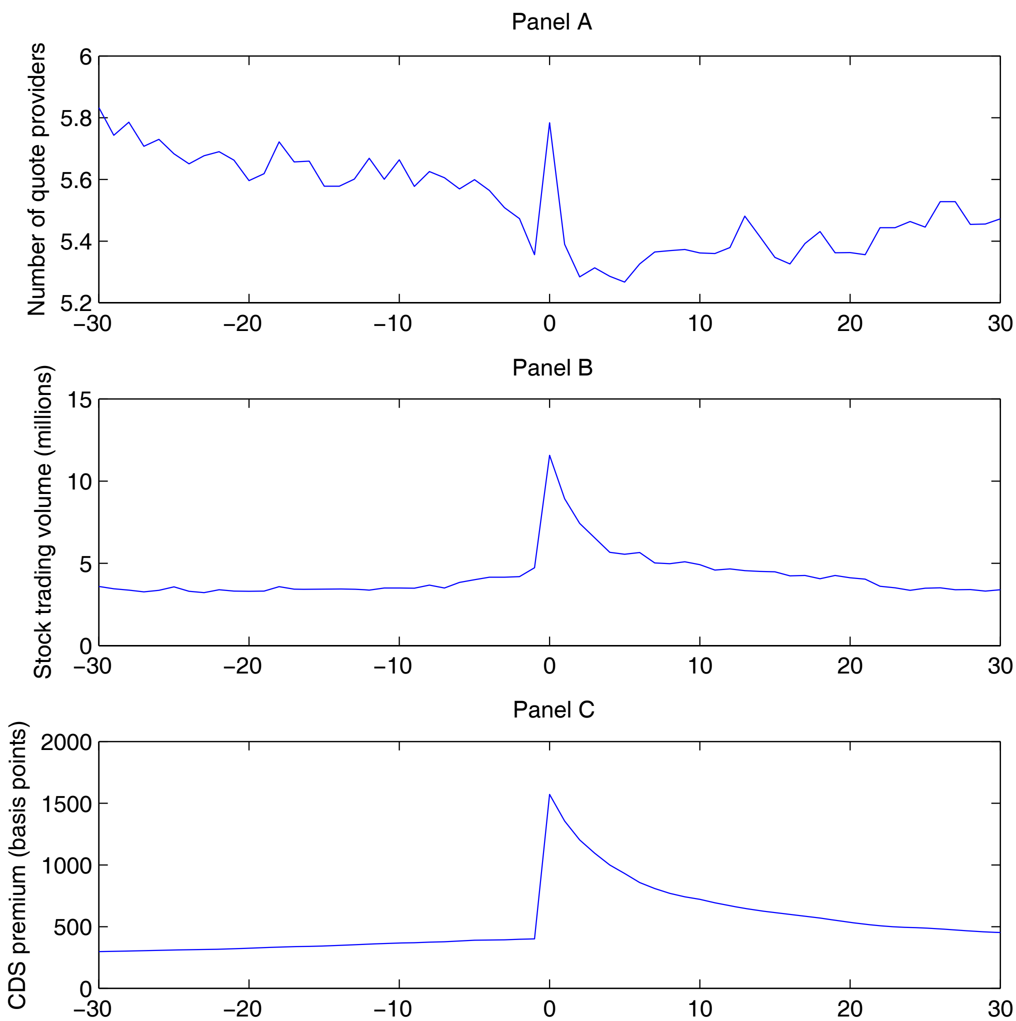

Table 1: Summary statistics

This table presents the summary statistics for the variables used in our study. The statistics are computed across all observations. CDS Premium is the daily composite five-year CDS premium in basis points. Number of Quote Providers is the daily number of dealers providing CDS quotes for each reference entity. Number of Banking Relationships is the number of unique lead lenders in the LPC DealScan database that have an ongoing lending relationship with the reference entity. Assets is the total assets of a firm in millions of dollars. Credit Rating is S&P's long term issuer credit rating obtained from Compustat; it converts the rating classes into a numerical scale from AAA (1) to D (22). Daily Trading Volume is the daily stock trading volume for sample firms. Number of Analysts is the number of analysts who follow each sample firm, as reported in the I/B/E/S dataset. Average Stock Return is a firm's annualized 252-day average stock return. Stock Return Volatility is a firm's annualized 252-day stock return standard deviation. Leverage is equal to (long term debt + debt in current liabilities) / (market value of equity + long term debt + debt in current liabilities). The sample period is from 2001 to 2008.

	Mean	Stdev	25th	Median	75th
CDS Premium	157	324	33	63	161
Number of Quote Providers	7.2	5.0	3	6	10
Number of Banking Relationships	6.0	6.4	0	5	9
Assets ($ million)	16,578	22,752	2,962	6,703	18,162
Crediting Rating	8.9	3.1	7	9	11
Daily Trading Volume (thousand)	2,901	8,227	354	950	2,457
Number of Analysts	11.6	6.8	6	11	16
Average Stock Return	0.13	0.39	-0.04	0.14	0.32
Stock Return Volatility	0.36	0.26	0.21	0.29	0.42
Leverage	0.32	0.22	0.14	0.27	0.46

Table 2: Correlation matrix

This table presents the correlations among the variables used in our study. The correlations are computed across all observations. The definitions of the variables are described in Table 1.

	CDS Premium	Number of Quote Providers	Number of Banking Relationships	Assets ($ million)	Credit Rating	Daily Trading Volume	Number of Analysts	Average Stock Return	Volatility	Leverage
CDS Premium	1									
Number of Quote Providers	-0.132	1								
Number of Banking Relationships	0.030	0.212	1							
Assets ($ million)	-0.103	0.257	0.108	1						
Crediting Rating	0.482	-0.182	0.028	-0.463	1					
Daily Trading Volume	0.061	0.082	0.018	0.340	-0.167	1				
Number of Analysts	-0.157	0.193	0.091	0.359	-0.338	0.324	1			
Average Stock Return	-0.307	-0.021	0.004	-0.047	0.021	-0.123	-0.008	1		
Stock Return Volatility	0.573	-0.142	-0.003	-0.048	0.282	0.181	-0.051	-0.427	1	
Leverage	0.466	-0.041	0.105	0.196	0.358	-0.033	-0.305	-0.241	0.321	1

Table 3: Cross-sectional determinants of CDS liquidity

This table reports the cross-sectional determinants of the number of CDS dealers. The dependent variable is the quarterly average number of CDS dealers for each reference entity. The explanatory variables are firm characteristics in the previous quarter. Heteroskedasticity-robust *t*-statistics adjusted for clustering within firms are in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)
Ln(Assets)	2.140***	2.236***	1.496***	1.427***	1.413***
	(15.84)	(16.45)	(7.47)	(7.77)	(6.94)
Credit Rating	-0.116**	0.752***	0.897***		0.827***
	(-2.38)	(4.23)	(5.22)		(4.72)
Credit Rating^2		-0.047***	-0.066***		-0.062***
		(-5.41)	(-7.33)		(-6.86)
High Rating (AAA to AA)				2.377***	
				(4.27)	
Medium Rating (A to BBB)				3.063***	
				(10.56)	
Leverage			12.79***	15.32***	12.495***
			(6.83)	(8.11)	(6.65)
Leverage^2			-9.69***	-12.96***	-9.55***
			(-4.89)	(-6.40)	(-4.73)
Stock Return Volatility			-1.002**	-1.14**	-1.038**
			(-2.17)	(-2.38)	(-2.27)
Log(Stock Trading Volume)			0.704***	0.693***	0.692***
			(3.95)	(4.01)	(3.94)
Number of Analysts			0.025	0.038	0.023
			(0.94)	(1.52)	(0.87)
Number of Banking Relationships					0.049***
					(2.59)
Two-Digit Industry dummies	Yes	Yes	Yes	Yes	Yes
Year/Quarter Dummies	Yes	Yes	Yes	Yes	Yes
Number of Observations	15,513	15,513	11,937	11,937	11,937
Adjusted R-squared	0.44	0.45	0.50	0.51	0.50

Table 4: Information flow from the CDS market to the stock market – Adverse credit conditions

This table presents the results of a pooled regression of daily stock returns on lagged CDS innovations and lagged stock returns as follows:

$$\left(\text{Stock Return}\right)_{it} = a + \sum_{k=1}^{5}\left(b_k + b_k^D\left(\text{Credit Condition Dummy}\right)_{it}\right)\left(\text{CDS Innovation}\right)_{i,t-k}$$
$$+\sum_{k=1}^{5}\left(c_k + c_k^D\left(\text{Credit Condition Dummy}\right)_{it}\right)\left(\text{Stock Return}\right)_{i,t-k} + \varepsilon_{it},$$

where the credit condition dummies are defined in two different ways: (A) the dummy is equal to one if the firm experiences a one-day increase in the CDS premium greater than 50 basis points within the next five, 30, or 90 days; (B) the dummy is equal to one if the firm experiences a one-day increase in the CDS premium greater than four standard deviations above the mean daily change within the next five, 30, or 90 days. Heteroskedasticity-robust *t*-statistics adjusted for clustering within firms are in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	Specification A			Specification B		
	5 days	30 days	90 days	5 days	30 days	90 days
a	0.0003*** (11.20)	0.0003*** (11.29)	0.0003*** (11.50)	0.0003*** (11.29)	0.0003*** (10.49)	0.0003*** (10.46)
$\sum_{k=1}^{5} b_k$	0.004** (2.08)	0.006*** (3.18)	0.006*** (3.07)	0.005** (2.56)	0.005** (2.46)	0.007*** (3.04)
$\sum_{k=1}^{5} b_k^D$	-0.069*** (4.21)	-0.049*** (5.11)	-0.036*** (5.02)	-0.085*** (5.49)	-0.038*** (4.84)	-0.028*** (5.08)
$\sum_{k=1}^{5} c_k$	-0.140*** (17.21)	-0.137*** (17.43)	-0.147*** (18.03)	-0.135*** (14.34)	-0.116*** (11.49)	-0.121*** (11.29)
$\sum_{k=1}^{5} c_k^D$	0.102*** (2.94)	0.059*** (2.79)	0.073*** (3.88)	0.125*** (3.41)	-0.007 (0.36)	0.006 (0.34)
Number of Observations	891,443	891,443	891,443	891,443	891,443	891,443

Table 5: Information flow from the CDS market to the stock market – By liquidity terciles

This table presents the relation between stock returns and CDS innovations across liquidity provision terciles. The liquidity provision terciles are defined as: Low ($N \leq 5$), Medium ($5 < N \leq 10$), and High ($N > 10$), where N refers to the number of CDS quote providers. For each liquidity provision tercile, we estimates a pooled regression of daily stock returns on lagged CDS innovations and lagged stock returns as follows:

$$\left(\text{Stock Return}\right)_{it} = a + \sum_{k=1}^{5}\left(b_k + b_k^D\left(\text{Credit Condition Dummy}\right)_{it}\right)\left(\text{CDS Innovation}\right)_{i,t-k}$$
$$+\sum_{k=1}^{5}\left(c_k + c_k^D\left(\text{Credit Condition Dummy}\right)_{it}\right)\left(\text{Stock Return}\right)_{i,t-k} + \varepsilon_{it},$$

where the credit condition dummy is equal to one if the firm experiences a one-day increase in the CDS premium greater than 50 basis points within the next 30 days. Heteroskedasticity-robust *t*-statistics adjusted for clustering within firms are in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	Full Sample	Number of CDS Quote Providers		
		Low ($N \leq 5$)	Medium ($5 < N \leq 10$)	High ($N > 10$)
a	0.0003*** (11.29)	0.0003*** (7.50)	0.0003*** (6.23)	0.0003*** (5.87)
$\sum_{k=1}^{5} b_k$	0.006*** (3.18)	0.006** (2.45)	0.015*** (3.33)	-0.0005 (0.11)
$\sum_{k=1}^{5} b_k^D$	-0.049*** (5.11)	-0.030*** (3.37)	-0.077** (2.12)	-0.178** (4.50)
$\sum_{k=1}^{5} c_k$	-0.137*** (17.43)	-0.132*** (11.76)	-0.172*** (12.24)	-0.104*** (9.14)
$\sum_{k=1}^{5} c_k^D$	0.059*** (2.79)	0.028 (0.93)	0.070 (1.47)	0.163*** (2.95)
Number of Observations	891,443	417,528	242,251	227,097

Table 6: Information flow from the CDS market to the stock market – Interactions with liquidity provision

This table presents the impact of liquidity provision on the relation between stock returns and CDS innovations. The specification in Column (1) is as follows:

$$\left(\text{Stock Return}\right)_{it} = a + b_1 \left(\text{CDS Innovation}\right)_{i,t-1} + \sum\nolimits_{k=1}^{5} c_k \left(\text{Stock Return}\right)_{i,t-k} + \varepsilon_{it}.$$

Column (2) allows the coefficient b_1 to depend on the sign of the lagged CDS innovation. The specification in Column (3) is as follows:

$$\left(\text{Stock Return}\right)_{it} = a + \left(b_1 + b_2 N_{it}\right)\left(\text{CDS Innovation}\right)_{i,t-1} + \sum\nolimits_{k=1}^{5} c_k \left(\text{Stock Return}\right)_{i,t-k} + \varepsilon_{it},$$

where *N* refers to the daily number of dealers providing CDS quotes for each reference entity. Column (4) allows both b_1 and b_2 to depend on the sign of the lagged CDS innovation. Column (5) expands the specification in Column (3) by adding interactions with a credit condition dummy, which equals one if the firm experiences a one-day increase in the CDS premium greater than 50 basis points within the next 30 days. Column (6) further includes the interactions between the CDS innovation and other firm characteristics. The definitions of these firm characteristics are described in Table 1. The coefficients on lagged stock returns are unreported. Heteroskedasticity-robust *t*-statistics adjusted for clustering within firms are in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
CDS Innovation$_{t-1}$	-0.001 (-1.16)		0.004** (2.53)		0.004*** (3.23)	-0.001 (-0.07)
CDS Innovation$^{+}_{t-1}$		-0.004*** (-2.53)		0.007*** (3.08)		
CDS Innovation$^{-}_{t-1}$		0.002 (1.38)		-0.0001 (-0.05)		
$N_t \times$ CDS Innovation$_{t-1}$			-0.001*** (-4.44)		-0.0006*** (-3.38)	-0.0005** (-2.39)
$N_t \times$ CDS Innovation$^{+}_{t-1}$				-0.002*** (-6.09)		
$N_t \times$ CDS Innovation$^{-}_{t-1}$				0.0006* (1.93)		
Credit Condition Dummy$_t$ $\times$ CDS Innovation$_{t-1}$					0.009 (1.43)	0.011 (1.43)
Credit Condition Dummy$_t$ $\times N_t \times$ CDS Innovation$_{t-1}$					-0.005*** (-2.91)	-0.005*** (-2.65)
Ln(Asset)$_t$ $\times$ CDS Innovation$_{t-1}$						-0.0001 (-0.07)
Leverage$_t$ $\times$ CDS Innovation$_{t-1}$						0.002 (0.37)
Volatility$_t$ $\times$ CDS Innovation$_{t-1}$						0.007 (0.56)
Average Stock Return$_t$ $\times$ CDS Innovation$_{t-1}$						0.013* (1.89)
Credit Rating$_t$ $\times$ CDS Innovation$_{t-1}$						0.00006 (0.10)
Credit Rating^2_t $\times$ CDS Innovation$_{t-1}$						6.43e-06 (0.63)
Number of Observations	913,552	913,552	908,469	908,469	908,469	811,528

Table 7: Information flow from the CDS market to the stock market – Interactions with liquidity provision and number of banking relationships

This table presents the impact of liquidity provision and the number of banking relationships on the flow of information from the CDS market to the stock market. Liquidity Provision, or *N*, refers to the daily number of dealers providing CDS quotes for each reference entity. Number of Banking Relationships is the number of unique lead lenders in the LPC DealScan database that have an ongoing lending relationship with the reference entity. The regression specification of Column (1) is:

$$\left(\text{Stock Return}\right)_{it} = a + \left(b_1 + b_2\left(\text{Number of Banking Relationships}\right)_{it}\right)\left(\text{CDS Innovation}\right)_{i,t-1} + \sum_{k=1}^{5} c_k\left(\text{Stock Return}\right)_{i,t-k} + \varepsilon_{it}.$$

In Column (2), we add an interaction with liquidity provision:

$$\left(\text{Stock Return}\right)_{it} = a + \left(b_1 + b_2\left(\text{Number of Banking Relationships}\right)_{it} + b_3 N_{it}\right)\left(\text{CDS Innovation}\right)_{i,t-1} + \sum_{k=1}^{5} c_k\left(\text{Stock Return}\right)_{i,t-k} + \varepsilon_{it}.$$

Columns (3) and (4) allow the coefficients of the interaction terms to depend on the sign of the lagged CDS innovation. The coefficients of lagged stock returns are unreported. Heteroskedasticity-robust *t*-statistics adjusted for clustering within firms are in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively. Columns (1)-(4) examine Acharya and Johnson's sample period of 01/01/2001-10/20/2004. Columns (5)-(8) examine the later sample period of 10/21/2004-12/31/2008.

	01/01/2001-10/20/2004				10/21/2004-12/31/2008			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CDS Innovation$_{t-1}$	0.003*	0.007***			-0.001	0.005*		
	(1.84)	(2.75)			(-0.38)	(1.94)		
CDS Innovation$^{+}_{t-1}$			0.007***	0.013***			-0.004	0.006*
			(2.64)	(3.54)			(-1.41)	(1.85)
CDS Innovation$^{-}_{t-1}$			-0.0005	0.0007			0.004	0.005
			(-0.21)	(0.20)			(1.17)	(1.12)
# of Banking Relationships$_t$ $\times$ CDS Innovation$_{t-1}$	-0.0008***	-0.0008***			0.00001	0.0002		
	(-2.70)	(-2.66)			(0.04)	(0.69)		
$N_t \times$ CDS Innovation$_{t-1}$		-0.0011**				-0.001***		
		(-2.09)				(-4.54)		
# of Banking Relationships$_t$ $\times$ CDS Innovation$^{+}_{t-1}$			-0.001***	-0.001***			-0.0002	0.0002
			(-3.31)	(-3.17)			(-0.54)	(0.49)
# of Banking Relationships$_t$ $\times$ CDS Innovation$^{-}_{t-1}$			-0.0003	-0.0003			0.0002	0.0001
			(-0.76)	(-0.83)			(0.59)	(0.36)
$N_t \times$ CDS Innovation$^{+}_{t-1}$				-0.002**				-0.002***
				(-2.01)				(-5.32)
$N_t \times$ CDS Innovation$^{-}_{t-1}$				-0.0003				0.0002
				(-0.47)				(0.49)
Number of Observations	285,253	283,751	285,253	283,751	628,299	624,718	628,299	624,718

Table 8: Time-series properties of CDS liquidity

This table documents the response of CDS liquidity to transaction demand, where CDS liquidity, or *N*, refers to the daily number of dealers providing CDS quotes for each reference entity, and transaction demand is proxied by the CDS return. In Column (3), we estimate the following regression specification:

$$\Delta N_{it} = a_0 + a_1 N_{i,t-1} + a_2 \Delta N_{i,t-1} + \left(a_3 + a_4 N_{i,t-1}\right)\text{CDS Return}_{i,t-1}$$
$$+\left(\text{Credit Condition Dummy}\right)_{it}\left[b_0 + b_1 N_{i,t-1} + b_2 \Delta N_{i,t-1} + \left(b_3 + b_4 N_{i,t-1}\right)\text{CDS Return}_{i,t-1}\right] + \varepsilon_{it}.$$

The credit condition dummy is equal to one if the firm experiences a one-day increase in the CDS premium greater than 50 basis points within the next 30 days. Column (1) includes only the intercept terms. Column (2) excludes the interaction between the CDS return and *N*. Column (4) includes the interactions between the CDS return and other firm characteristics both in and out of the 30-day pre-event window (only the latter are reported). Heteroskedasticity-robust *t*-statistics adjusted for clustering within firms are in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Coefficients	Variables	(1)	(2)	(3)	(4)
a_0	Intercept	0.003*** (14.09)	0.268*** (30.63)	0.268*** (30.64)	0.280*** (29.42)
a_1	N_{t-1}		-0.036*** (-40.47)	-0.036*** (-40.47)	-0.037*** (-40.16)
a_2	ΔN_{t-1}		-0.330*** (-122.22)	-0.331*** (-122.40)	-0.330*** (-117.97)
a_3	CDS $\text{Return}_{t\text{-}1}$		0.459*** (10.56)	0.386*** (5.46)	-0.436 (-0.80)
a_4	$N_{t-1} \times \text{CDS Return}_{t\text{-}1}$			0.013 (0.85)	0.001 (0.09)
b_0	Credit Condition Dummy_t	-0.008*** (-4.71)	0.012 (0.51)	0.007 (0.31)	0.016 (0.78)
b_1	Credit Condition $\text{Dummy}_t \times N_{t-1}$		-0.016*** (-3.10)	-0.015*** (-2.81)	-0.019*** (-4.44)
b_2	Credit Condition $\text{Dummy}_t \times \Delta N_{t-1}$		-0.070*** (-7.21)	-0.070*** (-7.20)	-0.063*** (-6.21)
b_3	Credit Condition $\text{Dummy}_t \times \text{CDS Return}_{t-1}$		-0.335** (-3.51)	0.285** (2.16)	-0.175 (-0.19)
b_4	Credit Condition $\text{Dummy}_t \times N_{t-1} \times \text{CDS Return}_{t-1}$			-0.153*** (-3.94)	-0.153*** (-3.77)
c_0	$\text{Ln(Asset)}_{t-1} \times \text{CDS Return}_{t-1}$				0.120** (2.33)
c_1	$\text{Leverage}_{t-1} \times \text{CDS Return}_{t-1}$				-1.132*** (-4.35)
c_2	$\text{Volatility}_{t-1} \times \text{CDS Return}_{t-1}$				-0.125 (-0.59)
c_3	Average Stock $\text{Return}_{t-1} \times \text{CDS Return}_{t-1}$				0.161 (1.03)
c_4	Credit $\text{Rating}_{t-1} \times \text{CDS Return}_{t-1}$				0.023 (1.10)
c_5	CDS $\text{Premium}_{t\text{-}1} \times \text{CDS Return}_{t-1}$				-0.0003 (-1.14)
c_6	Stock Trading $\text{Volume}_{t\text{-}1} \times \text{CDS Return}_{t-1}$				-0.002 (-0.65)
	Number of Observations	947401	940,415	940,415	837,832

Table 9: Effect of CDS liquidity on the CDS premium

This table documents the effect of CDS liquidity on the CDS premium. The regression specification in Column (2) is:

$$\text{CDS return}_{it} = a_0 + \sum_{k=1}^{5} a_{1k}\text{CDS return}_{i,t-k} + \sum_{k=1}^{5} a_{2k}\text{Stock return}_{i,t-k} + (a_3 + a_4 N_{i,t-1})\Delta N_{i,t-1}$$

$$+\left(\text{Credit condition dummy}\right)_{it}\left[b_0 + \sum_{k=1}^{5} b_{1k}\text{CDS return}_{i,t-k} + \sum_{k=1}^{5} b_{2k}\text{Stock return}_{i,t-k} + (b_3 + b_4 N_{i,t-1})\Delta N_{i,t-1}\right] + \varepsilon_{it},$$

where N refers to the daily number of dealers providing CDS quotes for each reference entity, and the credit condition dummy is equal to one if the firm experiences a one-day increase in the CDS premium greater than 50 basis points within the next 30 days. Column (1) excludes the interaction between ΔN and N. Column (3) replaces the interaction between ΔN and N with two other interaction terms, Medium $N \times \Delta N$ and High $N \times \Delta N$. Medium N is a dummy variable equal to one when $5 < N \leq 10$ and zero otherwise. High N is a dummy variable equal to one when $N > 10$ and zero otherwise. Heteroskedasticity-robust *t*-statistics adjusted for clustering within firms are in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Coefficients	Variables	(1)	(2)	(3)
a_0	Intercept	0.00003 (0.89)	-0.00001 (-0.40)	-0.00002 (-0.40)
$\sum_{k=1}^{5} a_{1k}$	CDS Return$_{t-k}$, $k=1,\ldots,5$	-0.003 (0.28)	-0.003 (0.31)	-0.003 (0.31)
$\sum_{k=1}^{5} a_{2k}$	Stock Return$_{t-k}$, $k=1,\ldots,5$	-0.256*** (24.28)	-0.256*** (24.42)	-0.256*** (24.44)
a_3	ΔN_{t-1}	-0.0002*** (-6.45)	-0.0006*** (-7.51)	-0.0004*** (-4.11)
a_4	$N_{t-1} \times \Delta N_{t-1}$		0.00004*** (5.66)	
a_5	Medium $N_{t-1} \times \Delta N_{t-1}$			-0.00001 (-0.10)
a_6	High $N_{t-1} \times \Delta N_{t-1}$			0.0004*** (3.81)
b_0	Credit condition dummy$_t$	0.012*** (23.56)	0.012*** (23.17)	0.035*** (21.02)
$\sum_{k=1}^{5} b_{1k}$	Credit condition dummy$_t$ × CDS Return$_{t-k}$, $k=1,\ldots,5$	-0.310*** (6.10)	-0.310*** (6.14)	-0.323*** (6.84)
$\sum_{k=1}^{5} b_{2k}$	Credit condition dummy$_t$ × Stock Return$_{t-k}$, $k=1,\ldots,5$	-0.174*** (5.66)	-0.173*** (5.63)	-0.122*** (4.03)
b_3	Credit condition dummy$_t$ × ΔN_{t-1}	-0.0003 (-1.49)	-0.002*** (-4.45)	-0.001** (-1.92)
b_4	Credit condition dummy$_t$ × $N_{t-1} \times \Delta N_{t-1}$		0.0002*** (4.67)	
b_5	Credit condition dummy$_t$ × Medium $N_{t-1} \times \Delta N_{t-1}$			0.00002 (0.02)
b_6	Credit condition dummy$_t$ × High $N_{t-1} \times \Delta N_{t-1}$			0.0017*** (2.98)
	Number of Observations	914,231	914,231	914,231