CDS Markets Informativeness and Related Hard-to-Value Stock Returns

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Abstract

This article investigates the debatable topic whether the Credit Default Swaps (CDS) market is informed relative to the equity market. To do this, we examine the impact of CDS price changes on stock returns calculated by transaction prices respect to various trading periods. We find that the stock returns overreact to credit news during the trading hours and partially reverse after the market closing. The CDS predictive effect mainly concentrates on "hard-to-value stocks". The reversal happens mainly because overconfident investors underestimate their signal precision errors of short-run distress risk. Limit-to-arbitrage such as stock illiquidity, short-sale constraint, funding liquidity constraint, and separate equilibrium hypothesis cannot fully explain our results. Further, the predictability links to a reduction on destabilization for hard-to-value stocks during the market turmoil. Overall, our evidence suggests that CDS informed traders step into hard-to-value stocks during times with good liquidity.

JEL classification: G12.

Keywords: Credit Default Swaps, Stock Overreaction, Market Efficiency.

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1. Introduction

The role of Credit default swap (CDS) remains a subject of the ambivalent topic to financial economics, policymakers, and market participants[1]. On one side, it allows trading of default risk separately from other market risks and significantly improve the overall credit market liquidity[2]. On the other side, there is a widespread concern that the CDS market gives rise to insider trading, market manipulations, and credit speculation. Acharya and Johnson (2007) used equity prices as proxies for public information and examine potential insider trading in the CDS market relying on relatively price discovery between equity and CDS market[3]. Consistent with Acharya and Johnson (2007), Berndt and Ostrovnaya (2007), Ni and Pan (2011), Qiu and Yu (2012), Kryzanowski, Perrakis, and Zhong (2017), and Lee, Naranjo, and Velioglu (2017) found increasing CDS spreads to lead to corresponding negative stock returns conditional on credit events. However, Norden and Weber (2009), Marsh and Wagner (2012), and Hilscher, Pollet, and Wilson (2015) showed increasing stock returns strongly and unconditionally predict adverse changes in CDS spreads, and not the other way around. Thus, there is a mixed result in the literature regarding whether the credit default swap market provides first information at all on the corresponding stock returns. An alternative perspective is whether the CDS market is less informed compared to the stock market.

In this article, we quantify how the CDS market affects the way that information is incorporated into subsequent stock prices by looking at price reactions of the stock market during different market hours (e.g., before market open, during market hours, and aftermarket close stock returns). Our primary focus on the short-term aspects of stock price reaction is motivated by Chordia, Roll, and Subrahmanyam (2005), who found that stock price adjustments to new information occur within a day, suggest that examining the subject of close-to-close stock returns may not be optimal to study the information role of the CDS market. We show that both changes and levels of CDS spread vigorously and negatively predict subsequent

[1]The CDS market is a derivatives market, which specializes in managing credit risk. The protection buyer or credit risk seller pays a periodic fee to the protection seller or credit risk buyer for a contingent payment associated with a reference entity's credit events.

[2]The CDS market has grown tremendously over the last two decades and is increasingly a critical market side by side the stock market.

[3]Price discovery is the process by which trading incorporates new information and market participants expectations into asset prices. The early price discovery in one capital market compared with the related capital market is evidence of informed trading. We focus on single-name CDS rather than a corporate bond because theory work by Oehmke and Zawadowski (2015a) indicates that single-name CDS is more efficient than underlying corporate bonds due to liquidity advantages. Indeed, empirical evidence shows that CDS leads underlying corporate bond because of more information efficiency of CDS markets (Blanco, Brennan, and Marsh (2005)). Furthermore, institutional investors such as mutual funds substitute corporate bonds by investing in CDS markets due to the liquidity advantage of CDS markets (Jiang and Zhu, 2016).

period's stock returns during market hours, but positively predict subsequent periods stock returns after market closing. By contrast, we find the weak CDS predictive power on daily close-to-close returns used in many existing studies.

To be more specific, our daily close-to-close stock returns decomposition is based on the monthly TAQ database during the period between 2001 and 2013. These returns are solely established based on a transaction price with a trading volume (include dividends and adjust for share split) rather than a quote price. By doing so, we can isolate real-time trading behaviors of stock markets from a pure bid-ask spread jump from a prior day's market close to a next day's market open or sentimental retail order flow (without an actual transaction) outside of conventional trading hours[4].

We start by examining the response of stock returns during different market hours respect to CDS spreads using (1) a Fama and MacBeth (1973) regression and (2) portfolio sorting approach. The empirical results reveal that both levels and changes of CDS spread negatively predict subsequent stock returns during the market hour (9:30 to dynamic market closing[5]) and positively predict following day's stock returns after market closing (dynamic market close to the last trade before the next day's 0:00.). Besides, there is no clear pattern of using close-to-close stock returns, or before the market open (0:00 to 9:30) stock returns[6]. The result can persist up to the monthly horizon, robust to different weighting schemes, and hold for different sub-samples.

Note although CDS levels cannot capture new information arrivals as changes of CDS spread do, their predictive power on stock returns reveal that levels are a crucial factor to drive the future stock returns. Conditional on credit deterioration, CDS prices impound information about adverse credit news faster than related stock prices (Acharya and Johnson (2007)). Our empirical results on the superior predictability of credit levels are likely to capture the *ex-ante* credit deterioration. To better connect to existing literature who use CDS changes as a proxy for credit news arrival, we conduct the portfolio sorting analysis using CDS changes but controlling for CDS levels[7]. By doing so, clear predictive patterns of CDS changes on stock returns emerge for various sample frequencies. It suggests that CDS markets contribute timely and speedy underlying credit risk information to cross-market price discovery.

[4]We notice that using, for instance, close to open stock returns (overnight) computed from CRSP generate materially economic magnitude difference compared with using the TAQ's transaction price based return measure due to close to open price jumps and sentimental retail order flow outside of regular working hours.

[5]That is, 16:00 if there is a typical working day, and 1:00 or 1:30, etc., if there is a holiday.

[6]Although changes of CDS spread can negatively predict close-to-close stock returns at a daily level, it fails to predict in more extended investment frequency like weekly and monthly.

[7]Namely; we split the sample into high and low CDS spreads and examine the CDS changes effect for each group accordingly.

We explore the potential mechanism that could link the unequivocal information flow from CDS to stock markets. The central thesis we are focusing on is an informed-trading hypothesis suggesting that informed investors in CDS markets select to trade in opaque stocks with high valuation uncertainty by using their original information extracted from lagged CDS prices. Because of the high information asymmetric risk premium[8] and relatively low execution costs of stock markets, informed traders[9] may likely to trade on the related hard-to-value stocks by using CDS news. This idea tilts to the strand of literatures suggesting that trading incentives of informed investors should being more significant for opaque firms (Seyhun(1986); Aboody, Hughes, and Liu (2005); Kumar (2009); Ben-David, Glushkov, and Moussawi (2010); Wu (2018); Chen, Kelly, and Wu (2018), and many others). For example, high valuation uncertainty can amplify uninformed investors' behavioral biases (Kumar (2009)), and thus relatively better-informed investors conditional on CDS prices attempt to exploit those biases. To test this, we further split the high CDS spread group by high/low information asymmetry and find that the CDS predictability only concentrates on the "hard-to-value" stocks.

We investigate the source of stock prices overreaction respect to CDS news in more depth. We posit that CDS prices carry two pieces of distress risk information that are usually difficult to tell apart by stock markets: (1) long-run probability of default that will reduce the short-run stock net profits or stock prices but will not cause the imminent danger of default; (2) short-run imminent danger of default, indicating real distress events in near future. In most CDS changes, just the long-run distress risk, not both long-run and short-run distress risk. However, during times of processing the short-run distress risk, asset price overreactions may stem from some investors overconfident for their short-run distress signal (Daniel, Hirshleifer, and Subrahmanyam (1998)). Overconfident investors tend to overweight risky assets given noisy signals mixed with credit news observed in CDS markets. The overweight behavior is stemmed from overconfident investors who understate the signal precision errors around the private signal. As results, it leads to asset price overreaction. If all informed investors know precisely how private signal looks like, the price will never overshoot no matter investors are overconfident or not. Based on this insight, we test by looking at the exogenous periods

[8]Where the price impact of privately informed trades cannot be fully diversified.

[9]The informed traders we refer to is cross-market arbitrageurs who have better access to both small markets (CDS) and large markets (Stock) described in Goldstein, Li, and Yang (2014). Trades are most likely happening simultaneously across two markets. For instance, informed speculators might speculate in the CDS market and hedge out their position in equity markets at the same time. However, that could also be the case where other constraint investors (namely those are a constraint to trade on CDS markets) becoming informed by learning from the price changes or trade behaviors of the existing informed investors in CDS markets. Alternatively, it could be the case where information-induced price changes in CDS markets (e.g., CDS price changes without trading activities) deliver signals to cross-market arbitrageurs and make them trade in stock markets because of its relatively low transaction cost.

with very low signal precision errors of short-run distress risk, and we expect to find no stock returns reversal after market close. We select downgrade days as exogenous periods with low signal precision errors because CDS prices seem to fully anticipate the upcoming downgrading events (see Figure 3 in the later section). We partition credit spreads sample into two parts: credit spreads during the following days of downgrade and credit spreads following days with no downgrade. We find that price reversal disappear during the coming downgrade days. Hence, this is consistent with our hypothesis.

We conduct several tests to show that limit-to-arbitrage hypothesis does not fully explain our results. Firstly, the CDS predictability may merely reflect the role of stock illiquidity (Amihud (2002), Pastor and Stambaugh (2003), and Achary and Pedersen (2005)). However, we find that the predictive results are significant for both high/low liquidity groups, suggesting that the stock illiquidity channel is unlikely to explain our findings fully. Secondly, the CDS predictability may be driven by the arbitrage asymmetry in the presence of the short-sale constraint. Using 2008 short-sale ban to split firms into banned/unbanned stocks, we find that the predictive power of banned stocks is, in fact, lower; Extracting short-sale volume data from "Reg SHO" file, we find that the average short volume of high information asymmetric group is significantly higher than that of low information asymmetric group. These suggest that our findings cannot be fully explained by short-sale constraint. Thirdly, the CDS predictability may capture the reduction in arbitrage abilities of primary investors when they face finding constraint. Proxy tightening funding conditions using shocks in primary dealers' aggregate capital ratio and shocks in TED spread, we find that the predictive power still exists in the less funding constraint episode, suggesting that funding liquidity constraint of primary financial institutions cannot fully explain our findings. Fourth, the CDS predictability could reflect the separate equilibrium result of Easley, O'Hara, and Srinivas (1998). By comparing the transaction costs between the two markets, we found that the CDS predictability is concentrated on the case where the bid-ask spread of related stocks are significantly lower than the CDS, suggesting that the degree of profitability in CDS market cannot be fully explained by the separate equilibrium hypothesis.

Having found the evidence of informed trading patterns of CDS markets among opaque firms, we turn to examine the key question of whether informed trading activities in CDS markets destabilize market quality? Consistent with Boehmer, Chava, and Tookes (2015), we find that a higher CDS spread improves the market quality[10] in good times but harms the market quality in bad times. In sharp contrast, we find that a completely reversed impact for hard-to-value stocks. Specifically, a higher CDS spread dampens their market

[10] An improvement of the market quality consists of a lower stock volatility, a lower CDS volatility, a higher stock/CDS market integration, and a narrower bid-ask spreads

qualities in good times but improves the market qualities in bad times. It suggests that informed investors act as liquidity providers during market turmoil to prevent the market from the further crash (Boulatov and George (2010)). Thus, we extend Boehmer, Chava, and Tookes (2015)s' findings to provide further evidence of informed trading activities of credit derivatives for related high information asymmetric stocks along business cycle.

Our study mainly relates to two strands of literature. Firstly, we contribute to the current debate of informed trading on CDS markets. Up to date, the empirical evidence on the debate can be categorized by either the CDS conditionally[11] lead the stock (e.g., Acharya and Johnson (2007) and many others) or the stock unconditional leads the CDS (e.g., Hilscher, Pollet, and Wilson (2015) and many others). We extend the literature by showing that the CDS can also unconditional lead the stock when the intra-day stock returns are examined, for the first time. It is consistent with the view that CDS markets are informed.

Secondly, the stock prices overreaction respect to CDS prices relates to the large body of literature on stock markets short-term reversal, that is, a well-established capital market phenomenon. For example, Lehmann (1990), Lo and MacKinlay (1990b), and Jegadeesh (1990) show that contrarian strategies that exploit the short-run stock return reversals in individual stocks generate abnormal returns. Bremer and Sweeney (1991) show that stocks with substantial negative 10-day returns are followed on average by following two-day return reversals. In summary, these studies primarily focus on prices reversal within the stock market itself. This paper documents that reversal actually can happen across related securities.

The rest of the paper is organized as follows. Section 2 presents the data and variables used in our primary analysis. Section 3 studies the impact of CDS markets on stock markets during different market hours. Section 4 investigates the source of predictability. Section 5 conducts additional analysis. Section 6 concludes.

2. Data, Variables, and Summary Statistics

2.1. Data and Variable Construction

We start by describing the data sample used in this analysis. We focus on U.S. firms with both stocks returns and CDS spreads between Jan 2001 and Dec 2013. Our stock returns information is mainly obtained from monthly Trade and Quote (TAQ)[12] and CDS information is acquired from Markit Group. We obtain accounting information from quarterly

[11] "Conditional" refers to conditional on information events such as downgrading rather than particular type of firm characteristic.

[12] We also replicate our finding using close-to-open and open-to-close daily stock returns from CRSP and obtain similar results.

Compustat database and macroeconomic variables from Economic Research at the St. Louis Fed (https://research.stlouisfed.org/). We detail constructions of the main variables below.

Stock Returns. We obtain stock return data from TAQ. We focus on common stocks. The opening price on day t is the first valid actual transaction price equal or after 9:30. The closing price on day t is the last valid transaction price on day t. The first trade price is the first transaction price before 9:30 but no earlier than 0:00 if there is a transaction volume attached to the price, otherwise we code the first price before market open as missing. The last trade price after the market close is defined as the last transaction price with a trading volume after 16:00 but no later than next-day 0:00, otherwise we code it as missing. Then we adjust the daily opening and closing prices for stock splits and dividends before computing returns. We compute daily close-to-close log stock (transaction) price change as a proxy for daily stock returns for firm i on day t as $R_{i,t} = \ln(P_{i,16:00,t}) - \ln(P_{i,16:00,t-1})$[13] where $P_{i,c,t}$ is the stock i's price on day t at clock time h:m, where h is hour and m, is minute. Further, we look at three different parts of daily stock returns:

- Stock return before market open, $R_{i,t}^{BM}$ is computed as the log difference between open market price at 9:30 on day t and first trade price during 0:00 to 9:30 on day t, if both first transaction price before the market open and the transaction price at the market open is available, otherwise the $R_{i,t}^{BM}$ is coded as missing.
- Stock returns during market hours $R_{i,t}^{MH}$ is computed as the log difference between dynamic market close price on day t and market open price at 9:30 on day t, if both transaction price at the market open and the transaction price at the market close are available, otherwise the $R_{i,t}^{MH}$ is coded as missing.
- Stock returns after market hours $R_{i,t}^{AM}$ is computed as the log difference between last trade after dynamic market close prior to 24:00 and dynamic market close price on day t, if both transaction price at the market close and the last transaction price after the market close are available, otherwise the $R_{i,t}^{AM}$ is coded as missing[14].

[13]We notice that markets close earlier at holiday, usually market closing time is adjusted from 16:00 to 13:00, 13:15, or 13:30 respectively. We identify and adjust for these situations by replacing market closing time from 16:00 to 13:00, 13:15, or 13:30 respectively, all else are the same.

[14]Some institutional background on what happens after conventional trading hours: In the U.S., most of the trades in stock markets happen in NYSE and Nasdaq from 9:30 to 16:00 Eastern Time. However, investors can still trade after the market hours. This is done by ECN (Instinet was the first ECN created in 1969.), which is an alternative SEC-permitted trading system or network that allows trading happens outside traditional exchange after trading hours. Stocks and currencies are the most widely traded products in ECN. Before the 1990s, the after-hours trading was primarily dominated by institutional investors. Afterward, ECNs attract different types of investors by such as (1) increase transparency by giving clients full access to their order books[15]; (2) Lower transaction cost. As results, higher the competition. In particular, most of the trades in the after-hours session happen between 16:00 and 18:30 Eastern Time.

To place an order on an ECN, individual investors must either have an account with a broker who can

Our decomposition of daily stock returns makes sure that there is no overlapping information when we conduct the price discovery test between equity and CDS markets. Daily CDS spreads are from Markit daily single-name CDS quotes as of 15:30 Eastern Time, which is earlier than the stock market closing time, 16:00 Eastern Time.

CDS Spreads and Returns. We obtain daily CDS spread data for five-year CDSs on senior, unsecured debt. We follow Hilscher, Pollet, and Wilson (2015) to restrict the CDS sample by selecting those with modified restructuring default clause before April 2009 CDS "big bang" because this is the restructuring convention that is most commonly used for U.S. firms. We require no restructuring clause onwards following Lee, Naranjo, and Velioglu (2017). We compute the 5-year CDS return or credit protection return by the percentage change in credit spread at a daily frequency. The increase of credit return reflects the loss of the credit protection seller. As noted by Hilscher, Pollet, and Wilson (2015), credit returns should equal to the percentage change in the quoted CDS spread adjusted by the ratio of two annuity factors. However, in practice, the percentage change of spread is a great proxy for CDS protection return because the annuity ratio will always be close to 1. Thus we use the percentage change of CDS protection return in our empirical analysis. We apply a filter to remove stale price observations, where define prices to be stale when we observe the same prices on at least five consecutive days. In such a case, we only consider the first of these observations and classify subsequent observations as not available. Papers use percentage change in credit spreads as a proxy for credit returns including Kapadia and Pu (2012), Hilscher, Pollet, and Wilson (2015), and Lee, Naranjo, and Velioglu (2017).

Merge Stock/CDS Sample. Our strategy of merging the two datasets following three steps. First, we link TAQ data to CRSP using TAQ-CRSP Link Table (tclink) provided by WRDS. Second, we attach PERMNO (unique identifier) obtained from CRSP to each reference entity with CDS using first six digit CUSIP that is both available at CRSP tapes and "RED" reference entity file provided by Markit. Third, for those firms cannot be matched in the second step, we manually match across two databases by using long-legal names. As a result, there are 1186 firms with both stock returns and CDS spreads.

Firm Characteristics. We consider a battery of firm Characteristics in our analysis.

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direct access ECN or need to be a subscriber. An execution occurs when the price of a buy order and the price of a sell order intersect on the ECN. Nowadays, almost any investor can trade through an ECN, including retail investors, institutional investors, market makers, and broker-dealers.

Using month TAQ database, we find that the aggregate after-market (from 16:00 at t-1 to 0:00 at t) trading volume increases from JAN 1993 to DEC 2013 based on all universe of firms in TAQ database. In particular, the aggregate (after-market hours) trading volume was about $5 trillion (Approximately $3 million per day per stock) in 1993. It increases to $119 trillion (Approximately $62 million per day per stock) in 2009 and decreases to $96 trillion (Approximately $52 million per day per stock) in 2013.

- *Bid-ask spread.* The percentage effective spread (ES) for day t is computed by $\mathrm{ES}_{i,t} = \frac{1}{N_{i,t}} \sum_{j=1}^{N_{i,t}} \frac{2\mathrm{D}_{i,j}(\mathrm{P}_{i,j} - \mathrm{M}_{i,j})}{\mathrm{M}_{i,j}}$, where i indicates firm, j indicates second, and N is the total number of trades of stock i in day t. Given day t, $\mathrm{P}_{i,j}$ is transaction price for firm i at second j. $\mathrm{M}_{i,j}$ is the bid-ask mid price between bidding quote and asking quote for each second. $\mathrm{D}_{i,j}$ is buy or sell indicator. In particular, $\mathrm{D}_{i,j} = 1$ if there is a buy, $\mathrm{D}_{i,j} = -1$ if there is a sell. The buy/sell indicator and merging between quote and trade database is using Lee and Ready (1991) algorithm. We also consider the percentage quoted spread (QS) in our robustness analysis. QS is computed by $\mathrm{QS}_{i,t} = \frac{1}{N_{i,t}} \sum_{j=1}^{N_{i,t}} (\mathrm{Ask}_{i,j} - \mathrm{Bid}_{i,j})/\mathrm{Ask}_{i,j}$. We consider CDS depth as measure for CDS market liquidity.
- *Trading volume turnover.* It is constructed as the ratio between total trading volume (during regular trading hours) and daily closing price.
- *Price impact coefficient λ.* The price impact coefficient is following the literature of Hasbrouck (2009), Goyenko, Holden, and Trzcinka (2009), who used five-minute return and five-minute trading volume. Specifically, for each firm-day, we estimate the price impact measure as the slope coefficient λ of the following regression: $r_n = a + \lambda \times SDVOL_n + e_n$ where n indicates five-minute interval, r_n is the five-minute stock return calculated as the natural log of the (mid) price change over the nth period. $SDVOL_n$ is the signed square-root dollar volume of n period that is calculated by $\sum_{k=1}^{K_n} sign_k \times \sqrt{DVOL_k}$, where $\sqrt{DVOL_k}$ is the dollar volume of the kth trade in the nth five-minute interval. K is the total number of trades in the nth period. The sign respect to each price interval is computed by Lee and Ready (1991) tick test. To ensure sufficient data point to estimate λ, we require the stock must have more than 100 data points within a trading day. The λ considers the rise (fall) in price that typically occurs with a buyer-initiated (seller-initiated) trade.
- *Price competition index* The price competition index (HHI) is computed by applying Herfindahl Index to the dollar price volume for each stock, each day.
- *Stock market capitalization.* The stock market capitalization is the multiplication between end-of-day share price and shares outstanding, which are obtained from the Center for Research in Security Prices (CRSP).
- *Volatility-based measure.* The idiosyncratic volatility is benchmarked by Fama and French 5 factor model using daily 1-year rolling window. Specifically, we project daily excess stock returns on Fama and French (2015) five-factor model and extract the sample standard deviation of residuals. The stock volatility is the realized volatility computed by sample standard deviation of intra-day (log) transaction price changes.

- *Market leverage.* Followed by Ericsson, Jacobs, and Oviedo (2009), the leverage ratio is computed as

$$\text{Lev} = \frac{\text{Book Value of Debt+Book Value of Preferred Equity}}{\text{Market Value of Equity+Book Value of Debt+Book Value of Preferred Equity}}$$

  where the Market value of equity is computed as shares outstanding (SHROUT) multiply by stock prices (PRC) from CRSP. The data of book value of debt and the book value of preferred equity is obtained from COMPUSTAT. The book value of debt is the sum of debt in current liability (DLCQ) and long-term debt (DLTTQ). Preferred stocks are labeled as PSTKQ in COMPUSTAT.
- *Stock price momentum.* Price momentum signal is constructed by accumulated past 12-month stock returns (skip the most recent month to avoid short-term reversal) using daily stock returns.
- *Primary dealers aggregate capital ratio* This is defined following He, Kelly, and Manela (2016) who match the New York Feds primary dealer list with CRSP/Compustat and Datastream data on their publicly traded holding companies

$$\eta_t = \frac{\sum_i \text{Market Equity}_{i,t}}{\sum_i (\text{Market Equity}_{i,t} + \text{Book Debt}_{i,t})} \tag{1}$$

  where firm i is a NY Fed primary dealer during day t. The accounting data is in quarterly frequency but the equity price is in daily frequency. Therefore, the primary dealers aggregate capital ratio $\Delta\eta_t$ is daily frequency. We compute the shock of η as $\Delta\eta_t = \eta_t - \eta_{t-1}$. The list of primary dealer designees is from Table A.1 of He, Kelly, and Manela (2016).

2.2. Summary Statistics

Summary statistics for the variables are given in Table 1. Our sample period is from 2001 to 2013. The statistics are calculated based on daily data for all firms in the sample.

[Table 1 about here]

Table 1A reports the summary statistics of the variables used in our analysis. We focus on stock returns with trading activity - that is, we remove stock return observations with zero trading volume. As a result, it yields 724051 firm-day observations for R^{BM}, 2050282 firm-day observations for R^{MH}, and 1966518 firm-day observations for R^{AM}. The sample average of after-market hours returns R^{AM} is about 0.009% return in daily basis, where before market hours returns (R^{BM}) and during market hours returns (R^{MH}) are negative at about -0.028% and -0.01% per day respectively. In terms of volatility, (R^{BM}) and (R^{MH}) are more volatile than R^{AM}. Average trading volume during market hours [16] is about 15 times (3602645/228010) larger than the average trading volume after the market close and 119 times (3602645/30255) larger than average trading volume before market open. The average 5-year CDS spreads is about 180 bps. The CDS returns have smaller mean but substantial volatility compared with equity (The sample mean on CDS returns is 0.002%, and volatility is about 4.25% compared with stock returns during different market hours). All returns are positively skewed, except for R^{AM}.

Table 1B reports the contemporaneous correlation between stock returns computed by using different market hours using TAQ and CRSP dataset respectively. We calculate the correlation by averaging out the cross-sectional correlation across different return measures among all the observations for each day. In Table 1B, we see that the correlation between $R^{OTC,CRSP}$ and R^{MH} is 99%, suggesting that TAQ-based market hour stock returns are closely related to CRSP-based stock return. As for the correlations between CRSP-based overnight returns, $R^{CTO,CRSP}$ and the TAQ-based overnight returns, we expect that they should be quite low as they measure at the different timestamp. Interestingly, the correlation between $R^{CTO,CRSP}$ and R^{BM} is 32.3% that is significantly higher than the correlation between $R^{CTO,CRSP}$ and R^{AM}, only 1.7%. It suggests that the CRSP-based overnight returns are mainly driven by R^{BM}. As we show later, while R^{BM} barely captures information, R^{AM} captures stock return reversal respect to CDS news. This information, however, is underestimated using CRSP-based overnight returns.

3. Baseline Results

Credit default swaps (CDS) prices benefit market participants through revealing market expectations about default risk. Even without triggering default events, CDS prices (e.g., spreads) still disclose useful information on credit risk for the reference entity. However, Hilscher, Pollet, and Wilson (2015) showed that stock returns strongly negatively predict CDS returns, and not the other way around, suggesting CDS markets are always uninformed relative to stock markets. This is because relatively low transaction cost of stock markets facilitates informed investors to process their private information, consistent with the separate equilibrium hypothesis proposed by Easley, O'Hara, and Srinivas (1998)[17].

[16] Aggregate within before, during, and after market hours for each stock and average across all stocks at the daily frequency.

[17] We replicate the critical empirical results of Hilscher, Pollet, and Wilson (2015) using daily close-to-close CRSP stocks returns and CDS returns (see Table A1 in Appendix). We show that information indeed

In this study, we show strong evidence that both levels and changes of CDS spread can predict subsequent period's stock returns when market hours and after-market hours stock returns are examined separately respect to CDS prices. By contrast, the predictability does not appear when the close-to-close stock returns are used. In the following section, we present the empirical evidence using both regression approach and portfolio sorting approach.

3.1. Regression test

We first examine the predictability of CDS prices on subsequent period's stock returns using Fama and MacBeth (1973) regression. The equation is specified as

$$\mathrm{R}_{i,t}^{\mathrm{Stock}} = \beta_0 + \beta_1 \mathrm{CDS}_{t-1} + \mathrm{X}_{i,t-1}\theta + \epsilon_{i,t} \tag{2}$$

where $\mathrm{R}_{i,t}^{\mathrm{Stock}}$ includes $\{\mathrm{R}_{i,t}^{\mathrm{BM}}, \mathrm{R}_{i,t}^{\mathrm{CTC}}, \mathrm{R}_{i,t}^{\mathrm{MH}}, \mathrm{R}_{i,t}^{\mathrm{AM}}\}$ and CDS includes level of CDS spreads $\mathrm{S}_{i,t-1}^{\mathrm{CDS}}$ for firm i at period t-1 or CDS percentage spread changes $\mathrm{R}_{i,t-1}^{\mathrm{CDS}}$ for firm i at period t-1. β_1 is the key variable of interest gauging the predictability of CDS prices or returns on the stock returns. X is a N by K matrix observed at t-1 consisting a set of control variables such as lagged stock returns during various trading period, log market size, percentage effective spread, rating dummies, log stock trading volume, market leverage, and stock price momentum[18]. θ is K by one vector consisting of slope coefficient on the control variable X. We perform our study in longer investment horizons by accumulating daily stock returns respect to different market hours into weekly (Wednesday to Wednesday) and monthly frequency[19]. For stock return predictors, we equally average the daily values within each week or month for each firm i. We run cross-sectional regressions every calendar time, and adjust standard errors for heteroskedasticity and autocorrelations using 12 lags.

[**Table 2A & 2B about here**]

Table 2 reports the results. The evidence in Table 2 indicates that CDS prices (both level,$\mathrm{S}_{t-1}^{\mathrm{CDS}}$ and changes, $\mathrm{R}_{t-1}^{\mathrm{CDS}}$) can predict market hours stock returns R_t^{MH} and negatively

unconditionally flows from stock returns to CDS returns and not vice versa using our sample.

[18]Most of the empirical studies focus on market hours returns or close to close daily returns, and there are few studies that work on the effect of characteristics on before or market hours returns because most of trading or price discovery happens from open to close. Nevertheless, we add the same set of controls variable to before, during, and after market hours stock returns for consistency. Studies investigate asset prices behavior using overnight stock returns include Berkman, Koch, Tuttle, and Zhang (2012) and Aboody, Even-Tov, and Lehavy (2018) who suggest that overnight stock returns can serve as the measure of firm-specific investor sentiment. Bollerslev, Li, and Todorov (2016) found that market betas associated with intraday discontinuous and overnight returns contain significant risk premiums.

[19]For example, at December, we aggregate the daily market hour stock returns into monthly returns by $\mathrm{R}_{i,Dec}^{\mathrm{MH}} = \mathrm{R}_{i,Dec1st}^{\mathrm{MH}} + \mathrm{R}_{i,Dec2nd}^{\mathrm{MH}} + ... + \mathrm{R}_{i,Dec31th}^{\mathrm{MH}}$

predict after-market hours stock returns R_t^{AM}. However, they cannot predict close-to-close stock returns $R_t^{CTC,TAQ}$ and before market hours stock returns R_t^{BM}. The following summarizes the key empirical observations.

- CDS level S_{t-1}^{CDS} and CDS change R_{t-1}^{CDS} negatively predict the stock returns during market hours R_t^{MH}. As for S_{t-1}^{CDS} reported in Panel A of Table 2A, the point estimates of β_1 on S_{t-1}^{CDS} are -1.2% (t-stat = -5.9) at daily, -5.69% (t-stat=-5.4) at weekly, and -22.45% (t-stat=-5.1) at monthly. Similarly, as for R_{t-1}^{CDS} reported in Panel A of Table 2B, the point estimates of β_1 on R_{t-1}^{CDS} are -0.31% (t-stat = -5.6) at daily, -1.14% (t-stat=-2.7) at weekly, and -2.84% (t-stat=-0.7) at monthly. The results indicate that the stock value drops if the past CDS spread increases. Additionally, the economic magnitude of CDS level is much larger than CDS change.
- CDS level $\mathrm{S}_{t-1}^{\mathrm{CDS}}$ and CDS change $\mathrm{R}_{t-1}^{\mathrm{CDS}}$ positively predict next day stock returns $\mathrm{R}_t^{\mathrm{AM}}$ after market closing. As we can see from Panel B of Table 2A and Table 2B, the stock returns exhibit a slight reversal after market closing. For instance, all β_1s are positive statistical significant for $\mathrm{S}_{t-1}^{\mathrm{CDS}}$: 0.24% (t-stat=3.7) at daily frequency, 1.10% (t-stat=3.7) at weekly frequency, and 4.67% (t-stat=3.5) at monthly frequency. β_1, is positive but not significant for $\mathrm{R}_{t-1}^{\mathrm{CDS}}$ at daily frequency. The predictability comes back when we look at the longer horizon: β_1=0.33% (t-stat=2.3) at weekly frequency, and β_1=1.55% (t-stat=1.8) at monthly frequency for $\mathrm{R}_{t-1}^{\mathrm{CDS}}$.
- No clean empirical pattern observed from predicting the close-to-close stock returns ($\mathrm{R}_t^{\mathrm{CTC}}$) and $\mathrm{R}_t^{\mathrm{BM}}$. We find that the CDS level ($\mathrm{S}_{t-1}^{\mathrm{CDS}}$) deliver no predictive power on $\mathrm{R}_t^{\mathrm{CTC}}$. Although the CDS changes ($\mathrm{R}_{t-1}^{\mathrm{CDS}}$) negatively predict the $\mathrm{R}_t^{\mathrm{CTC}}$ at daily frequency (Panel D of Table 2B). However, the predictability does not hold for longer horizons, suggesting that the information content of $\mathrm{R}_{t-1}^{\mathrm{CDS}}$ is the most likely transient.

In sum, the analysis so far shows that stock market returns overreact to the CDS prices from regular market hours to after-market closing.

3.2. Portfolio test

We conduct a further test using portfolio sorts. At the beginning of every calendar day, all stocks are sorted in ascending order on both the level of CDS spread ($\mathrm{S}^{\mathrm{CDS}}$) and the change of CDS spread ($\mathrm{R}^{\mathrm{CDS}}$) in the prior day. The ranked stocks are assigned to one of 5 quintile portfolios. We compute the spread portfolio H/L portfolio, which goes long quintile five stocks with high CDS prices and short quintile one stocks with low CDS prices. Table 3 consists of the portfolio test result for both equal-weighted and value-weighted case at a daily frequency. Table 4 consists of H/L average returns at longer frequencies.

[Table 3 & 4 about here]

In Table 3, we find a negative relation between CDS spreads and subsequent day's market hours stock returns $\mathrm{R}_{t+1}^{\mathrm{MH}}$ and a positive relation between CDS spreads and subsequent day's after-market hours stock returns $\mathrm{R}_{t+1}^{\mathrm{AMH}}$. To be more precise, as for the equal-weight case as shown in Panel A, we find that $\mathrm{R}_{t}^{\mathrm{MH}}$ is monotonically decreasing respect to both levels of CDS spread ($\mathrm{S}^{\mathrm{CDS}}$) and changes of CDS spread ($\mathrm{R}^{\mathrm{CDS}}$). The H/L portfolio, which goes long quintile 5 stocks with high $\mathrm{S}^{\mathrm{CDS}}$ and $\mathrm{R}^{\mathrm{CDS}}$ and short quintile 1 stocks with low $\mathrm{S}^{\mathrm{CDS}}$ and $\mathrm{R}^{\mathrm{CDS}}$, has an average return of -0.131% (t-stat=-5.5) for $\mathrm{S}^{\mathrm{CDS}}$ and -0.036 (t-stat=-5.2) for $\mathrm{R}^{\mathrm{CDS}}$. Note that, although the pattern in the $\mathrm{R}_{t+1}^{\mathrm{AMH}}$ is not monotonic increasing in historical $\mathrm{S}^{\mathrm{CDS}}$ and $\mathrm{R}^{\mathrm{CDS}}$, sorting on these variables generate a positively and statistically significant spread of H/L: 0.024% (t-stat=7.7) for $\mathrm{S}^{\mathrm{CDS}}$ and 0.008 (t-stat=3.9) for $\mathrm{R}^{\mathrm{CDS}}$. The results for value-weighted portfolios, as shown in Panel B, are nearly identical. In Table 4, we report the average return of H/L across portfolio sorted by $\mathrm{S}^{\mathrm{CDS}}$ and $\mathrm{R}^{\mathrm{CDS}}$ respectively in weekly and monthly frequency and show that the predictability of $\mathrm{S}^{\mathrm{CDS}}$ and $\mathrm{R}^{\mathrm{CDS}}$ can persist over monthly horizon. The result, overall, are consistent with those reported in Fama and MacBeth regression of Table 2 suggesting that stock market overreact to CDS prices.

3.3. Predictability for High/Low CDS Level

Next, we purge the information of levels and changes of CDS spread together into future stock returns. The aim is to show that variations of CDS spreads can significantly predict stock returns when we control for levels of CDS spread. Thus we can use changes of CDS spread as a proxy for credit news arrival to investigate the source of the information content of CDS prices in stock returns. To be more precise, we conduct a double sorting strategy such that at the beginning of every calendar day (week and month), we independently split all stocks into high CDS spread group and low CDS spread group based on the cross-sectional median of CDS spread level observed at prior day (week and month). Within each CDS spread group, we rank firms by five groups based on their changes of CDS spread from t-2 to t-1 and form 5 portfolios. We mainly focus on the H/L portfolio at different investment horizons, and we do not report all portfolio results from Low CDS changes to high CDS changes here due to space constraint. The results of the test are reported in Table 5.

[Table 5 about here]

In Column (5) of Panel A, we find that the $\mathrm{R}_{t-1}^{\mathrm{CDS}}$ negatively and significantly predict the next period's stock returns during market hours given a high level of CDS spread (valued at t-1). The means of H/L equal-weighted portfolio are -0.058% (t-stat = -5.6), -0.241% (t-stat=-1.8), and -2.199% (t-stat=-2.8) are significant at 1%, 10%, 1% level respect to daily, weekly, and monthly frequency. In a sharp contrast, column (6) shows that means of H/L equal-weighted portfolio respect to $\mathrm{R}_{t-1}^{\mathrm{CDS}}$ given a low level of CDS spread (valued at t-1) do not deliver any significance for all frequencies. Similarly, $\mathrm{R}_{t-1}^{\mathrm{CDS}}$ positively predicts the next period's after market closing return $\mathrm{R}_{t}^{\mathrm{AM}}$ with means of H/L equal-weighted portfolio are 0.013% (t-stat =3.4), 0.125% (t-stat=2.5), and 0.768% (t-stat=3.4) respect to daily, weekly, and monthly frequency given a large level of CDS spread (Column 7) but does exhibit any predictive power given a small level of CDS spread (Column 8). Consistent with our prior finding, $\mathrm{R}_{t-1}^{\mathrm{CDS}}$ does not provide much useful information to predict next day's close-to-close and before market opening stock returns regardless of levels of CDS spread, as shown in column (1) to (4). The results for value-weighted portfolios, as shown in Panel B, are nearly identical to the equal-weighted cases reported in Panel A.

Overall, the empirical evidence suggests that CDS news, as a proxy by the change of CDS spread, can deliver useful information in predicting subsequent day's stock returns overreaction given a group of firms with high levels of CDS spread. In the next section, we examine the economic mechanism.

4. Mechanism

In this section, we explore the potential economic mechanisms. According to the empirical results uncovered in the earlier section, two interesting questions remain unsolved: (1) what is the source of the CDS predictability? And (2) Why does the stock market overreact to CDS price/news?

To address the first question, we focus on an informed-trading hypothesis, suggesting that informed investors in CDS markets trade in opaque stocks with high valuation uncertainty by using their original information extracted from lagged CDS prices. As such, the CDS returns are more likely to lead stock returns for opaque firms.

To address the second question, we posit that CDS prices carry two pieces of distress risk information that are usually hard to tell apart - (1) long-run high default probability that leads to the short-run stock net profit falls, and (2) short-run imminent danger of default (e.g., downgrade, default, and bankruptcy filing events etc.). Case (2) rarely happen, but it confuses the stock markets with case (1) all the time. As a result, the stock market tends to overreact to the short-run imminent danger of default during normal times.

4.1. Hypothesis Development

Informed Trading Hypothesis - where does the predictability come from? CDS markets are sophisticated markets operated by a small set of primary dealers who are likely to be large financial institutions. This is because banks are expected to have better access to reference entities' credit status through established borrow/lending relationships of the reference entity. This could be a source of private information embedded in CDS changes. Consistent with this view, Acharya and Johnson (2007) found that CDS prices are more informative for firms with a higher number of bank relations. Lee, Naranjo, and Velioglu (2017) found that bank-related insider trading information seemed to be fully reflected in the CDS spread reactions rather than related stock prices. Additionally, Siriwardane (2015) showed that in 2011 about 50% of total net Credit Derivative Swaps (CDS) protection in the U.S. was sold by the top five dealers.

Informed trading should be more profitable for opaque firms. This is because the firms' external information environments decide the signal precision of uninformed investors. Thus it turns out to be a crucial factor driving the informed investors trade incentives (Seyhun (1986)). Theories of endogenous information acquisition suggest that the incentives to acquire private information are inversely related to the informativeness of public information (Grossman and Stiglitz (1980), Verrecchia (1982), Diamond (1985), among many other studies.). In accounting literature, Aboody et al. (2005) found that insider trading activities are more pronounced for firms with poor earnings quality. Frankel and Li (2004) found that insider traders prefer to trade in firms whose financial statements are less value-relevant. Using exogenous reductions of analyst coverage due to closures and mergers of the brokerage firm as a proxy for an increase of information asymmetry, Wu (2018) found that informed trading profits increase significantly, and Chen, Kelly, and Wu (2018) found that hedge funds trade more aggressively. Taken together, if CDS markets consist of a large portion of informed traders and they should have direct impacts on stock markets, we thus expect that

Hypothesis 1: CDS returns lead stock returns for high information asymmetric firms.

Overconfidence Hypothesis - Why does the stock market overreact to CDS price? It could be that CDS prices carry two pieces of distress risk information that are usually difficult to tell apart by stock market investors. The first type of distress risk information is the long-run probability of default that will reduce the short-run stock net profits or stock prices. The second type of distress risk information is the short-run imminent danger of default, indicating real distress events in the near future. In most CDS change, it just shows the long-run distress risk, not both long-run and short-run distress risk. However, stock markets may need time to screen out the noisy information. Precisely, during times of processing the second type of distress risk, asset price overreactions may stem from some investors overconfident for their short-run distress signal (Daniel, Hirshleifer, and Subrahmanyam (1998)). The short-run distress signal driving the asset price may consist of two parts - (1) true distress signal (i.e., default comes shortly), and (2) white noise or signal precision errors (i.e., for the regular days without default). Overconfident investors tend to underweight their signal precision errors or to overweight the impact of credit news on detecting the true signal of short-run default. When the noisy signals reduce after market close, the inefficient price deviation should partially be corrected (i.e., reversal).

We look at the periods with low signal precision errors (i.e., markets are right about the short-run default) and we expect to find no stock returns reversal after market close. We focus on downgrade events (realization of short-run distress risk). It should associate with low price uncertainty because CDS spreads can anticipate downgrade event (see, e.g., Lee, Naranjo, and Velioglu (2017)). Precisely, we separate ceases with 1-day ahead credit rating drop following the CDS prices. Thus we predict

Hypothesis 2: There is no stock return reversal for days with credit downgrade following the CDS prices.

Limit-to-Arbitrage Hypothesis Transaction cost is an endogenous factor determining asset price behavior. For instance, Grossman and Miller (1988), Jegadeesh and Titman (1995), and many other studies suggest that stock liquidity embeds information on the slope of aggregate demand curve of the stocks. The illiquid stock is supposed to have a steeper demand curve compared with liquid stocks. This insight is fundamental building block among existing liquidity-based asset pricing models (Amihud (2002), Pastor and Stambaugh (2003), and Acharya and Pedersen (2005)). Hypothetically, if (the level of) CDS spread increases in the level of stock transaction costs[20], it should proxy for the stepper slope of aggregate demand curve of an individual stock. In Table A3, we present an example that CDS spreads levels positively correlate to the stock liquidity (effective spreads)[21]. As such, given credit news arrival that shifts the aggregate liquidity demand of the stocks given net exogenous liquidity supply, the probability of positive net demand at the market closed should be higher. Thus, it is more likely to observe a return reversal afterward (e.g., overreaction).

[**Table A3 about here**]

[20]Studies such as Brogaard, Li, and Xia (2017) found that a causal relation between stock liquidity and default risk.

[21]Specifically, we run a panel regression by (contemporaneously) regressing effective spreads on CDS spreads. We find a statistically significant loading of CDS spread on effective spreads (0.019 with a t-statistic of 67.49) and an adjusted R-square of 46.4%

[Figure 1 about here]

To be more specific, we present an example to show how this idea works. As shown in Figure 1, suppose that the total net supply (assume to be perfectly inelastic) at day t is affected credit information arrives at day t-1 by 10 unit during market hours. The liquid stock (red demand curve with flat slope) should receive a greater price impact than the illiquid stock (blue demand curve with steep slope) - that is, given such 10 unit total demand shift, the price impact on the illiquid stock is |P(t-1)-P1(t)| and for the liquid stocks is |P(t-1)-P2(t)| where |P(t-1)-P1(t)| > |P(t-1)-P2(t)|. A total net supply shifts backward between 30 and 20 after market hours locating along the quality axis between the 20 and 30[22] implying greater price reversal for illiquid stocks than liquidity stocks. It suggests that price reversal will more likely happen after market close for illiquid stocks compared with liquid stocks.

Further, the earlier price discovery regarding the two related securities may primarily occur in the one with lower transaction costs. Easley, O'Hara, and Srinivas (1998) suggested informed investors will proceed their private information in related securities with a smaller transaction. Ni and Pan (2011) showed that CDS prices were more informative when the underlying stocks were banned. Thus, it is likely that the predictability of a CDS to a stock market is due to a more liquid CDS market. Also, the predictability may due to the high funding liquidity risk faced by the primary dealers who suppose to serve as the liquidity providers across the stock and the CDS market. The CDS predictability can be view as liquidity premium charged by the financial intermediaries. Overall, we form our third hypothesis.

Hypothesis 3: The CDS predictability is because of limit-to-arbitrage.

4.2. Empirical Results

4.2.1. Results of Hypothesis 1

We conduct a portfolio sorting approach to test the hypothesis one. At the beginning of every calendar day, all stocks are independently split into groups of high/low CDS spread level based on the cross-sectional median of CDS spread level observed at prior day. Within each CDS spread group, we split stocks by two groups based on the median of information asymmetric scores observed at prior day. Then, we split stocks by median of prior day's CDS spread changes. H/L is the raw return of a zero-cost portfolio of going long stocks of above median CDS changes and short stocks of below median CDS changes. We expect

[22] lie between Q=20 and Q=30 to generate excess demand, for example, suppose least risk-averse short-seller shorts at P(t-1) but cannot buy back at Q=30.

that H/L portfolios generate the larger economic magnitude of returns for high information asymmetric stock portfolio. Table 6 reports the results[23]. In panel A, we report the case of stocks returns with lagged CDS spreads above their cross-sectional median, and in panel B we report the case of stocks returns with lagged CDS spreads below their cross-sectional median.

[Table 6A & Figure 2 about here]

Table 6A shows that, at a daily frequency, the CDS predictive relation is indeed much stronger for high information asymmetric stocks. In panel A of Table 6A, we see that R^{MH} strongly react to lag CDS price changes for asymmetric information group as shown in Column (1). A long-short strategy or H/L of high R^{CDS} (-0.105% with a t-statistics of-2.9) and low R^{CDS} (-0.046 with a t-statistics of-1.4) generates -0.059% (t-stat=-4.7) daily returns. By contrast, the H/L of low information asymmetric stocks generate many inferior returns, -0.023% (t-stat=-2.7). The long-short portfolio (Diff) between column (1) and (2) is statistically significant (-0.036% with a t-statistics of -2.6), suggesting that the CDS predictive effect is mainly concentrating on high information asymmetric stocks. In a similar vein, we see that the R^{AH} price reaction is much stronger for a high information asymmetric group (Column(1)) than the low information asymmetric group (Column(2)). A long-short strategy or H/L of high R^{CDS} (0.035% with a t-statistics of 5.6) and low R^{CDS} (0.018 with a t-statistics of 4.8) generates 0.017% (t-stat=3.1) after-market hours daily H/L returns. In sharp contrast, there are no statistically significant results in the low information asymmetric group regarding R^{AH}. Panel B of Table 6A confirms Table 5 that CDS changes have weak impacts on stocks returns when the CDS level is low. Figure 2 summarizes the key finding of Table 6. Overall, the evidence is consistent with Hypothesis 1, suggesting that CDS lead stock markets for more opaque firms. In Table 6B, we repeat the analysis at a monthly frequency and find that the results remain consistent with Table 6A.

[Table 6B about here]

4.2.2. Results of Hypothesis 2

Hypothesis 2 predicts there is no return reversal following days with downgrading. This hypothesis relies on two important assumptions: (1) private signal precision errors of short-

[23]We only report the daily, equal-weighted case due to space constraint. In unreported results, we find that the results for more extended investment frequencies such as weekly and monthly and value-weighted aggregated scheme within high CDS level are consistent with the daily equal-weighted case reported in the following table.

run distress risk are the only driving force in the outcome of price overreaction. It implies if all informed traders know precisely how private signal looks like, the price will never overshoot no matter investors are overconfident or not. (2) private signal precision errors of short-run distress risk should be tiny during downgrading because CDS spreads can anticipate such bad credit event.

We first present empirical evidence that CDS spreads can anticipate downgrading by event study. We adjust daily changes in five-year CDS spreads by using benchmark portfolio that is constructed using equal-weighted CDS portfolio across all firms within our sample. We then compute the abnormal cumulative CDS spreads changes and look at [-30,30] days event window. Figure 3 reports the result based on the equal-weighted portfolio of all CDS firms who experience a downgrade.

[**Figure 3 about here**]

In Figure 3, one clearly see that the accumulated abnormal CDS price changes react before the downgrading event. The reaction accelerates approximately three days before the downgrade events and does not reverse afterward. It shows that downgrade information is already captured by CDS even before the event happens, suggesting that bad news of downgrading are priced in CDS markets. Hence, signal precision errors are shown to be low for downgrading. Further, we run regression to test whether the overreaction effect disappears following downgrading. In particular, we check whether β_1 is indifferent from zero.

$$R_{i,t}^{\text{Stock}} = \beta_0 + \beta_1 S_{i,t-1}^{\text{CDS}} \times \text{Downgrade}_{i,t+1} + \beta_2 S_{i,t-1}^{\text{CDS}} \times \text{No Downgrade}_{i,t+1} + \text{Controls}_{i,t-1} + \delta_i + \epsilon_{i,t} \tag{3}$$

where $\text{Downgrade}_{i,t}$ is dummy variables equals to 1 for downgrading days and zero otherwise. $\text{No Downgrade}_{i,t}$ is dummy variables equals to 1 for non-downgrading days and zero otherwise. We include firm-fixed effect in the model. Table 7A reports the results using all observation. We further separate the whole sample into two sub-sample consisting of high information asymmetric group (Table 7B) and low information asymmetric group (Table 7C). The partition is based on the cross-sectional median of IVOL at t-1.

[**Table 7A, 7B, and 7C about here**]

In Table 7A, we find that point estimates of $S_{i,t-1}^{CDS} \times Downgrade_{i,t+1}$ is no long significant for R_t^{AM} (Column (3)), suggesting that there is no return reversal when the signal errors of short-run distress risk is low. Further, we show that the effect documented in Table 7A are mainly concentrated on high information asymmetric stocks. Specifically, we observe no return reversal for $Downgrade_{t+1}$ for both S^{CDS} and R^{CDS} compared with the cases of existence of return reversal for $NoDowngrade_{t+1}$ for both S^{CDS} and R^{CDS}. We do not observe a statistically significant pattern for low information asymmetric stocks for Table 7C. Overall, the result suggests that the overreaction is least likely to exist when signal processing errors of short-run distress risk are small (the point that signal processing errors is small during downgrading days is supported by Figure 3 suggesting that CDS prices can anticipate the downgrading event.).

4.2.3. Results of Hypothesis 3

Hypothesis 3 posits that the CDS predictability is due to stock market frictions. To test this, we consider four-dimensional limit-to-arbitrage: (1) stock illiquidity, (2) short-sale constraint, (3) funding liquidity constraint, and (4) relative market illiquidity (see Hilscher, Pollet, and Wilson (2015)).

4.2.4. Stock Illiquidity

It is possible that our results are driven by stock illiquidity. To test this, we further split the high information asymmetric firms (Column (1)) in Table 6 by two groups based on a stock illiquid measure consisting of (1) percentage effective spread (ES), (2) price impact coefficient or Kyle's λ, percentage quoted spread (QS), realized spread (RS), stock volume turnover ($Turn$), and the count of total number of trades during a day (TC).

[Table 8 about here]

Table 8 reports the result. Even though the predictive effect can be partially explained by liquidity hypothesis, the statistically insignificant results of "Diff" for major cases indicating that stock liquidity cannot fully explain our findings. Interestingly, we find that the CDS predictability is stronger for portfolios with high turnover and high trading activities. It suggests that informed investors select to participate in top information asymmetric stocks during times of good liquidity, implying that the marginal value of their private information is higher than the marginal cost (maybe high bid-ask spread). This phenomenon is highlighted recently by Collin-Dufresne and Fos (2016), who posited that informed investors select the timing with better liquidity to trade.

4.2.5. Short-sale Constraint

We further examine the alternative explanation whether the predictive relation from CDS to stock markets is because of short-sale constraint in underlying stocks. CDS markets become an ideal venue for informed investors to proceed private information when the related stocks face a short-sale constraint (Ni and Pan (2011)). If it holds, the CDS predictability should be stronger for the banned stocks. To test this, we build two distinct empirical designs. Firstly, we consider an experiment using 2008 short-sale ban as shocks for a short-sale opportunity in stock markets. In particular, we redo the long-short portfolio H/L of Table 6 under high information asymmetric group by splitting the sample into (1) portfolio of banned stocks (treatment group), and (2) portfolio of non-banned stocks (control group). To see the time-variation effect before and after the short-ban, we focus on two sample period: (1) short-ban period from 2008-09-19 to 2008-10-17; (2) one month before the banned period from 2008-08-19 to 2008-09-18. We use the market model (CAPM)[24] to isolate the overall impact received from the Global Financial Crisis. Secondly, we examine whether the high information asymmetric group experiences greater short-sale activities than the low information asymmetric group. If it does, it suggests that our results are less likely to be explained by short-sale constraint. To test this, we combine our sample with a 2005-2007 period of "Reg SHO" from TAQ.

[Table 9 about here]

Table 9A reports the result of the short-sale ban. Panel A reports the H/L returns of high information asymmetric stocks 1-month before the short-sale ban. Panel B states the results of the short-sale ban. As shown in Panel A, H/L for banned stocks has significantly more negative returns than non-banned stocks before the Short-sale ban period. It suggests the CDS-to-stock information flow is stronger for banned stocks. However, after the Short-sale ban took into place, the average returns of the banned stock drops to zero during market hours. Also, the return difference (Diff) between banned stocks and the non-banned stock is statistically insignificant.

Table 9B reports the results that considering the short sale activities during 2005-2007. Panel A shows that CDS spread changes continue to predict stock returns during market hours, however negatively, we do not observe the overreaction during this period (as shown in Panel B). Panel C indicates that the average short volume in high information asymmetric group is significantly larger than that of the low information asymmetric group. Also, the economic magnitude of the average short volume is significant: the average short volume within high $\mathrm{R}^{\mathrm{CDS}}$ group accounts for 13% of total trading volume within the top information asymmetric group.

Overall, the evidence suggests that the short-sale constraint is not the main reason for the observed informed information flow from CDS to stock markets.

[24]Similar results have been found if we use Fama and French 5 factor model.

4.2.6. Funding Liquidity Constraint

Recent studies suggest that large financial institutions serve as marginal investors that shaping the efficiency across different asset markets (He and Krishnamurthy (2012, 2013), Brunnermeier and Sannikov (2014), and He, Kelly, and Manela (2016)). The funding liquidity conditions are thus a crucial fact that driving their trading activities (Gromb and Vayanos (2002), Brunnermeier and Pedersen (2009), and He, Kelly, and Manela (2016)).

In this section, we test the alternative hypothesis whether the predictability reflects the funding liquidity constraints faced by large financial institutions, who supposed to be key users of private information of CDS markets. We consider two measures of funding liquidity risk: (1) the shock of TED spread, and (2) the shock of primary dealers' capital ratio. We consider a tightening funding condition if we observe a positive shock of TED spread or a negative shock of capital ratio. We proxy the shock using a first order difference. We partition our results by high/low funding liquidity conditions, and if it is the key driver of our findings, and expect that the predictability is solely existing under the case of a tightening funding condition.

[Table 10 about here]

Table 10 reports the results. Pane A reports the results of good funding liquidity condition, and Panel B reports the results of poor funding liquidity condition. Column (1) proxies funding constraint using first order difference of primary dealers' capital ratio and column (2) uses first order difference of TED spread. As for the R^{MH}, we find that the average returns of H/L are indeed higher for tightening funding constraint (as shown in Panel B) than less constraint case (as shown in Panel A), however the H/L are statistically significant for both constraint and fewer constraint cases. Similar results can be found in R^{AH}. Overall, the results reject the conjecture that the arbitrage activities of large financial institutions solely drive the predictive results. More importantly, the results reveal that the small group of sophisticated investors perhaps consistently take advantage of uninformed traders during periods of high disagreement via hiding their trade behind the massive order flows.

4.2.7. Separate Equilibrium Hypothesis

According to the theoretical prediction of Easley, O'Hara, and Srinivas (1998), informed investors would like to select a market that is relatively easier for them to proceed the private information. It comes with three assumptions to select a favorable market: (1) low transaction costs; (2) high sensitivity of the security to the information that will eventually become public; and (3) a high proportion of uninformed traders.

Hilscher, Pollet, and Wilson (2015) found that stock returns unconditional lead CDS returns because the transaction costs of stock markets are lower than CDS markets that are significantly supporting the first assumption. If it is true, the predictive results we documented earlier should because relatively low transaction costs in CDS markets attract informed traders that facilitate information impound in the CDS spreads. It suggests CDS markets should have relatively low transaction costs compared with stock markets given the high information asymmetric and high CDS level sample. We test this conjecture by employing a relative bid-ask spread between two markets as a direct measurement on relative transaction costs between the two markets. In particular, we retrieve the bid-ask spread of CDS quoted prices (scale by the mid-price) from Markit liquidity file from 2010 to 2013, and merge with correspondingly stock percentage effective spread (scale by the mid-price). We then construct the measure by taking bid-ask spread ratio of stock over CDS

$$\text{Relative Liquidity Ratio} = \frac{\frac{P_{Ask,i,t}-P_{Bid,i,t}}{(\mathrm{P}_{Ask,i,t}+P_{Bid,i,t})/2}}{\frac{S_{Ask,i,t}-S_{Bid,i,t}}{(S_{Ask,i,t}+S_{Bid,i,t})/2}}$$

The Relative Liquidity Ratio is bounded between zero and positive infinity. If the ratio is larger than 1, it indicates that CDS is more liquid than stock. If the ratio is smaller than 1, it suggests that CDS is less liquid than stock. We redo Table 6 using 2010 to 2013 sample, which the CDS bid-ask spread is available.

[Table 11 about here]

Table 11 reports the results. The H/L of R^{MH} is -0.046% (t-stat=-2.8). A small reversal (insignificant) is observed respect to the sample period. Overall, it is consistent with our baseline finding in Table 6. Interestingly, the Relative Liquidity Ratio for the high information asymmetric group is only 0.01, which indicates that the stock markets are overall 100 times more liquid than the CDS markets. If our results are solely explained by the relatively low transaction of the stock markets pleasing the informed trading activities, we should not observe the negative and significant results of H/L, R^{MH}. Thus, we rule out the potential explanation of low transaction cost of stock markets.

5. Additional Analysis

5.1. Predict Idiosyncratic Stock Returns

Marsh and Wagner (2016) found that the unconditional information flow from stocks to CDS documented by Hilscher, Pollet, and Wilson (2015) mainly came from systematic stock returns, and found no evidence of predictability of idiosyncratic stock returns. More recently, Lee, Naranjo, and Velioglu (2017) found that CDS returns significantly predict future idiosyncratic stock returns. Here, we examine this issue by decomposing stock returns and CDS returns into the systematic component and idiosyncratic components using a market model followed by Lee, Naranjo, and Velioglu (2017), and we redo the empirical setting of Table 6 by using the idiosyncratic returns. Table 12 reports the results.

[**Table 12 about here**]

Our result shows that "firm-specific" information of CDS returns are indeed the strong predictor for future idiosyncratic stock returns. Consistent with the baseline results reported in Table 6, the CDS returns negatively predict stock returns during market hours and positively predict stock returns after market closing for "hard-to-value" firms. Controlling for the market factor barely affect the results. Overall, these suggest that CDS returns contain quick and valuable firm-specific information.

5.2. Control For Daily Stock Return Reversal

Stock and CDS returns are contemporaneously and negatively correlated via the structure framework established by Merton (1973). The documented CDS predictability could due to the lagged CDS returns that are inversely related to lagged stock market movements. In other words, CDS predictability could reflect a stock market short-term reversal. To investigate the possibility, we conduct a non-parametric sorting strategy by splitting our sample by short-term stock reversal as well as 1-day lagged CDS price changes conditional on above cross-sectional median CDS spreads. We measure short-term stock reversal by using 1-day lagged close-to-close stock returns. If our results are driven by stock return reversal, we should expect a significant negative "Diff" and insignificant "H/L". Table 13 reports the results.

[**Table 13 about here**]

Table 13 shows that a statistically insignificant "Diff" for both market hours stock returns (see Panel A) and aftermarket hours stock returns (see Panel B), suggesting that the CDS predictability is independent of stock return reversal. Within both high and low $R_{t-1}^{CTC,TAQ}$, the "H/L"s are statistically significant for both market hours and aftermarket hours stock returns, suggesting that the CDS predictability exists for within stock reversal. Overall, the evidence indicates that the CDS predictability cannot be replaced by stock return information.

5.3. Impact on Market Qualities

In this section, we present the evidence on the controversial view between information flow of informed CDS markets and capital market quality. The classical perspective on the impacts of informed trading on market quality suggesting that informed trading improves the price informativeness. However, other views such as complex multi-security trading strategies, as in Biais and Hillion (1994) or various opinions of trade in CDS markets, as in Goldstein, Li, and Yang (2014) suggest that informed trades reduce the equity market quality. Boehmer, Chava, and Tookes (2015) found that the negative impacts of CDS trading on the stock market quality mainly come from economic bad times. They found no impacts or even positive impacts of CDS trading on the market quality during good times.

We investigate the impact of CDS price changes on the future dynamic of market qualities, which consist of two measurements of stock/CDS market integration: (i) hedge ratio between stock and CDS and (ii) the covariance between CDS returns and stock returns, and four measurements of stock/CDS market quality by itself: (i) stock volatility, (ii) stock bid-ask spread spread, (iii) CDS volatility, and (iv) stock market beta. All the market quality proxies are calculated based on 1-month daily data. We construct hedge ratio following Schaefer and Strebulaev (2008), Augustin, et al. (2018). A more negative hedge ratio or stock/CDS covariance suggests a greater integration between the two markets (Kapadia and Pu (2012), Augustin, et al. (2018)).

We rely on a firm-fixed effect panel regression model. We focus on the impacts of CDS price changes on future changes of market quality proxies (β_{12}). Moreover, to understand whether the impacts of CDS price changes vary given different firm information environments and macro conditions, we consider three intermediate variables: (1) CDS price level, (2) information asymmetric score, and (3) Global financial crisis (GFC) indicator. The joint impacts are capturing via the point estimates of (β_1), (β_3), (β_5), and (β_{10}) respectively. The full specification is following:

$$
\begin{aligned}
&\Delta MQ_{i,t+1} = \alpha + \beta_1 \times R^{CDS}_{i,t} \times S^{CDS}_{i,t} * InfoAsy_{i,t} \times GFC + \beta_2 \times R^{CDS}_{i,t} \times \mathrm{S}^{CDS}_{i,t} \times GFC \\
&+ \beta_3 \times R^{CDS}_{i,t} \times InfoAsy_{i,t} \times GFC + \beta_4 \times S^{CDS}_{i,t} \times InfoAsy_{i,t} \times GFC + \beta_5 R^{\mathrm{CDS}}_{i,t} \times GFC \\
&+ \beta_6 S^{CDS}_{i,t} \times GFC + \beta_7 InfoAsy_{i,t} \times GFC + \beta_8 S^{CDS}_{i,t} \times \mathrm{R}^{CDS}_{i,t} \times InfoAsy_{i,t} \\
&+ \beta_9 S^{CDS}_{i,t} \times R^{CDS}_{i,t} + \beta_{10} R^{\mathrm{CDS}}_{i,t} \times InfoAsy_{i,t} + \beta_{11} S^{CDS}_{i,t} \times InfoAsy_{i,t} + \beta_{12} \mathrm{R}^{CDS}_{i,t} \\
&+ \beta_{13} S^{CDS}_{i,t} + \beta_{14} InfoAsy_{i,t} + \beta_{15} GFC + \delta_i + e_{i,t+1}
\end{aligned} \tag{4}
$$

where $\Delta MQ_{i,t+1}$ is market quality changes from t to t+1. It consists of (1) hedge ratio

($Hedge$), (2) stock and CDS covariance (COV), (3) stock volatility (σ^{STK}), (4) CDS volatility (σ^{CDS}), (4) effective spread (ES), (5) quoted spread (QS), and (6) stock market beta (β); δ_i is firm-fixed effect dummy; the standard errors are clustered at monthly level; The regression is at monthly frequency.

The variables of interest are $\{\beta_1, \beta_3, \beta_5, \beta_{10}, \beta_{12}\}$. A negative (positive) of any point estimate indicates a positive (negative) impact on market qualities.

[**Table 14 about here**]

Table 14 reports the results. During the good times, negative β_{12}s suggest that CDS spread changes improve the overall market quality. In particular, it enhances the stock market integration, reduces volatilities of both markets, and reduces the effective spreads. However, in contrast with unconditional healthy impact delivered by CDS prices, we find the positive β_{10}, suggesting that CDS spread changes induce excess volatilities and widen the bid-ask spread within hard-to-value firms.

During the bad times, CDS spread changes destabilize the overall market quality by increasing volatilities and stock transaction costs ($\beta_5 > 0$). Interestingly, CDS prices changes within hard-to-value firms deliver a positive impact on market qualities by reducing volatility and narrow down the bid-ask spread $\beta_3 < 0$. It suggests that informed investors may act as a liquidity provider that inject additional liquidity in the market during the market turmoil period that prevents the markets from the further crash.

6. Conclusion

Do CDSs convey useful information on stock returns? This paper establishes a strong and previously unexplored link between CDS spread and stock returns during different market hours. In market hours we see that lagged CDS negatively influences stock returns spreads that are both statistically and economically significant. However, after a market closing period, the positive relation between stocks returns and lagged CDS spreads suggests stock returns reversal after market hours. To understand the source of return predictability, we explore an informed trading mechanism. Price movements of CDS markets reveal the trading activities of a small set of informed cross-market arbitrageurs who have better access to both small markets (CDS) and large markets (Stock) described in Goldstein, Li, and Yang (2014). It could be the case where constraint (namely investors with small information set that could not trade in stock markets) and less informed investors gradually become informed by learning from insights conveyed from price changes or trade behaviors induced by the existing informed investors in CDS markets. For instance, less informed investors can learn the actions that informed traders speculate in the CDS market and hedge out their position in equity markets simultaneously and CDS predictability can be viewed as information processing costs (Grossman and Stiglitz (1980); Verrecchia (1982)). Overall, our evidence suggests that informed traders step into hard-to-value stocks during times with good liquidity, consistent with theoretical prediction offered by Collin-Dufresne and Fos (2016).

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Table 1A: Summary statistics

This table reports the descriptive statistics of the main variables used this study from 2001 to 2013. S^{CDS} is 5-year CDS spreads. R^{CDS} is percentage change of 5-year CDS spreads. Stock returns consist (1) stock returns computed based on close-to-close stock price $R^{CTC}_{i,t}$, (2) stock returns before market open $R^{BM}_{i,t}$, (3) stock returns during market hours $R^{MH}_{i,t}$, and (4) stock returns after market hours $R^{AM}_{i,t}$. VOLA is realized stock volatility. LEV is market leverage. MOM is price momentum. ES is percentage effective spreads. QS is percentage quoted spread. Short volume is the aggregate daily short volume from 2005 to 2007. Relative liquidity ratio of bid-ask spread between stock and CDS from 2010 to 2013. TURN is stock trading volume turnover. SUM_Trade is total number of transaction made during conventional trading hours. Price Impact λ is price impact coefficient. IVOL is idiosyncratic volatility computed based on the Fama and French 5 factor model using past 1-year rolling window. Trading volumes and Stock capitalization (SIZE) are reported in terms of \$ 1000s. Statistics include sample mean (Mean), sample standard deviation (Stdv), sample skewness (Skew), and sample kurtosis (Kurt).

	Nobs	Mean	Stdv	Skew	Kurt
S^{CDS}	2050282	180.938	339.479	8.29	118
R^{CDS}	2050282	0.002	4.450	0.50	358
R^{CTC}	2050282	0.003	3.090	3.59	1569
R^{BM}	724051	-0.028	2.554	257.28	119046
R^{MH}	2050282	-0.010	2.365	17.13	6169
R^{AM}	1966518	0.009	0.823	-1.43	15574
Trading Volume (AM)	1966518	228010	1637458	247.72	121967
Trading Volume (BM)	724051	30255	981999	444.17	324799
Trading Volume (MH)	2050282	3602645	14122111	42.00	3473
VOLA	2050282	0.087	0.339	70.88	10131
LEV	2050282	0.404	0.281	0.68	2
MOM	2050282	0.132	0.376	0.33	13
IVOL	2050282	0.017	0.012	3.72	30
ES	2050282	0.001	0.004	40.25	4696
QS	2050282	0.002	0.005	53.13	9251
RS	2050282	0.001	0.009	246.670	105277
SIZE	2050282	16282105	33590738	5.59	47
TURN	2050282	10.516	101.37	205.334	57928
SUM_Trade	2050282	11334.458	23440.68	11.362	351
Price Impact λ	2050282	0.015	0.33	1225.470	1659180
Short Volume	540181	308852.6	550269.8	8.7	265.6
Relative Liquidity	276259	0.001	0.001	21.6	1293.6

Table 1B: Correlation Table of Stock Returns Computed by Different Market Hours using TAQ and CRSP Database

This table reports the contemporaneous correlation table for stock returns from 2001 to 2013. Stock returns consist (1) stock returns before market open $R_{i,t}^{BM}$, (2) stock returns during market hours $R_{i,t}^{MH}$, and (3) stock returns after market hours $R_{i,t}^{AM}$, (4) close-to-close stock returns $R_t^{CTC,TAQ}$ computed by TAQ, (5) close-to-close stock returns $R_t^{CTC,CRSP}$ computed by CRSP, (6) open-to-close stock returns $R_t^{OTC,CRSP}$ computed by CRSP, and (7) close-to-open stock returns $R_t^{CTO,CRSP}$ computed by CRSP. $\mathrm{R}_{i,t}^{\mathrm{BM}}$, $\mathrm{R}_{i,t}^{\mathrm{MH}}$, and $\mathrm{R}_{i,t}^{\mathrm{AM}}$ are computed using TAQ dataset. All units are expressed in terms of percentage.

	R^{BM}	R^{MH}	R^{AM}	$R^{CTC,TAQ}$	$R^{CTC,CRSP}$	$R^{OTC,CRSP}$	$R^{CTO,CRSP}$
R^{BM}	100	-3.6	0.5	15.8	16.4	-3.1	32.3
R^{MH}		100	-7.9	73.7	77.1	99.9	-7.2
R^{AM}			100	-4.8	-5.1	-7.3	1.7
$R^{CTC,TAQ}$				100	99.7	73.8	50.6
$R^{CTC,CRSP}$					100	77.6	53.3
$R^{OTC,CRSP}$						100	-7.4
$R^{CTO,CRSP}$							100

Table 2A: Fama and MacBeth (1973) Regression

This table reports Fama and MacBeth (1973) predictive regressions of stock returns respect to different market hours using CDS market information at a daily, weekly, and monthly frequency. The dependent variables include (1) market hours stock returns, $\mathrm{R}_t^{\mathrm{MH}}$ in Panel A, (2) after market hours stock returns, $\mathrm{R}_t^{\mathrm{AM}}$ in Panel B, (3) before market hours stock returns, $\mathrm{R}_t^{\mathrm{BM}}$ in Panel C, and close to close stock return, $\mathrm{R}_t^{\mathrm{CTC}}$ in Panel D. The key variable of interest is 5-year CDS spread level, $\mathrm{S}^{\mathrm{CDS}}$. The control variables include idiocycradic volatility computed by Fama and French 5-factor model ($IVOL_{t-1}$), (log) stock market capitalization ($Size_{t-1}$), stock percentage effective spreads (ES_{t-1}), credit rating ($Rating_{t-1}$), and (log) total trading volume for each stock ($Volume_{t-1}$), market leverage (Lev_{t-1}), and stock price momentum (Mom_{t-1}). Cross-sectional regressions are run every period and the time-series standard errors are adjusted for heteroskedasticity and autocorrelation (12 lags). The sample period covers January 2001 through December 2013. Newey-west t-statistics are reported in the brackets.

Panel A:R_t^{MH}													
	Intercept	S_{t-1}^{CDS}, β_1	R_t^{BM}	R_{t-1}^{MH}	R_{t-1}^{AM}	$IVOL_{t-1}$	$Size_{t-1}$	ES_{t-1}	$Rating$	$Volume_{t-1}$	Lev_{t-1}	MOM_{t-1}	AdjR2
Daily	0.48	**-1.20**	-11.62	0.95	-0.43	-3.72	-0.01	-2.74	0.00	-0.07	0.01	0.05	11.6%
	(6.3)	**-(5.9)**	-(9.1)	(4.1)	-(0.6)	-(5.9)	-(3.6)	-(1.6)	-(3.1)	-(1.6)	(0.6)	(2.8)	
Weekly	2.02	**-5.69**	-8.24	3.12	-3.03	-2.80	-0.05	-17.55	-0.02	-0.31	0.02	0.18	11.8%
	(6.1)	**-(5.4)**	-(4.5)	(7.1)	-(2.4)	-(3.6)	-(2.9)	-(2.7)	-(3.0)	-(1.6)	(0.2)	(2.1)	
Monthly	9.16	**-22.45**	-15.68	10.23	-1.01	-2.31	-0.13	-76.18	-0.09	-2.14	0.06	0.35	12.8%
	(7.9)	**-(5.1)**	-(2.9)	(6.8)	-(0.3)	-(2.4)	-(2.6)	-(3.0)	-(3.6)	-(3.6)	(0.1)	(0.9)	
Panel C:R_t^{AM}													
	Intercept	S_{t-1}^{CDS}, β_1	R_t^{BM}	R_t^{MH}	R_{t-1}^{AM}	$IVOL_{t-1}$	$Size_{t-1}$	ES_{t-1}	$Rating$	$Volume_{t-1}$	Lev_{t-1}	MOM_{t-1}	AdjR2
Daily	-0.17	**0.24**	-0.77	-2.73	1.39	0.49	0.00	0.90	0.00	0.07	0.00	-0.01	6.2%
	-(6.7)	**(3.7)**	-(0.7)	-(21.1)	(6.1)	(2.8)	-(2.2)	(1.8)	-(2.3)	(7.2)	(0.4)	-(2.6)	
Weekly	-0.60	**1.10**	-0.57	-3.18	2.86	0.61	-0.01	0.33	0.00	0.27	0.00	-0.05	6.8%
	-(4.5)	**(3.7)**	-(0.6)	-(13.1)	(5.0)	(3.4)	-(2.5)	(0.1)	-(1.7)	(5.5)	-(0.2)	-(2.2)	
Monthly	-2.52	**4.67**	-1.06	-4.77	2.55	0.33	-0.04	7.33	-0.02	1.17	0.03	-0.31	7.7%
	-(3.3)	**(3.5)**	-(1.7)	-(9.2)	(3.1)	(1.3)	-(1.8)	(0.5)	-(1.1)	(4.8)	(0.4)	-(1.9)	
Panel C:R_t^{BM}													
	Intercept	S_{t-1}^{CDS}, β_1	R_{t-1}^{BM}	R_{t-1}^{AM}	R_{t-1}^{MH}	$IVOL_{t-1}$	$Size_{t-1}$	ES_{t-1}	$Rating$	$Volume_{t-1}$	Lev_{t-1}	MOM_{t-1}	AdjR2
Daily	0.22	**0.21**	1.52	-1.25	0.12	-0.31	0.00	-2.68	0.00	-0.08	-0.01	0.00	6.4%
	(5.6)	**(1.1)**	(3.4)	-(3.3)	(1.3)	-(1.4)	-(0.9)	-(2.9)	-(1.4)	-(5.1)	-(0.9)	(0.3)	
Weekly	0.87	**0.29**	0.37	-0.61	-0.21	-0.26	-0.01	-8.64	-0.01	-0.23	-0.03	0.02	7.2%
	(4.8)	**(0.6)**	(0.5)	-(1.1)	-(1.4)	-(1.1)	-(3.3)	-(2.3)	-(1.6)	-(3.3)	-(1.0)	(1.0)	
Monthly	3.81	**0.67**	2.89	-1.90	-0.49	-0.16	-0.04	-30.95	-0.06	-1.17	-0.09	0.09	6.3%
	(4.2)	**(0.3)**	(2.1)	-(1.6)	-(1.4)	-(0.9)	-(2.7)	-(1.9)	-(1.6)	-(3.5)	-(0.9)	(0.8)	
Panel D:R_t^{BM}													
	Intercept	S_{t-1}^{CDS}, β_1	R_t^{C2C}			$IVOL_{t-1}$	$Size_{t-1}$	ES_{t-1}	$Rating$	$Volume_{t-1}$	Lev_{t-1}	MOM_{t-1}	AdjR2
Daily	-0.13	**0.13**	-1.22			-1.37	-0.01	1.92	0.00	0.15	-0.03	0.02	9.7%
	-(1.4)	**(0.4)**	-(3.8)			-(1.5)	-(3.8)	(0.8)	-(2.5)	(3.2)	-(1.8)	(0.8)	
Weekly	-0.54	**0.26**	-1.51			-0.48	0.00	7.60	-0.01	0.33	-0.08	0.06	9.7%
	-(1.3)	**(0.9)**	-(2.9)			-(0.4)	-(1.6)	(0.8)	-(1.7)	(1.8)	-(1.1)	(0.4)	
Monthly	-0.40	**0.12**	-0.27			-0.26	0.00	27.01	-0.07	0.43	-0.29	0.17	9.5%
	-(0.2)	**(0.4)**	-(0.3)			-(0.3)	-(1.0)	(0.7)	-(1.9)	(0.6)	-(0.7)	(0.3)	

Table 2B: Fama and MacBeth (1973) Regression

This table reports Fama and MacBeth (1973) predictive regressions of stock returns respect to different market hours using CDS market information at a daily, weekly, and monthly frequency. The dependent variables include (1) market hours stock returns, R_t^{MH} in Panel A, (2) after market hours stock returns, R_t^{AM} in Panel B, (3) before market hours stock returns, R_t^{BM} in Panel C, and close to close stock return, R_t^{CTC} in Panel D. The key variable of interest is percentage price changes of 5-year CDS spread level, R^{CDS}. The control variables include idiocycradic volatility computed by Fama and French 5-factor model ($IVOL_{t-1}$), (log) stock market capitalization ($Size_{t-1}$), stock percentage effective spreads (ES_{t-1}), credit rating ($Rating_{t-1}$), and (log) total trading volume for each stock ($Volume_{t-1}$), market leverage (Lev_{t-1}), and stock price momentum (Mom_{t-1}). Cross-sectional regressions are run every period and the time-series standard errors are adjusted for heteroskedasticity and autocorrelation (12 lags). The sample period covers January 2001 through December 2013. Newey-west t-statistics are reported in the brackets.

Panel A: R_t^{MH}													
	Intercept	R_{t-1}^{CDS}, β_1	R_t^{BM}	R_{t-1}^{MH}	R_{t-1}^{AM}	$IVOL_{t-1}$	$Size_{t-1}$	ES_{t-1}	$Rating$	$Volume_{t-1}$	Lev_{t-1}	MOM_{t-1}	AdjR2
Daily	0.61	**-0.31**	-11.67	1.04	-0.44	-5.36	-0.01	-2.75	-0.01	-0.14	-0.01	0.06	11.0%
	(7.2)	**-(5.6)**	-(8.7)	(4.5)	-(0.7)	-(7.9)	-(2.2)	-(1.6)	-(4.9)	-(2.8)	-(1.1)	(3.6)	
Weekly	2.64	**-1.14**	-7.90	3.29	-3.18	-4.30	-0.03	-18.81	-0.03	-0.64	-0.07	0.26	10.9%
	(6.7)	**-(2.7)**	-(4.0)	(7.3)	-(2.5)	-(5.1)	-(1.5)	-(2.9)	-(5.1)	-(2.8)	-(1.0)	(2.7)	
Monthly	11.53	**-2.84**	-15.30	10.74	-1.64	-3.45	-0.02	-83.20	-0.13	-3.56	-0.24	0.61	12.1%
	(7.7)	**-(0.7)**	-(2.9)	(7.2)	-(0.6)	-(3.2)	-(0.4)	-(3.2)	-(4.9)	-(5.0)	-(0.5)	(1.6)	
Panel B: R_t^{AM}													
	Intercept	R_{t-1}^{CDS}, β_1	R_t^{BM}	R_t^{MH}	R_{t-1}^{AM}	$IVOL_{t-1}$	$Size_{t-1}$	ES_{t-1}	$Rating$	$Volume_{t-1}$	Lev_{t-1}	MOM_{t-1}	AdjR2
Daily	-0.19	**0.02**	-0.73	-2.73	1.37	0.80	0.00	0.90	0.00	0.08	0.00	-0.02	5.9%
	-(7.2)	**(0.9)**	-(0.7)	-(20.9)	(6.0)	(4.3)	-(3.1)	(1.8)	-(1.5)	(7.8)	(1.3)	-(3.4)	
Weekly	-0.69	**0.33**	-0.60	-3.19	2.84	0.89	-0.01	0.23	0.00	0.32	0.01	-0.07	6.5%
	-(4.9)	**(2.3)**	-(0.6)	-(13.2)	(5.1)	(4.8)	-(3.2)	(0.1)	-(0.9)	(6.0)	(0.8)	-(2.7)	
Monthly	-3.00	**1.55**	-0.98	-4.81	2.60	0.52	-0.06	9.44	-0.01	1.46	0.08	-0.37	7.3%
	-(4.1)	**(1.8)**	-(1.5)	-(9.3)	(3.0)	(2.2)	-(2.2)	(0.7)	-(0.7)	(5.2)	(1.0)	-(2.0)	
Panel C: R_t^{BM}													
	Intercept	R_{t-1}^{CDS}, β_1	R_{t-1}^{BM}	R_{t-1}^{AM}	R_{t-1}^{MH}	$IVOL_{t-1}$	$Size_{t-1}$	ES_{t-1}	$Rating$	$Volume_{t-1}$	Lev_{t-1}	MOM_{t-1}	AdjR2
Daily	0.21	**-0.04**	1.50	-1.22	0.10	-0.10	0.00	-2.80	0.00	-0.07	0.00	0.00	6.1%
	(5.4)	**-(1.3)**	(3.3)	-(3.2)	(1.0)	-(0.4)	-(1.5)	-(2.9)	-(1.3)	-(4.2)	-(0.5)	-(0.5)	
Weekly	0.84	**0.04**	0.33	-0.59	-0.26	-0.21	-0.02	-8.83	-0.01	-0.22	-0.02	0.00	6.6%
	(4.8)	**(0.1)**	(0.4)	-(1.0)	-(1.7)	-(0.9)	-(3.3)	-(2.3)	-(1.5)	-(3.1)	-(0.9)	(0.2)	
Monthly	3.83	**0.06**	2.98	-2.03	-0.49	-0.11	-0.04	-34.36	-0.05	-1.17	-0.08	0.04	5.8%
	(4.3)	**(0.0)**	(2.1)	-(1.7)	-(1.5)	-(0.5)	-(2.4)	-(2.0)	-(1.6)	-(3.6)	-(0.9)	(0.3)	
Panel D: R_t^{CTC}													
	Intercept	R_{t-1}^{CDS}, β_1	R_t^{C2C}			$IVOL_{t-1}$	$Size_{t-1}$	ES_{t-1}	$Rating$	$Volume_{t-1}$	Lev_{t-1}	MOM_{t-1}	AdjR2
Daily	-0.15	**-0.38**	-1.27			-1.25	-0.01	1.65	0.00	0.15	-0.02	0.02	9.1%
	-(1.5)	**-(3.4)**	-(4.0)			-(1.3)	-(3.3)	(0.6)	-(2.1)	(3.0)	-(1.7)	(0.9)	
Weekly	-0.56	**-0.23**	-1.58			-0.41	0.00	8.69	-0.01	0.33	-0.08	0.06	8.9%
	-(1.3)	**-(1.7)**	-(3.1)			-(0.4)	-(1.7)	(0.9)	-(1.5)	(1.8)	-(1.0)	(0.4)	
Monthly	-0.72	**-0.52**	-0.33			-0.43	0.00	32.18	-0.06	0.56	-0.24	0.17	8.9%
	-(0.4)	**-(1.3)**	-(0.4)			-(0.4)	-(1.0)	(0.8)	-(1.4)	(0.7)	-(0.6)	(0.3)	

Table 3: Stock Portfolios Sorted By CDS Information at Daily Frequency
This table reports calendar time equally weighted portfolio raw returns at daily frequency. At the beginning of every calendar day, all stocks are sorted in ascending order on the level of CDS spread (S^{CDS}) or the change of CDS spread (S^{CDS}) in the prior day. The ranked stocks are assigned to one of 5 quintile portfolios. The portfolios are rebalanced every day. Equal-weighted stock returns constructed by lagged S^{CDS} are reported in Panel A and equal-weighted stock returns constructed by lagged R^{CDS} are reported in Panel B. H/L is the raw return of a zero-cost portfolio of going long high level (change) of CDS spread stocks and short low level (change) of CDS spread stocks. The average returns are expressed as **percentage units**. Column (1) is the close-to-close stock return (R_t^{CTC}). Column (2), (3), and (4) consist of before market open (R_t^{BM}), during market hours (R_t^{MH}), and after market close stock return (R_t^{AM}) respectively constructed using transaction price from TAQ. The sample period covers January 2001 through December 2013. Newey-west t-statistics adjusted for 12 lags are reported in the brackets. ***,**, and * denote significance at 1%, 5%, and 10% level respectively.

Equal-weighted Portfolio Returns at Daily Frequency

	(1)	(2)	(3)	(4)
Panel A: Sorted by CDS Level	R_t^{CTC}	R_t^{BM}	R_t^{MH}	R_t^{AM}
Low S_{t-1}^{CDS}	-0.002	-0.012***	0.034**	0.004*
	-(0.1)	-(5.6)	(2.4)	(1.8)
2	0.006	-0.008**	0.024	0.003
	(0.3)	-(2.5)	(1.5)	(1.3)
3	0.000	-0.006**	0.014	0.000
	(0.0)	-(2.6)	(0.8)	(0.1)
4	0.007	-0.009***	0.005	0.004
	(0.3)	-(3.2)	(0.2)	(1.5)
High S_{t-1}^{CDS}	-0.010	-0.011**	-0.097***	0.028***
	-(0.2)	-(2.1)	-(2.8)	(7.8)
H/L	-0.009	0.001	-0.131***	0.024***
	-(0.3)	(0.3)	-(5.5)	(7.7)
Panel B: Sorted by CDS Change	R_t^{CTC}	R_t^{BM}	R_t^{MH}	R_t^{AM}
Low R_{t-1}^{CDS}	0.014	-0.011***	0.011	0.005**
	(0.5)	-(3.2)	(0.5)	(2.3)
2	0.011	-0.009***	-0.001	0.008***
	(0.5)	-(3.3)	-(0.1)	(3.5)
3	0.014	-0.004	-0.001	0.005*
	(0.6)	-(1.2)	-(0.1)	(1.9)
4	0.002	-0.007*	-0.004	0.007***
	(0.1)	-(1.7)	-(0.2)	(3.0)
High R_{t-1}^{CDS}	-0.022	-0.014***	-0.024	0.013***
	-(0.8)	-(3.6)	-(1.1)	(5.2)
H/L	-0.037***	-0.003	-0.036***	0.008***
	-(4.1)	-(0.8)	-(5.2)	(3.9)

Table 4: Stock Portfolios Sorted By CDS Information at A Longer Frequency
This table reports calendar-time portfolio H/L raw returns at daily using value-weight, weekly, and monthly frequency. At the beginning of every calendar time, all stocks are sorted in ascending order on the level of CDS spread (S^{CDS}) or the change of CDS spread (S^{CDS}) in the prior day or week or month. The ranked stocks are assigning to one of 5 quintile portfolios. The portfolios are rebalanced every day, week, and month accordingly. H/L is the raw return of a zero-cost portfolio of going long high level (change) of CDS spread stocks, and short low level (change) of CDS spread stocks. We mainly focus on the H/L portfolio at different investment horizons, and we do not report all portfolio results of Low CDS prices due to space constraint. Column (1) is the close-to-close stock return (R_t^{CTC}). Column (2), (3), and (4) consist of before market open (R_t^{BM}), during market hours (R_t^{MH}), and aftermarket close stock return (R_t^{AM}) respectively constructed using transaction price from TAQ. The sample period covers January 2001 through December 2013. Newey-west t-statistics adjusted for 12 lags are reported in the brackets. ***,**, and * denote significance at 1%, 5%, and 10% level respectively.

	(1) R_t^{CTC}	(2) R_t^{BM}	(3) R_t^{MH}	(4) R_t^{AM}
Daily, Value-weight				
H/L S_{t-1}^{CDS}	-0.034	0.015	-0.095***	0.015***
	-(1.3)	(1.5)	-(4.5)	(3.5)
Daily, Value-weight				
H/L R_{t-1}^{CDS}	-0.038***	-0.001	-0.031***	0.007**
	-(3.3)	-(0.3)	-(3.6)	(2.3)
Weekly, Equal-weight				
H/L S_{t-1}^{CDS}	-0.040	0.011	-0.603***	0.111***
	-(0.3)	(0.5)	-(4.0)	(6.0)
Weekly, Value-weight				
H/L S_{t-1}^{CDS}	-0.142	0.078	-0.433***	0.056***
	-(1.0)	(1.4)	-(3.6)	(3.2)
Monthly, Equal-weight				
H/L S_{t-1}^{CDS}	-0.240	0.042	-2.623***	0.460***
	-(0.4)	(0.4)	-(3.3)	(4.0)
Monthly, Value-weight				
H/L S_{t-1}^{CDS}	-0.604	0.403*	-2.074***	0.289***
	-(0.9)	(1.9)	-(3.2)	(3.4)
Weekly, Equal-weight				
H/L R_{t-1}^{CDS}	-0.080	0.090	-0.104**	0.032***
	-(0.5)	(1.4)	-(2.3)	(3.2)
Weekly, Value-weight				
H/L R_{t-1}^{CDS}	0.274	0.070	-0.052	0.042
	(1.2)	(0.7)	-(1.3)	(1.4)
Monthly, Equal-weight				
H/L R_{t-1}^{CDS}	-0.052	0.060	-0.378**	0.150**
	-(0.3)	(1.3)	-(2.0)	(2.6)
Monthly, Value-weight				
H/L R_{t-1}^{CDS}	-0.060	-0.011	-0.003	-0.028
	-(0.3)	-(0.1)	(0.0)	-(0.4)

Table 5: Stock Portfolios Sorted by CDS Returns When CDS Levels are Controlled

This table reports calendar-time portfolio of H/L returns given high and low CDS spreads at a daily, weekly, and monthly frequency. H/L is the raw return of a zero-cost portfolio of going long stocks of high CDS changes quintile and short stocks of low CDS change quintile. To be more precise, we conduct a double sorting strategy such that at the beginning of every calendar day or week or month, we independently split all stocks into high CDS levels and low CDS levels based on their cross-sectional median observed at prior day or week or month. Within each CDS level group, we further rank firms by quintile based on their CDS changes from t-2 to t-1 and form 5 portfolios. The portfolios are rebalanced every day, week, and month accordingly. Equal-weighted returns are reported in Panel A, and value-weighted returns are reported in Panel B. We mainly focus on the H/L portfolio at different investment horizons, and we do not report all portfolio results due to space constraint. The average returns are expressed as **percentage units**. Column (1) & (2) report the H/L strategy of close-to-close stock return ($\mathrm{R}_t^{\mathrm{CTC}}$) given Hign/ Low CDS spread; column (3) & (4) report the H/L strategy of before market open ($\mathrm{R}_t^{\mathrm{BM}}$) given Hign/ Low CDS spread; column (5) & (6) report the H/L strategy of before market open ($\mathrm{R}_t^{\mathrm{MH}}$) given Hign/ Low CDS spread; column (7) & (8) report the H/L strategy of before market open ($\mathrm{R}_t^{\mathrm{AM}}$) given Hign/ Low CDS spread. The stock returns are constructed by transaction price from TAQ. The sample period covers January 2001 through December 2013. Newey-west t-statistics adjusted for 12 lags are reported in the brackets. ***,**, and * denote significance at 1%, 5%, and 10% level respectively.

	(1) HS_{t-1}^{CDS} R_t^{CTC}	(2) LS_{t-1}^{CDS} R_t^{CTC}	(3) HS_{t-1}^{CDS} R_t^{BM}	(4) LS_{t-1}^{CDS} R_t^{BM}	(5) HS_{t-1}^{CDS} R_t^{MH}	(6) LS_{t-1}^{CDS} R_t^{MH}	(7) HS_{t-1}^{CDS} R_t^{AM}	(8) LS_{t-1}^{CDS} R_t^{AM}
Panel A: EW								
Daily								
H/L R_{t-1}^{CDS}	-0.043**	0.002	-0.010	0.004	**-0.058*** **	-0.004	**0.013*** **	0.002
	-(2.1)	(0.2)	-(1.6)	(1.0)	**-(5.6)**	-(0.7)	**(3.4)**	(1.2)
Weekly								
H/L R_{t-1}^{CDS}	-0.007	0.076*	0.056	0.006	**-0.241***	0.032	**0.125** **	-0.007
	(0.0)	(1.8)	(0.9)	(0.4)	**-(1.8)**	(0.9)	**(2.5)**	-(0.7)
Monthly								
H/L R_{t-1}^{CDS}	-0.693	0.246	0.611**	0.020	**-2.199*** **	-0.001	**0.768*** **	-0.027
	-(1.1)	(1.5)	(2.4)	(0.4)	**-(2.8)**	(0.0)	**(3.4)**	-(0.4)
Panel B: VW								
Daily								
H/L R_{t-1}^{CDS}	-0.032	0.001	-0.019**	0.004	**-0.042*** **	-0.003	**0.008***	0.002
	-(1.6)	(0.1)	-(2.2)	(0.7)	**-(3.0)**	-(0.5)	**(1.7)**	(0.8)
Weekly								
H/L R_{t-1}^{CDS}	-0.099	0.076*	0.026	0.002	**-0.167** **	0.024	**0.061*** **	-0.003
	-(1.5)	(1.8)	(1.3)	(0.1)	**-(2.5)**	(0.8)	**(3.2)**	-(0.3)
Monthly								
H/L R_{t-1}^{CDS}	-0.565**	0.298**	0.143	0.009	**-0.794*** **	0.072	**0.250** **	-0.001
	-(2.2)	(2.0)	(1.5)	(0.2)	**-(3.1)**	(0.5)	**(2.4)**	(0.0)

Table 6A: Stock Portfolios Sorted by CDS Returns given High CDS Levels When Information Asymmetries are controlled

This table reports daily equal-weighted H/L calendar time portfolio returns for high and low information asymmetric groups when CDS level is above cross-sectional medians. At the beginning of every calendar day, all stocks are independently split into groups of high/low CDS spread level based on the cross-sectional median of CDS spread level observed at prior day. Within each CDS spread group, we split stocks by two groups based on a median of information asymmetric scores observed at prior day. Then, we split stocks by median of prior day's CDS spread changes. The degree of information asymmetry is measured by idiosyncratic volatility based on a Fama and French 5 factor model. H/L is the raw return of a zero-cost portfolio of going long stocks of above median CDS changes and short stocks of below median CDS changes. Panel A reports stock returns with lagged CDS spread above the lagged cross-sectional median and Panel B reports stock returns with lagged CDS spread below the lagged cross-sectional median. The average returns are expressed as **percentage units**. Column (1) is mean test results of stock returns under high information asymmetric group and Column (2) is mean test results of stock returns under low information asymmetric group, and Column (3) (Diff) reports the strategy of long Column (1) and shorting Column (2). The sample period covers January 2001 through December 2013. Newey-west t-statistics adjusted for 12 lags are reported in the brackets. ***,**, and * denote significance at 1%, 5%, and 10% level respectively.

	(1) High IVOL	(2) Low IVOL	(3) Diff
Panel A: CDS Spread Above Median			
Market Hours			
High R^{CDS}	-0.105***	-0.001	-0.105***
	-(2.9)	(0.0)	-(5.2)
Low R^{CDS}	-0.046	0.022	-0.069***
	-(1.4)	(1.1)	-(3.5)
H/L	-0.059***	-0.023***	-0.036***
	-(4.7)	-(2.7)	-(2.6)
After Market Hours			
High R^{CDS}	0.035***	0.001	0.034***
	(5.6)	(0.4)	(5.9)
Low R^{CDS}	0.018***	0.001	0.016***
	(4.8)	(0.5)	(4.9)
H/L	0.017***	0.000	0.018***
	(3.1)	-(0.2)	(3.2)
	High IVOL	Low IVOL	Diff
Panel B: CDS Spread Below Median			
Market Hours			
High R^{CDS}	0.027	0.032**	-0.004
	(1.5)	(2.2)	-(0.4)
Low R^{CDS}	0.030	0.024	0.006
	(1.6)	(1.6)	(0.6)
H/L	-0.002	0.008	-0.010
	-(0.2)	(1.2)	-(0.9)
After Market Hours			
High R^{CDS}	0.004	0.001	0.003
	(0.9)	(0.4)	(0.7)
Low R^{CDS}	0.005**	0.002	0.003
	(2.1)	(0.8)	(1.4)
H/L	-0.001	-0.001	0.000
	-(0.2)	-(0.4)	(0.0)

Table 6B: Stock Portfolios Sorted by CDS Returns given High CDS Levels When Information Asymmetries are controlled

This table reports monthly equal-weighted H/L calendar time portfolio returns for high and low information asymmetric groups when CDS level is above cross-sectional medians. At the beginning of every month, all stocks are independently split into groups of high/low CDS spread level based on the cross-sectional median of CDS spread level observed at prior month. Within each CDS spread group, we split stocks by two groups based on a median of information asymmetric scores observed at prior month. Then, we split stocks by median of prior month's CDS spread changes. The degree of information asymmetry is measured by idiosyncratic volatility based on a Fama and French 5 factor model. H/L is the raw return of a zero-cost portfolio of going long stocks of above median CDS changes and short stocks of below median CDS changes. Panel A reports stock returns with lagged CDS spread above the lagged cross-sectional median and Panel B reports stock returns with lagged CDS spread below the lagged cross-sectional median. The average returns are expressed as **percentage units**. Column (1) is mean test results of stock returns under high information asymmetric group and Column (2) is mean test results of stock returns under low information asymmetric group, and Column (3) (Diff) reports the strategy of long Column (1) and shorting Column (2). The sample period covers January 2001 through December 2013. Newey-west t-statistics adjusted for 12 lags are reported in the brackets. ***,**, and * denote significance at 1%, 5%, and 10% level respectively.

	(1) High IVOL	(2) Low IVOL	(3) Diff
Panel A: CDS Spread Above Median			
Market Hours			
High R^{CDS}	-2.009*	0.079	-2.088***
	-(1.8)	(0.2)	-(2.7)
Low R^{CDS}	-1.362	0.207	-1.568***
	-(1.5)	(0.6)	-(2.8)
H/L	-0.647**	-0.128	-0.519*
	-(2.0)	-(1.0)	-(1.7)
After Market Hours			
High R^{CDS}	0.609***	0.033	0.576***
	(3.2)	(0.7)	(3.4)
Low R^{CDS}	0.389***	0.017	0.372***
	(2.9)	(0.3)	(3.7)
H/L	0.221**	0.016	0.204*
	(2.2)	(0.5)	(1.7)
	High IVOL	Low IVOL	Diff
Panel B: CDS Spread Below Median			
Market Hours			
High R^{CDS}	0.602**	0.544**	0.057
	(2.4)	(2.5)	(0.4)
Low R^{CDS}	0.405	0.569**	-0.164
	(1.2)	(2.4)	-(0.9)
H/L	0.197	-0.024	0.221
	(1.2)	-(0.2)	(1.2)
After Market Hours			
High R^{CDS}	0.092	0.042	0.050
	(1.4)	(1.0)	(1.1)
Low R^{CDS}	0.117*	-0.003	0.119***
	(1.7)	-(0.1)	(2.8)
H/L	-0.025	0.045**	-0.070
	-(0.5)	(2.2)	-(1.4)

Table 7A: Long-run Versus Short-run Default Risk

This table reports the results of following regression

$$R^{\text{Stock}}_{i,t} = \beta_0 + \beta_1 S^{\text{CDS}}_{i,t-1} \times \text{Downgrade}_{i,t+1} + \beta_2 S^{\text{CDS}}_{i,t-1} \times \text{No Downgrade}_{i,t+1} + \text{Controls}_{i,t-1} + \delta_i + \epsilon_{i,t}$$

where $Downgrade_{i,t}$ is dummy variables equals to 1 for downgrading days and zero otherwise. $NoDowngrade_{i,t}$ is dummy variables equals to 1 for non-downgrading days and zero otherwise. We include firm-fixed effect in the model. ***,**, and * denote significance at 1%, 5%, and 10% level respectively.

	(1) R_t^{BM}	(2) R_t^{MH}	(3) R_t^{AM}	(4) R_t^{BM}	(5) R_t^{MH}	(6) R_t^{AM}
R_{t-1}^{BM}	0.004			0.004		
	(1.43)			(1.43)		
$S_{t-1}^{CDS} \times Downgrade_{t+1}$	0.011	-2.987***	0.108			
	(0.04)	(-3.85)	(0.17)			
$S_{t-1}^{CDS} \times NoDowngrade_{t+1}$	0.247	-2.151***	0.927***			
	(1.47)	(-5.83)	(8.27)			
$R_{t-1}^{CDS} \times Downgrade_{t+1}$				-1.062	-1.852*	0.029
				(-1.45)	(-1.95)	(0.12)
$R_{t-1}^{CDS} \times NoDowngrade_{t+1}$				-0.043	-0.184***	0.030
				(-1.03)	(-3.24)	(1.38)
R_{t-1}^{MH}		0.015***			0.015***	
		(3.10)			(3.19)	
R_{t-1}^{AM}			0.017***			0.018***
			(3.01)			(3.12)
Intercept	-0.014***	0.030***	-0.008***	-0.010***	-0.009***	0.009***
	(-4.71)	(4.43)	(-4.00)	(-314.00)	(-197.40)	(172.73)
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
N	2047929	2047929	2047929	2047929	2047929	2047929
R-sq	0.001	0.004	0.003	0.001	0.003	0.002
adj. R-sq	0.000	0.003	0.003	0.000	0.003	0.002

Table 7B: Long-run Versus Short-run Default Risk within High Information Asymmetric Group

This table reports the results of following regression for high information asymmetric group

$$R_{i,t}^{\text{Stock}} = \beta_0 + \beta_1 S_{i,t-1}^{\text{CDS}} \times \text{Downgrade}_{i,t+1} + \beta_2 S_{i,t-1}^{\text{CDS}} \times \text{No Downgrade}_{i,t+1} + \text{Controls}_{i,t-1} + \delta_i + \epsilon_{i,t}$$

where $Downgrade_{i,t}$ is dummy variables equals to 1 for downgrading days and zero otherwise. $NoDowngrade_{i,t}$ is dummy variables equals to 1 for non-downgrading days and zero otherwise. We include firm-fixed effect in the model. ***,**, and * denote significance at 1%, 5%, and 10% level respectively.

	(1) R_t^{BM}	(2) R_t^{MH}	(3) R_t^{AM}	(4) R_t^{BM}	(5) R_t^{MH}	(6) R_t^{AM}
R_{t-1}^{BM}	0.005			0.005		
	(1.19)			(1.18)		
$S_{t-1}^{CDS} \times Downgrade_{t+1}$	0.003	-3.239***	-0.030			
	(0.01)	(-3.54)	(-0.04)			
$S_{t-1}^{CDS} \times NoDowngrade_{t+1}$	0.295	-2.188***	0.994***			
	(1.54)	(-5.48)	(8.29)			
$R_{t-1}^{CDS} \times Downgrade_{t+1}$				-1.446	-2.488**	0.113
				(-1.57)	(-2.09)	(0.36)
$R_{t-1}^{CDS} \times NoDowngrade_{t+1}$				-0.096	-0.466***	0.096**
				(-1.33)	(-5.00)	(2.56)
R_{t-1}^{MH}		0.021***			0.021***	
		(3.74)			(3.78)	
R_{t-1}^{AM}			0.014***			0.015***
			(3.66)			(3.83)
Intercept	-0.021***	0.021*	-0.011***	-0.013***	-0.039***	0.016***
	(-3.92)	(1.91)	(-3.41)	(-255.47)	(-173.04)	(246.86)
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
N	1023020	1023020	1023020	1023020	1023020	1023020
R-sq	0.001	0.005	0.004	0.001	0.005	0.003
adj. R-sq	0.000	0.004	0.003	0.000	0.004	0.002

Table 7C: Long-run Versus Short-run Default Risk within Low Information Asymmetric Group

This table reports the results of following regression for low information asymmetric group

$$R^{\text{Stock}}_{i,t} = \beta_0 + \beta_1 S^{\text{CDS}}_{i,t-1} \times \text{Downgrade}_{i,t+1} + \beta_2 S^{\text{CDS}}_{i,t-1} \times \text{No Downgrade}_{i,t+1} + \text{Controls}_{i,t-1} + \delta_i + \epsilon_{i,t}$$

where $Downgrade_{i,t}$ is dummy variables equals to 1 for downgrading days and zero otherwise. $NoDowngrade_{i,t}$ is dummy variables equals to 1 for non-downgrading days and zero otherwise. We include firm-fixed effect in the model. ***,**, and * denote significance at 1%, 5%, and 10% level respectively.

	(1) R_t^{BM}	(2) R_t^{MH}	(3) R_t^{AM}	(4) R_t^{BM}	(5) R_t^{MH}	(6) R_t^{AM}
R_{t-1}^{BM}	0.003			0.003		
	(1.04)			(1.04)		
$S_{t-1}^{CDS} \times Downgrade_{t+1}$	-0.012	0.738	-0.011			
	(-0.04)	(0.40)	(-0.04)			
$S_{t-1}^{CDS} \times NoDowngrade_{t+1}$	-0.001	0.842	-0.012			
	(-0.00)	(0.43)	(-0.04)			
$R_{t-1}^{CDS} \times Downgrade_{t+1}$				0.406	0.140	-0.67
				(1.64)	(0.20)	(-1.62)
$R_{t-1}^{CDS} \times NoDowngrade_{t+1}$				0.026	0.199	-0.057
				(0.65)	(0.81)	(-1.47)
R_{t-1}^{MH}		-0.011			-0.010	
		(-0.71)			(-0.70)	
R_{t-1}^{AM}			0.026			0.026
			(1.40)			(1.41)
Intercept	-0.007***	0.014	0.001	-0.007***	0.021	0.001
	(-2.86)	(0.99)	(0.52)	(-2.76)	(1.26)	(0.50)
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
N	1023343	1023343	1023343	1023343	1023343	1023343
R-sq	0.001	0.002	0.002	0.001	0.002	0.002
adj. R-sq	0.000	0.001	0.001	0.000	0.001	0.001

Table 8: Do Stock Illiquidity Explain the Results?

This table reports daily equal-weighted H/L calendar time portfolio returns for **high information asymmetric** groups when CDS level is **above cross-sectional medians** given high and low level of individual stock illiquidity. At the beginning of every calendar day, all stocks are independently split into groups of high/low CDS spread level based on the cross-sectional median of CDS spread level observed at prior day. Within each CDS spread group, we split stocks by two groups based on a median of information asymmetric scores observed at prior day. Then, we split stocks by median of prior day's idiosyncratic CDS spread changes. The degree of information asymmetry is measured by idiosyncratic volatility based on a Fama and French 5-factor model. H/L is the raw return of a zero-cost portfolio of going long stocks of above median CDS changes and short stocks of below median CDS changes. The average returns are expressed as **percentage units**. The illiquidity proxies include (1) percentage effective spread (ES), (2) price impact coefficient or Kyle's λ, percentage quoted spread (QS), realized spread (RS), stock volume turnover ($Turn$), and the count of total number of trades during a day (TC. Diff reports the strategy of longing "High" and shorting "Low". The sample period covers January 2001 through December 2013. Newey-west t-statistics adjusted for 12 lags are reported in the brackets.

	(1)	(2)	' (3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	High	Low	Diff	High	Low	Diff	High	Low	Diff	High	Low	Diff	High	Low	Diff	High	Low	Diff
	ES	ES		K's λ	K's λ		QS	QS		RS	RS		Turn	Turn		TC	TC	
Panel A : Market Hours																		
High R^{CDS}	-0.13	-0.05	-0.08	-0.09	-0.11	0.02	-0.12	-0.08	-0.05	-0.11	-0.10	0.00	-0.14	-0.04	-0.10	-0.13	-0.07	-0.06
	-(3.2)	-(1.8)	-(3.6)	-(2.5)	-(2.8)	(1.3)	-(2.9)	-(2.4)	-(2.0)	-(2.8)	-(2.8)	-(0.3)	-(3.6)	-(1.3)	-(5.6)	-(3.5)	-(1.8)	-(3.6)
Low R^{CDS}	-0.06	-0.01	-0.05	-0.04	-0.05	0.01	-0.06	-0.02	-0.04	-0.05	-0.03	-0.01	-0.06	0.00	-0.06	-0.06	-0.02	-0.04
	-(1.6)	-(0.3)	-(2.5)	-(1.3)	-(1.4)	(0.6)	-(1.5)	-(0.6)	-(1.9)	-(1.2)	-(1.1)	-(0.6)	-(1.8)	-(0.1)	-(3.6)	-(1.6)	-(0.6)	-(1.7)
H/L	-0.07	-0.05	-0.02	-0.05	-0.06	0.01	-0.06	-0.06	0.00	-0.06	-0.07	0.01	-0.08	-0.04	-0.04	-0.08	-0.05	-0.03
	-(4.2)	-(3.3)	-(1.1)	-(2.8)	-(3.3)	(0.5)	-(3.7)	-(3.5)	-(0.1)	-(3.5)	-(4.1)	(0.3)	-(4.8)	-(2.8)	-(1.9)	-(4.6)	-(2.9)	-(1.2)
Panel B : After Market Hours																		
High R^{CDS}	0.05	0.01	0.04	0.03	0.04	-0.01	0.05	0.01	0.04	0.04	0.03	0.01	0.05	0.02	0.03	0.04	0.03	0.02
	(6.1)	(1.4)	(5.1)	(4.5)	(4.9)	-(0.6)	(5.8)	(2.1)	(4.4)	(5.5)	(3.8)	(1.7)	(5.7)	(2.8)	(3.9)	(5.0)	(4.7)	(1.9)
Low R^{CDS}	0.03	0.00	0.03	0.01	0.02	-0.01	0.03	0.00	0.02	0.03	0.01	0.02	0.02	0.01	0.02	0.02	0.01	0.01
	(5.8)	-(0.7)	(4.8)	(3.2)	(4.4)	-(1.1)	(5.5)	(0.6)	(3.5)	(5.9)	(1.0)	(3.4)	(5.3)	(1.7)	(2.9)	(4.5)	(3.5)	(1.5)
H/L	0.02	0.01	0.01	0.02	0.02	0.00	0.02	0.01	0.01	0.01	0.02	-0.01	0.02	0.01	0.01	0.02	0.01	0.01
	(2.8)	(1.8)	(1.1)	(2.5)	(2.3)	(0.1)	(2.9)	(1.2)	(1.6)	(2.1)	(2.6)	-(0.6)	(2.9)	(1.4)	(1.6)	(2.6)	(2.1)	(0.8)

Table 9A: Does Short-sale Constraint Explain the CDS Predictability? The Role of Short Ban

This table reports daily equal-weighted H/L calendar time portfolio returns for above-median information asymmetric groups when CDS level is above cross-sectional medians around short-ban period. In particular, we split the sample into (1) stocks that are included in the short-ban program, and (2) stocks that are not included in the short-ban program . To see the time-variation impact in Short-ban, we conduct our analysis using two sample period: (1) short-ban period from 2008-09-19 to 2008-10-17; (2) one month before the banned period from 2008-08-19 to 2008-09-18. We use the market model to isolate the systematic impact received from the Global Financial Crisis. The average returns are expressed as **percentage units**. Column (1) reports the H/L market adjusted returns constructed by solely the banned stocks. Column (2) reports the H/L market adjusted returns by the non-banned stocks. Column (3) reports the difference between Columns (1) and (2). Panel A reports the results constructed based on a sample consisting 1-month before the short-ban period (from 2008-08-19 to 2008-09-18). Panel B reports the results of short-ban periods (from 2008-09-19 to 2008-10-17). The sample period covers 2008-08-19 through 2008-10-17. Newey-west t-statistics adjusted for 12 lags are reported in the brackets. ***,**, and * denote significance at the 1%, 5%, and 10% level respectively.

CDS Spread Above Median			
	(1)	(2)	(3)
Panel A: 1-Month Prior	Ban	Non Ban	Diff
2008-08-19 to 2008-09-18			
R^{MH}, H/L	-0.006***	-0.001	-0.005**
	-(2.7)	-(1.1)	-(2.4)
R^{AM}, H/L	0.001	0.000	0.001
	(0.8)	(1.6)	(0.6)
Panel B: Short-Ban	Ban	Non Ban	Diff
2008-09-19 to 2008-10-17			
R^{MH}, H/L	0.004	-0.003	0.008
	(0.4)	-(0.8)	(0.7)
R^{AM}, H/L	0.008*	0.000	0.007*
	(1.9)	(0.4)	(1.7)

Table 9B: Does Short-sale Constraint Explain the CDS Predictability? The Role of Short Volume

This table reports daily equal-weighted H/L calendar time portfolio returns for high/low information asymmetric groups when CDS level is above cross-sectional medians from 2005 to 2007 when the short-sale volume is available from "Reg SHO". At the beginning of every calendar day, all stocks are independently split into groups of high/low CDS spread level based on the cross-sectional median of CDS spread level observed at prior day. Within each CDS spread group, we split stocks by two groups based on a median of information asymmetric scores observed at prior day. Then, we split stocks by median of prior day's CDS spread changes. The degree of information asymmetry is measured by idiosyncratic volatility based on a Fama and French 5-factor model. H/L is the raw return of a zero-cost portfolio of going long stocks of above median CDS changes and short stocks of below median CDS changes. Panel A reports results of market hours returns R_t^{MH}, and Panel B reports results of aftermarket close stock return R_t^{AM}, and Panel C reports the equal-weight daily aggregate short volume within each high and low CDS change group. The average returns are expressed as **percentage units**. Column (1) is mean test results of stock returns under high information asymmetric group and Column (2) is mean test results of stock returns under low information asymmetric group, and Column (3) reports the strategy of long Column (1) and shorting Column (2). The sample period covers January 2005 through July 2007. Newey-west t-statistics adjusted for 12 lags are reported in the brackets. ***,**, and * denote significance at 1%, 5%, and 10% level respectively.

	CDS Spread Above Median		
	(1)	(2)	(3)
	High IVOL	Low IVOL	Diff
	Panel A : Market Hours		
High $R_{i,t-1}^{CDS}$	-0.036	0.031	-0.067***
	-(1.1)	(1.4)	-(3.8)
Low $R_{i,t-1}^{CDS}$	-0.010	0.029	-0.039**
	-(0.3)	(1.4)	-(2.4)
H/L	-0.026**	0.002	-0.028**
	-(2.0)	(0.2)	-(2.0)
	Panel B : After Market Hours		
High $R_{i,t-1}^{CDS}$	0.014**	0.002	0.013***
	(2.6)	(0.4)	(3.4)
Low $R_{i,t-1}^{CDS}$	0.011**	0.006	0.005
	(2.6)	(1.2)	(1.4)
H/L	0.003	-0.005*	0.008
	(0.8)	-(1.7)	(1.5)
	Panel C: Short Volume		
High $R_{i,t-1}^{CDS}$	421350***	213267***	208083***
	(41.1)	(39.6)	(25.7)
Low $R_{i,t-1}^{CDS}$	426039***	220571***	205467***
	(42.9)	(50.9)	(23.3)
H/L	-4688.210	-7304.460	
	-(0.6)	-(1.3)	

Table 10: Does Funding Liquidity Constraint Explain the CDS Predictability? This table reports daily equal-weighted H/L calendar time portfolio returns for high and low information asymmetric groups when CDS level is above cross-sectional medians are given different funding constraint episodes. At the beginning of every calendar day, all stocks are independently split into groups of high/low CDS spread level based on the cross-sectional median of CDS spread level observed at prior day. Within each CDS spread group, we split stocks by two groups based on a median of information asymmetric scores observed at prior day. Then, we split stocks by median of prior day's CDS spread changes. The degree of information asymmetry is measured by idiosyncratic volatility based on a Fama and French 5-factor model. The average returns are expressed as **percentage units**. Column (1) is mean test results of stock returns under high information asymmetric group and Column (2) is mean test results of stock returns under low information asymmetric group. The sample period covers January 2001 through December 2013. We consider two proxies for funding liquidity constraint: (1) primary dealers' aggregate capital ratio changes, and (2) TED spread changes. Tightening funding liquidity constraint is given by negative primary dealers' aggregate capital ratio changes or positive TED spread changes. Less funding liquidity constraint is given by positive primary dealers' aggregate capital ratio changes, or negative TED spread changes. We split the sample period by high and low funding liquidity constraint. Panel A reports the case of less funding constraint and panel B reports the case of Tightening funding constraint. The sample period covers January 2001 through December 2013. Newey-west t-statistics (two-tail) are reported in the brackets. ***,**, and * denote significance at 1%, 5%, and 10% level respectively.

CDS Spread Above Median		
	(1)	(2)
	Primary Dealer	TED Spread
	High IVOL	High IVOL
Panel A : Not Constraint		
Market Hours, H/L	-0.051***	-0.039***
	-(3.1)	-(2.6)
After Market, H/L	0.017**	0.022***
	(2.3)	(3.0)
Panel B : Constraint		
Market Hours, H/L	-0.053***	-0.066***
	-(3.4)	-(3.5)
After Market, H/L	0.022***	0.017**
	(2.7)	(2.0)

Table 11: Does Separate Equilibrium Hypothesis Explain the CDS Predictability?

This table reports portfolio sorting results are consisting of periods from 2010 to 2013 when the CDS bid-ask spread is available. At the beginning of every calendar day, all stocks are independently split into groups of high/low CDS spread level based on the cross-sectional median of CDS spread level observed at prior day. Within the high CDS spread group, we further split stocks by two groups using the median of idiosyncratic volatility observed at prior day. Further, we split stocks by median of prior period's CDS spread changes. The equal-weighted stock returns are computed within each group. H/L is the raw return of a zero-cost portfolio of going long stocks of high CDS changes and short stocks of low CDS changes. The average returns are expressed as **percentage units**. The equal-weighted relative liquidity ratio is computed for both high information asymmetric group (Column (1)) and low information asymmetric group (Column (2)). Column (3) is the long-short difference between Column (1) and Column (2). We consider a relative bid-ask spread between two markets as a direct measurement on relative transaction costs between the two markets. In particular, we retrieve the bid-ask spread of CDS quoted prices (scale by the mid-price) from Markit liquidity file from 2010 to 2013, and merge with correspondingly stock percentage effective spread (scale by the mid-price). We then construct the measure by taking bid-ask spread ratio of stock over CDS

$$\text{Relative Liquidity Ratio} = \frac{\frac{P_{Ask,i,t}-P_{Bid,i,t}}{(\mathrm{P}_{Ask,i,t}+P_{Bid,i,t})/2}}{\frac{S_{Ask,i,t}-S_{Bid,i,t}}{(S_{Ask,i,t}+S_{Bid,i,t})/2}}$$

The Relative Liquidity Ratio is bounded between zero and positive infinity. If the ratio is larger than 1, it indicates that CDS is more liquid than stock. If the ratio is smaller than 1, it indicates that CDS is less liquid than stock. We redo Table 6 using 2010 to 2013 sample, which the CDS bid-ask spread is available. The sample period covers January 2010 through December 2013. Newey-west t-statistics (two-tail) are reported in the brackets. ***,**, and * denote significance at the 1%, 5%, and 10% level respectively.

	CDS Spread Above Median		
	(1)	(2)	(3)
	High IVOL	Low IVOL	Diff
Market Hours, H/L	-0.046***	-0.001	-0.045**
	-(2.8)	-(0.1)	-(2.2)
After Market, H/L	0.010	0.002	0.009
	(1.4)	(0.4)	(1.0)
Relative Liquidity Ratio	0.010	0.004	0.006***
			(9.2)

Table 12: Predict Idiosyncratic Stock Returns using Idiosyncratic CDS Returns, the Role of Information Asymmetry

This table reports daily equal-weighted H/L calendar time portfolio idiosyncratic stock returns for high and low information asymmetric groups when CDS level is above cross-sectional medians. Idiosyncratic returns for both stock and CDS are adjusted using a market model following Lee, Naranjo, and Velioglu (2017). At the beginning of every calendar day, all stocks are independently split into groups of high/low CDS spread level based on the cross-sectional median of CDS spread level observed at prior day. Within each CDS spread group, we split stocks by two groups based on a median of idiosyncratic volatility observed at prior day. Then, we split stocks by median of prior day's idiosyncratic CDS spread changes. The degree of information asymmetry is measured by idiosyncratic volatility based on a Fama and French 5-factor model. H/L is the raw return of a zero-cost portfolio of going long stocks of above median CDS changes and short stocks of below median CDS changes. Panel A reports results of market hours returns R_t^{MH}, and Panel B reports results of aftermarket close stock return R_t^{AM}. The average returns are expressed as **percentage units**. Column (1) is mean test results of stock returns under high information asymmetric group and Column (2) is mean test results of stock returns under low information asymmetric group, and Column (3) reports the strategy of long Column (1) and shorting Column (2). The sample period covers January 2001 through December 2013. Newey-west t-statistics adjusted for 12 lags are reported in the brackets. ***,**, and * denote significance at 1%, 5%, and 10% level respectively.

	CDS Spread Above Median		
	(1)	(2)	(3)
Panel A: Market Hours	High IVOL	Low IVOL	Diff
High $R_{i,t-1}^{CDS}$	-0.128***	-0.032***	-0.096***
	-(6.2)	-(3.0)	-(5.9)
Low $R_{i,t-1}^{CDS}$	-0.075***	-0.018*	-0.057***
	-(3.9)	-(1.7)	-(3.9)
H/L	-0.054***	-0.014**	-0.039***
	-(4.6)	-(2.0)	-(2.9)
Panel B: Market Hours			
High $R_{i,t-1}^{CDS}$	0.039***	0.002	0.037***
	(6.1)	(0.7)	(6.1)
Low $R_{i,t-1}^{CDS}$	0.019***	0.005**	0.014***
	(5.3)	(2.0)	(4.2)
H/L	0.020***	-0.003	0.023***
	(3.4)	-(1.5)	(3.9)

Table 13: Stock Portfolios Sorted by CDS Returns given High CDS Levels When Information Asymmetries are controlled

This table reports daily equal-weighted H/L calendar time portfolio returns for high and low information asymmetric groups when CDS level is above cross-sectional medians. At the beginning of every day, all stocks are independently split into groups of high/low CDS spread level based on the cross-sectional median of CDS spread level observed at prior day. Within each CDS spread group, we split stocks by two groups based on a median of past 1-day close-to-close stock returns observed. Then, we split stocks by median of prior month's CDS spread changes. H/L is the raw return of a zero-cost portfolio of going long stocks of above median CDS changes and short stocks of below median CDS changes. Panel A reports stock returns with lagged CDS spread above the lagged cross-sectional median and Panel B reports stock returns with lagged CDS spread below the lagged cross-sectional median. The average returns are expressed as **percentage units**. Column (1) is mean test results of stock returns under high past 1-day stock returns and Column (2) is mean test results of stock returns under low past 1-day stock returns, and Column (3) (Diff) reports the strategy of long Column (1) and shorting Column (2). The sample period covers January 2001 through December 2013. Newey-west t-statistics adjusted for 12 lags are reported in the brackets. ***,**, and * denote significance at 1%, 5%, and 10% level respectively.

	CDS Spread Above Median		
	(1)	(2)	(3)
	High $R_{t-1}^{CTC,TAQ}$	Low $R_{t-1}^{CTC,TAQ}$	Diff
Panel A: Market Hours			
High R_{t-1}^{CDS}	-0.059**	-0.062**	0.003
	-(2.1)	-(2.0)	(0.2)
Low R_{t-1}^{CDS}	-0.017	-0.023	0.006
	-(0.6)	-(0.8)	(0.4)
H/L	-0.041***	-0.039***	-0.003
	-(4.2)	-(3.6)	-(0.2)
Panel B: After Market Hours			
High R_{t-1}^{CDS}	0.013***	0.020***	-0.007
	(4.2)	(3.9)	-(1.4)
Low R_{t-1}^{CDS}	0.009***	0.010***	-0.001
	(3.3)	(2.8)	-(0.3)
H/L	0.005*	0.010**	-0.006
	(1.7)	(2.0)	-(1.0)

Table 14: Informed CDS trading and Market Quality

This table reports the impacts of CDS prices on market quality. We rely on a firm-fixed effect panel regression model. We focus on the impacts of CDS price changes on future changes of market quality proxies (β_{12}). Moreover, to understand whether the impacts of CDS price changes vary given different firm information environments and macro conditions, we consider three intermediate variables: (1) CDS price level, (2) information asymmetric score, and (3) Global financial crisis (GFC) indicator. The joint impacts are capturing via the point estimates of (β_1), (β_3), (β_5), and (β_{10}) respectively. The full specification is following:

$$
\begin{aligned}
\Delta \mathrm{MQ}_{i,t+1} = \alpha &+ \beta_1 \times \mathrm{R}^{\mathrm{CDS}}_{i,t} \times \mathrm{S}^{\mathrm{CDS}}_{i,t} * \mathrm{InfoAsy}_{i,t} \times \mathrm{GFC} + \beta_2 \times \mathrm{R}^{\mathrm{CDS}}_{i,t} \times \mathrm{S}^{\mathrm{CDS}}_{i,t} \times \mathrm{GFC} \\
&+ \beta_3 \times \mathrm{R}^{\mathrm{CDS}}_{i,t} \times \mathrm{InfoAsy}_{i,t} \times \mathrm{GFC} + \beta_4 \times \mathrm{S}^{\mathrm{CDS}}_{i,t} \times \mathrm{InfoAsy}_{i,t} \times \mathrm{GFC} + \beta_5 \mathrm{R}^{\mathrm{CDS}}_{i,t} \times \mathrm{GFC} \\
&+ \beta_6 \mathrm{S}^{\mathrm{CDS}}_{i,t} \times \mathrm{GFC} + \beta_7 \mathrm{InfoAsy}_{i,t} \times \mathrm{GFC} + \beta_8 \mathrm{S}^{\mathrm{CDS}}_{i,t} \times \mathrm{R}^{\mathrm{CDS}}_{i,t} \times \mathrm{InfoAsy}_{i,t} \\
&+ \beta_9 \mathrm{S}^{\mathrm{CDS}}_{i,t} \times \mathrm{R}^{\mathrm{CDS}}_{i,t} + \beta_{10} \mathrm{R}^{\mathrm{CDS}}_{i,t} \times \mathrm{InfoAsy}_{i,t} + \beta_{11} \mathrm{S}^{\mathrm{CDS}}_{i,t} \times \mathrm{InfoAsy}_{i,t} + \beta_{12} \mathrm{R}^{\mathrm{CDS}}_{i,t} \\
&+ \beta_{13} \mathrm{S}^{\mathrm{CDS}}_{i,t} + \beta_{14} \mathrm{InfoAsy}_{i,t} + \beta_{15} \mathrm{GFC} + \delta_i + e_{i,t+1}
\end{aligned}
$$

where $\Delta \mathrm{MQ}_{i,t+1}$ is market quality changes from t to t+1. It consists of (1) hedge ratio (Hedge), (2) stock and CDS covariance (COV), (3) stock volatility (σ^{STK}), (4) CDS volatility (σ^{CDS}), (4) effective spread (ES), (5) quoted spread (QS), and (6) stock market beta (β); δ_i is firm-fixed effect dummy; the standard errors are clustered at monthly level; The regression is at monthly frequency. T-statistics (two-tail) are reported in the brackets. ***,**, and * denote significance at the 1%, 5%, and 10% level respectively.

	(1) $\Delta\mathrm{Hedge}_{t+1}$	(2) $\Delta\mathrm{COV}_{t+1}$	(3) $\Delta\sigma^{\mathrm{STK}}_{t+1}$	(4) $\Delta\sigma^{\mathrm{CDS}}_{t+1}$	(5) $\Delta\mathrm{ES}_{t+1}$	(6) $\Delta\mathrm{QS}_{t+1}$	(7) $\Delta\beta_{t+1}$
(1) $\mathrm{R}^{\mathrm{CDS}}_t \times \mathrm{S}^{\mathrm{CDS}}_t \times \mathrm{InfoAsy} \times \mathrm{GFC}$	-0.001	-0.001	-0.000	0.000	-0.000	-0.000*	0.000
	(-0.53)	(-0.85)	(-1.38)	(1.29)	(-0.28)	(-1.94)	(1.51)
(2) $\mathrm{R}^{\mathrm{CDS}}_t \times \mathrm{S}^{\mathrm{CDS}}_t \times \mathrm{GFC}$	0.053	0.098	0.006	-0.014	0.002	0.005**	-0.001
	(0.62)	(0.93)	(1.12)	(-1.20)	(0.63)	(2.44)	(-1.47)
(3) $\mathrm{R}^{\mathrm{CDS}}_t \times \mathrm{InfoAsy} \times \mathrm{GFC}$	-0.185	-0.323	-0.073***	-0.149***	-0.073***	-0.051***	0.013***
	(-0.87)	(-1.33)	(-4.95)	(-4.10)	(-10.02)	(-8.61)	(4.64)
(4) $\mathrm{S}^{\mathrm{CDS}}_t \times \mathrm{InfoAsy} \times \mathrm{GFC}$	-0.000	-0.000	-0.000*	0.000	-0.000	0.000	-0.000
	(-1.17)	(-1.39)	(-1.85)	(1.11)	(-1.55)	(1.51)	(-1.62)
(5) $\mathrm{R}^{\mathrm{CDS}}_t \times \mathrm{GFC}$	-2.944	3.358	7.474***	4.460**	4.705***	3.086***	-0.252
	(-0.24)	(0.23)	(8.07)	(2.07)	(10.68)	(9.11)	(-1.49)
(6) $\mathrm{S}^{\mathrm{CDS}}_t \times \mathrm{GFC}$	0.001	0.001	0.000	-0.000	0.000***	-0.000	0.000
	(1.05)	(1.61)	(1.08)	(-1.51)	(2.93)	(-0.76)	(1.61)
(7) $\mathrm{InfoAsy} \times \mathrm{GFC}$	0.002	0.004*	0.001***	-0.000	0.001***	0.001***	0.000
	(0.93)	(1.74)	(8.64)	(-0.75)	(17.75)	(10.24)	(0.10)
(8) $\mathrm{R}^{\mathrm{CDS}}_t \times \mathrm{S}^{\mathrm{CDS}}_t \times \mathrm{InfoAsy}$	-0.001*	-0.001	-0.000	-0.000	-0.000	-0.000**	-0.000**
	(-1.85)	(-1.38)	(-0.93)	(-0.47)	(-1.21)	(-2.49)	(-2.13)
(9) $\mathrm{R}^{\mathrm{CDS}}_t \times \mathrm{S}^{CDS}_t$	0.052*	0.040	0.003*	0.003	0.003**	0.002***	0.001**
	(1.73)	(1.21)	(1.65)	(0.89)	(2.18)	(3.79)	(2.11)
(10) $\mathrm{R}^{\mathrm{CDS}}_t \times \mathrm{InfoAsy}$ (β_{10})	0.117	0.162	0.048***	0.086***	0.011***	0.007***	-0.001
	(1.03)	(1.22)	(5.52)	(3.65)	(2.62)	(2.60)	(-0.41)
(11) $\mathrm{S}^{\mathrm{CDS}}_t \times \mathrm{InfoAsy}$	-0.000	-0.000	0.000	0.000**	-0.000**	-0.000***	0.000***
	(-0.19)	(-0.03)	(1.56)	(2.03)	(-2.22)	(-4.77)	(5.97)
(12) $\mathrm{R}^{\mathrm{CDS}}_t$ (β_{12})	-14.753**	-22.860***	-4.754***	-10.767***	-0.605**	0.034	0.136*
	(-2.10)	(-2.92)	(-8.58)	(-7.48)	(-2.38)	(0.20)	(1.85)
(13) $\mathrm{S}^{\mathrm{CDS}}_t$	0.000	-0.000	-0.000**	-0.000***	-0.000	0.000***	-0.000***
	(0.22)	(-0.15)	(-2.50)	(-3.24)	(-1.14)	(2.60)	(-5.17)
(14) InfoAsy	0.000	-0.003***	-0.001***	-0.000***	-0.001***	-0.001***	0.000***
	(0.65)	(-3.05)	(-40.87)	(-3.99)	(-28.11)	(-24.83)	(4.85)
(15) GFC	0.000	0.009	0.015***	0.094***	-0.023***	0.029***	-0.004*
	(0.00)	(0.08)	(2.76)	(6.74)	(-6.79)	(10.02)	(-1.68)
(16) Intercept	-0.051	0.056	0.054***	0.002	0.016***	0.005***	0.003***
	(-1.20)	(1.24)	(26.32)	(0.41)	(12.90)	(4.52)	(3.43)
N	13628	13628	92495	92495	92495	92495	92274
Firm Fixed Effect	Y	Y	Y	Y	Y	Y	Y
Cluster Standard Error	Y	Y	Y	Y	Y	Y	Y
R-sq	0.054	0.059	0.016	0.009	0.032	0.053	0.031
adj. R-sq	-0.027	-0.022	0.004	-0.004	0.020	0.041	0.019

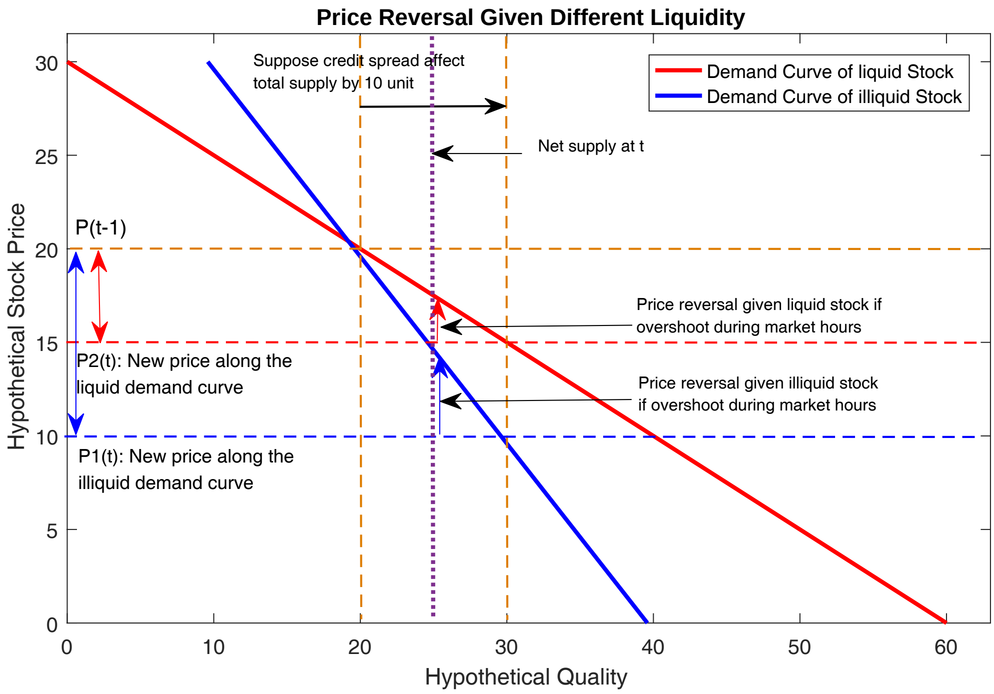

Figure 1: This figure contains economics analysis in Hypothesis 3.

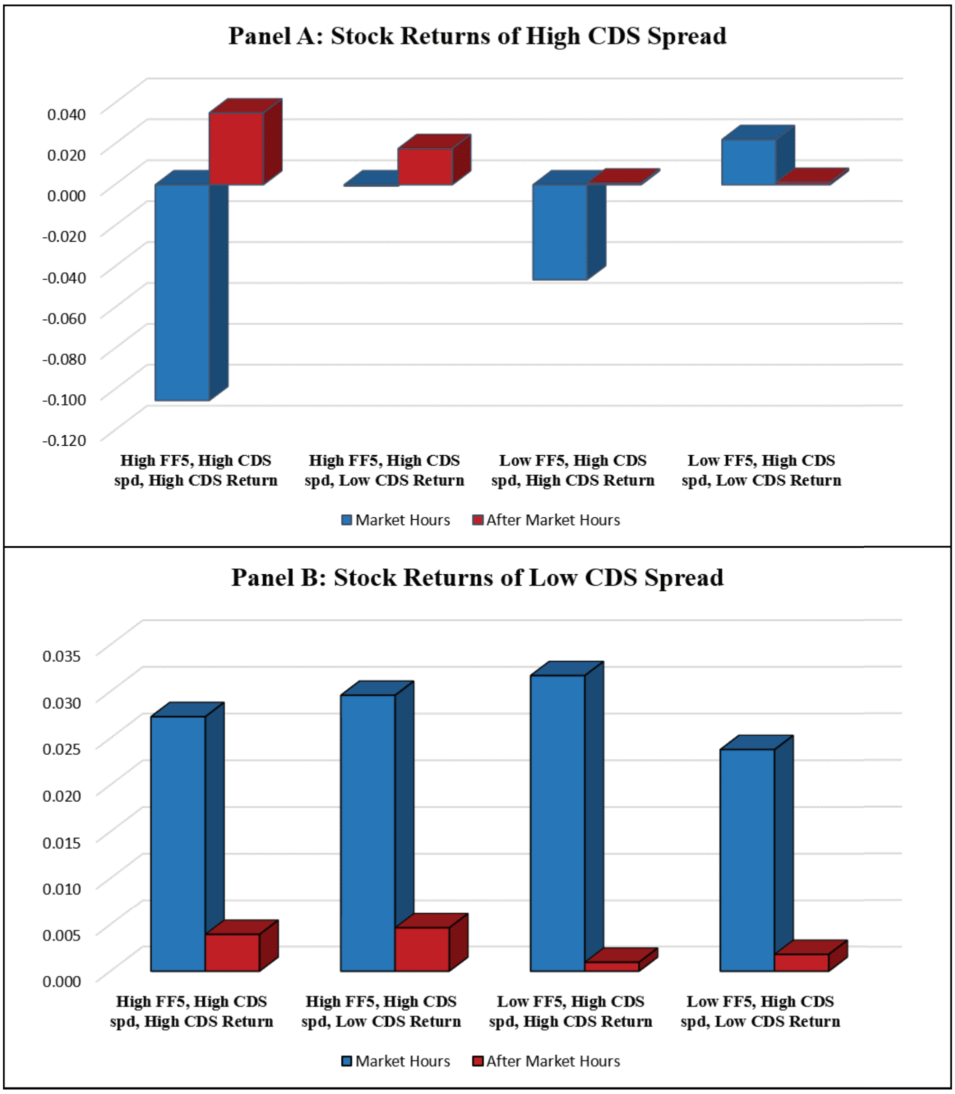

Figure 2: This figure summarizes the results of Table 6.

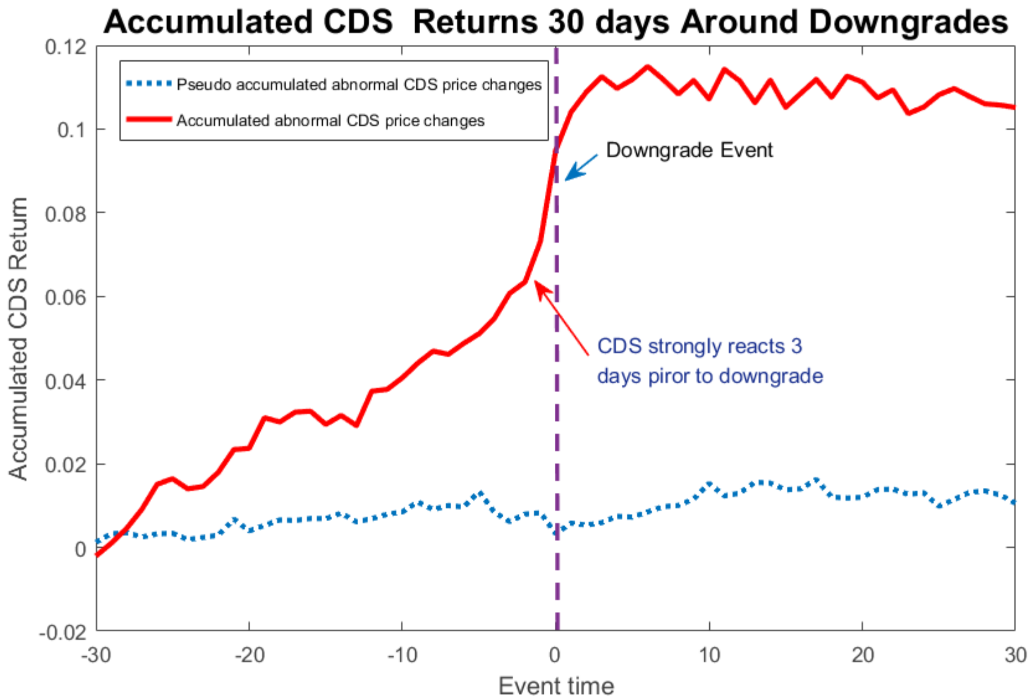

Figure 3: The red line is accumulated abnormal CDS price changes reacts before the downgrading event. The blue dot line is the pseudo accumulated abnormal CDS price changes reacts before the downgrading event by randomly assigning firms do not experience downgrade events to the downgrade dates (Average of 500 times random assignment).

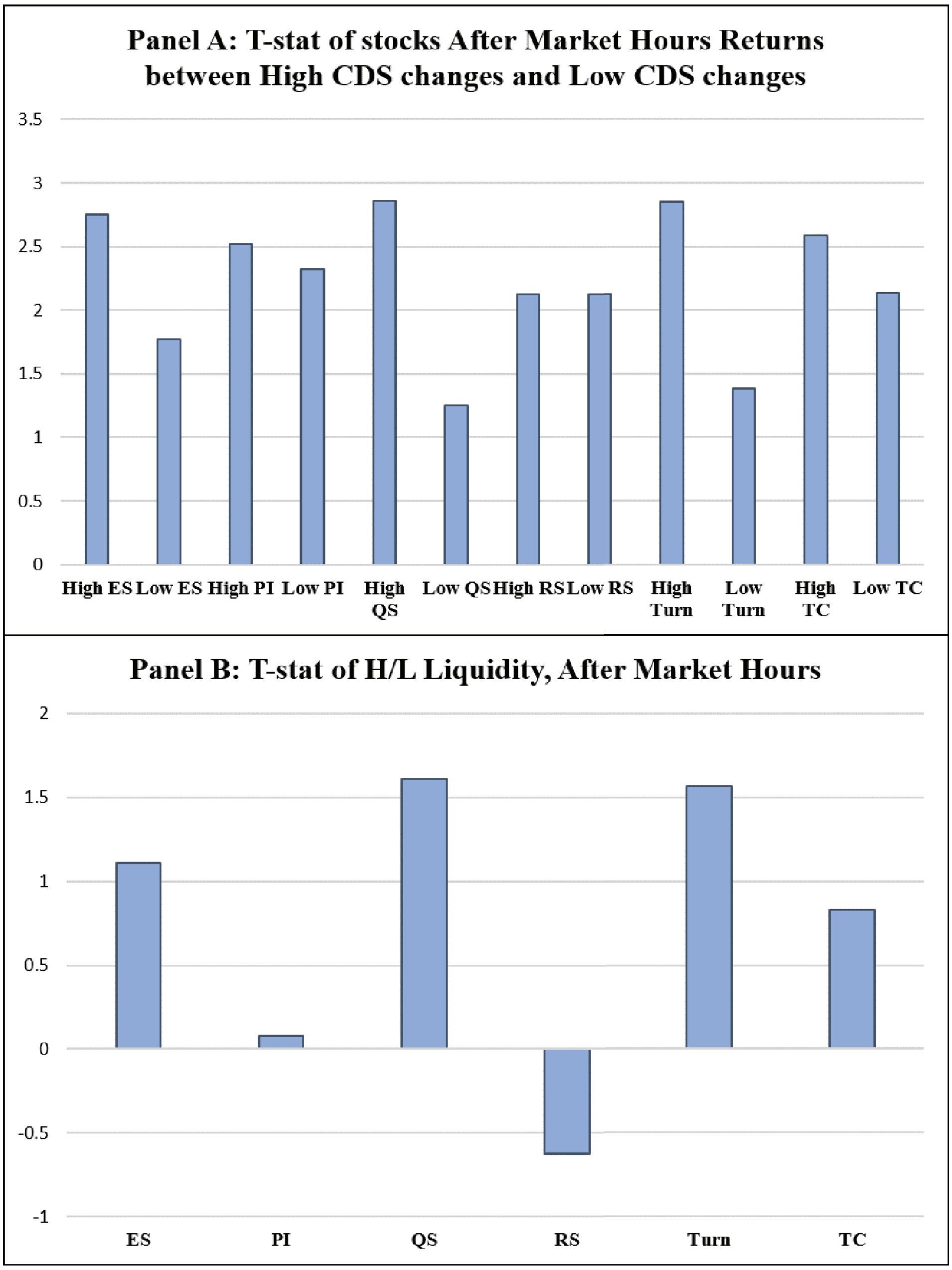

Figure 4: This figure summarizes the results of Panel A of Table 8.

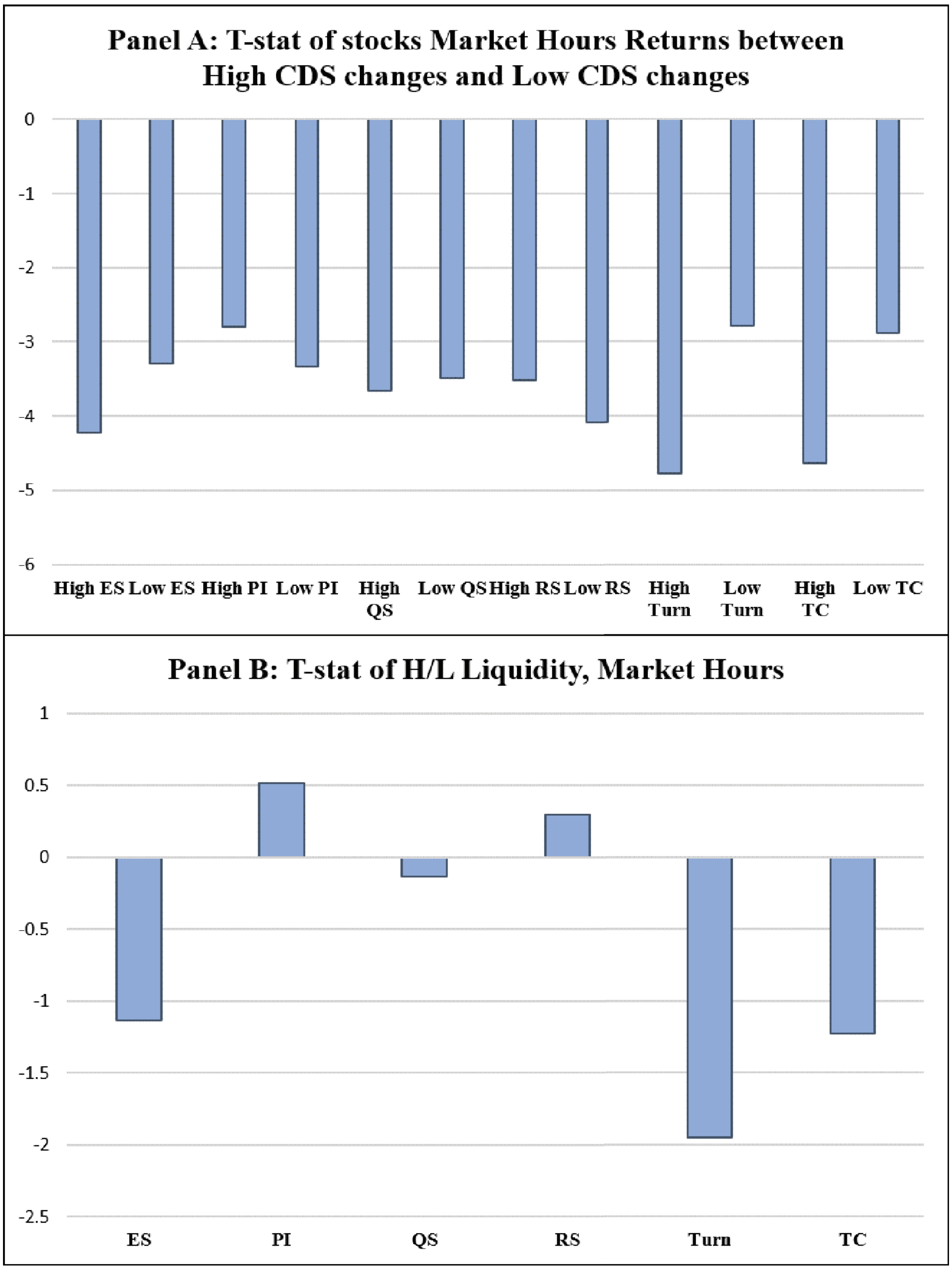

Figure 5: This figure summarizes the results of Panel B of Table 8.

Appendix

The Appendix reports additional supportive empirical test results.

Table A1: Replication of Hilscher, Pollet, and Wilson (2015)s' Panel VAR result This table presents our replication of Hilscher et al. (2015), and an extension of their findings from 2001 to 2013. A Panel VAR(3) model is specified as following

$$\begin{pmatrix} R_{i,t}^{\text{Stock}} \\ R_{i,t}^{\text{CDS}} \end{pmatrix} = \begin{pmatrix} \beta_{0,\text{Stock}} \\ \beta_{0,\text{CDS}} \end{pmatrix} + \sum_{k=1}^{3} \begin{pmatrix} \beta_{\text{k,Stock,Stock}} & \beta_{\text{k,Stock,CDS}} \\ \beta_{\text{k,CDS,Stock}} & \beta_{\text{k,CDS,CDS}} \end{pmatrix} \begin{pmatrix} R_{i,t-k}^{\text{Stock}} \\ R_{i,t-k}^{\text{CDS}} \end{pmatrix} + \begin{pmatrix} \epsilon_{i,t}^{\text{Stock}} \\ \epsilon_{i,t}^{CDS} \end{pmatrix}$$

where $\text{R}_{i,t}^{\text{Stock}}$ is the daily close-to-close stock returns and $R_{i,t}^{CDS}$ is the daily percentage change of CDS spread or protection return, for firm i on day t. k indicates number of lags. We consider three lags following Hilscher et al. (2015). Panel A considers firms with rating of A or above. Panel B considers firms with rating of BBB. Panel C consider firms with below or equal BB rating. Hilscher et al. (2015) is reported in column (1) using data from 2001 to 2007. Our replication results are reported in column (2) based on the same sample period. Column (3) is the extension using data from 2001 to 2013. All regressions include firm fixed-effects. t-statistics from heteroscedasticity-robust standard errors clustered by dates are reported in parentheses. *, and ** indicate significance at the 5% and 1% levels, respectively.

		Equity return t			CDS return t		
		Hilscher et al. (2015)	Replication 2001-2007	Extended 2001-2013	Hilscher et al. (2015)	Replication 2001-2007	Extended 2001-2013
		(1)	(2)	(3)	(1)	(2)	(3)
Panel A. A, Above							
Equity return, R^{Stock}	t-1	-0.023	-0.022	-0.045**	-0.158**	-0.155**	-0.170**
		-(1.87)	(-1.93)	(-4.51)	-(12.78)	(-6.86)	(-11.34)
	t-2	-0.013	-0.012	-0.017	-0.105**	-0.109**	-0.063**
		-(1.17)	(-1.42)	(-0.96)	-(8.09)	(-8.12)	(-8.97)
	t-3	-0.007	-0.007	-0.003	-0.077**	-0.085**	-0.030**
		-(0.62)	(-1.04)	(-0.19)	-(6.19)	(-9.72)	(-3.43)
CDS return, R^{CDS}	t-1	0.000	-0.001	-0.002	-0.020**	-0.026**	0.038
		(0.20)	(-0.55)	(-0.60)	-(3.00)	(-3.42)	(1.27)
	t-2	0.000	0.000	0.002	0.019**	0.013**	0.049**
		(0.20)	(0.04)	(0.70)	(3.49)	(2.97)	(5.17)
	t-3	0.002	0.002	0.010**	0.001	-0.007	0.012*
		(0.88)	(1.30)	(3.43)	(0.25)	(-1.11)	(2.07)
Number of observations		261750	239257	494519	261252	239257	494519
Panel B. BBB							
Equity return, R^{Stock}	t-1	-0.010	-0.011	-0.027**	-0.127**	-0.139**	-0.127**
		-(1.07)	(-1.48)	(-3.50)	-(15.64)	(-10.09)	(-19.44)
	t-2	-0.013	-0.011	-0.014	-0.083**	-0.091**	-0.052**
		-(1.32)	(-1.41)	(-1.32)	-(10.24)	(-9.16)	(-8.46)
	t-3	0.002	0.000	-0.000	-0.068**	-0.068**	-0.028**
		(0.20)	(0.09)	(-0.04)	-(7.68)	(-5.25)	(-4.85)
CDS return, R^{CDS}	t-1	-0.001	-0.001	-0.002	0.011	0.015	0.079**
		-(0.47)	(-0.69)	(-0.68)	(1.53)	(0.75)	(3.12)
	t-2	0.000	-0.001	-0.001	0.027**	0.024**	0.059**
		(0.12)	(-1.11)	(-0.30)	(5.44)	(4.06)	(8.82)
	t-3	0.002	0.001	0.008*	0.016**	0.002	0.022**
		(0.08)	(1.44)	(2.46)	(2.94)	(0.74)	(5.22)
Number of observations		325722	359806	772066	325028	359806	772066
Panel C. BB, Below							
Equity return, R^{Stock}	t-1	0.009	0.005	0.004	-0.109**	-0.138**	-0.111**
		(1.04)	(1.07)	(1.33)	-(14.66)	(-10.33)	(-22.16)
	t-2	-0.008	-0.010	-0.008	-0.067**	-0.089**	-0.054**
		-(0.91)	(-1.46)	(-1.50)	-(10.44)	(-8.44)	(-9.94)
	t-3	-0.004	-0.000	-0.002	-0.046**	-0.063**	-0.031**
		-(0.48)	(-0.06)	(-0.29)	-(6.33)	(-6.65)	(-5.45)
CDS return, R^{CDS}	t-1	-0.004	-0.001	-0.006*	-0.056**	-0.051*	0.045
		-(1.16)	(-1.03)	(-2.35)	-(6.46)	(-2.10)	(1.79)
	t-2	-0.005	-0.001	-0.005*	0.006	-0.008	0.048**
		-(1.72)	(-1.33)	(-1.98)	(0.88)	(-0.61)	(6.26)
	t-3	-0.002	-0.000	0.005	-0.003	0.002	0.020**
		-(1.67)	(-0.90)	(1.64)	-(0.44)	(1.12)	(5.10)
Number of observations		162911	466444	786064	162318	466444	786064

Table A2: Stock Portfolios Sorting By CDS Information - Compute Close-to-close, Open-to-close, and Overnight Return Using CRSP

	(1) $R_t^{CTC,CRSP}$	(2) $R_t^{OTC,CRSP}$	(3) $R_t^{CTO,CRSP}$
Daily, Equal-weight			
H/L $\mathbf{S}_{t-1}^{\mathbf{CDS}}$	-0.013	-0.125	0.110
	-(0.5)	-(5.1)	(11.3)
Daily, Value-weight			
H/L $\mathbf{S}_{t-1}^{\mathbf{CDS}}$	-0.034	-0.092	0.059
	-(1.3)	-(4.3)	(4.8)
Weekly, Equal-weight			
H/L $\mathbf{S}_{t-1}^{\mathbf{CDS}}$	-0.050	-0.572	0.518
	-(0.4)	-(3.8)	(8.7)
Weekly, Value-weight			
H/L $\mathbf{S}_{t-1}^{\mathbf{CDS}}$	-0.138	-0.416	0.281
	-(1.0)	-(3.4)	(4.0)
Monthly, Equal-weight			
H/L $\mathbf{S}_{t-1}^{\mathbf{CDS}}$	-0.277	-2.495	2.194
	-(0.4)	-(3.2)	(5.9)
Monthly, Value-weight			
H/L $\mathbf{S}_{t-1}^{\mathbf{CDS}}$	-0.561	-1.999	1.361
	-(0.9)	-(3.1)	(3.7)
Daily, Equal-weight			
H/L $\mathbf{R}_{t-1}^{\mathbf{CDS}}$	-0.041	-0.036	0.003
	-(4.5)	-(5.1)	(0.5)
Daily, Value-weight			
H/L $\mathbf{R}_{t-1}^{\mathbf{CDS}}$	-0.037	-0.031	0.003
	-(3.2)	-(3.5)	(0.5)
Weekly, Equal-weight			
H/L $\mathbf{R}_{t-1}^{\mathbf{CDS}}$	-0.037	-0.105	0.059
	-(0.8)	-(2.3)	(2.0)
Weekly, Value-weight			
H/L $\mathbf{R}_{t-1}^{\mathbf{CDS}}$	-0.003	-0.052	0.038
	-(0.1)	-(1.3)	(1.2)
Monthly, Equal-weight			
H/L $\mathbf{R}_{t-1}^{\mathbf{CDS}}$	-0.118	-0.390	0.341
	-(0.6)	-(2.0)	(2.1)
Monthly, Value-weight			
H/L $\mathbf{R}_{t-1}^{\mathbf{CDS}}$	0.236	-0.013	0.255
	(1.1)	-(0.1)	(1.5)

A3: Credit Spread and Liquidity

This table reports the single panel regression results for Effective spread at day t on CDS spreads and lagged effective spread by running the follow specification:

$$ES_{i,t} = \beta_0 + \beta_1 S^{\mathrm{CDS}}_{i,t-1} + \beta_2 ES_{i,t-1} + \delta_i + \epsilon_{i,t}$$

The model includes firm fixed-effect δ_i and we conduct tests using the heteroscedasticity-robust standard errors clustered by dates. ***,**, and * denote significance at the 1%, 5%, and 10% level respectively and numbers in the parentheses are t-statistics.

	(1)	(2)	(3)
	Effective Spread	Effective Spread	Effective Spread
CDS 5 Year	0.019***		0.009***
	(67.49)		(13.38)
Lag Effective Spread		0.516***	0.503***
		(13.63)	(13.26)
Intercept	0.001***	0.001***	0.000***
	(132.51)	(12.93)	(12.95)
Firm fixed effect	Yes	Yes	Yes
Cluster for SE	Yes	Yes	Yes
N	2057244	2055896	2055896
R-sq	0.464	0.606	0.609
adj. R-sq	0.463	0.606	0.609