The Profitability in the CDS Market

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Abstract

The strategy by buying the CDS with the most negative past 1-day stock return and selling the CDS with the most positive past 1-day stock return generates 0.26 daily Sharpe ratio from 2002 to 2016. The profitability concentrates on the most liquid CDS with more quote counts, more market makers, and less bid-ask spreads. Our paper challenges this notion by proposing a hypothesis based on informed speculation and partially informed hedging in segmented stock and CDS markets to explain the profitability. One implication of the hypothesis is that CDS-based trading strategy captures information asymmetry of different hedging and speculative demands given distress risk. Consistent with the distress nature of the strategy, we find that the return dynamic represents the distress risk factor, which is priced in U.S. market. Particularly, using portfolio approach following Fama-French (1993), we find the positive distress risk and return trade-off. Additionally, we show that the momentum crashes (by Daniel and Moskowitz (2015)) is because loser stocks bear more distress risk thus earn higher distress risk premium than winner stocks.

JEL-Classification: G12, G14

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1. Introduction

Stock returns unconditionally lead CDS returns for few days whereas CDS returns conditionally lead stock returns contingent on bad credit news. Unconditional stock leading pattern has been documented in two papers: Hilscher, Pollet, and Wilson (2015) (HPW hereafter) and Marsh and Wagner (2016); the conditional CDS leading pattern has been documented in at least four papers: Norden and Weber (2004), Acharya and Johnson (2007), Ni and Pan (2011), and Bai, Hu, Liu, and Zhu (2017).

The leading explanation is proposed by Easley, O'Hara, and Spinvas (1998) originally used in studying informed trading in option market and is later borrowed by HPW to explain why the stock market always lead the CDS market. Informed traders who have private information across two markets choose to trade only in one market with low transaction cost. Since the stock market has low transaction cost, it reflects the most up-to-date information thus trades or price discovery first happens in stock market. As a result, the stock market leads the CDS market because lack of informed trading or arbitrage activities in the CDS market. This, in turn, delays the price responses of the CDS market respect to the equity market.

After replicating HPW's empirical results, we extend HPW's original sample into a broader sample covering firms from not only U.S. but also from UK, Japan, and Europe from 2002 to 2016. We further transform HPW's lead-lag predictive regression setting into the profitable trading strategy. This is the first paper to conduct the trading strategy and find the remarkably large and persistent trading profit in the CDS market.

Particularly, for each day, all firms are sorted into quintile portfolios based on their stock returns at t-1[1]. We track 1-day post-formation CDS protection returns and equally group them into quintile portfolios. Next we long the CDS quintile with the most negative stock returns at t-1 and short the CDS quintile with the most negative stock returns at t-1. We term it as CDS-based trading strategy (namely, using the stock market information to trade in the CDS market.). We plot its performance in the Figure 1.

As in the upper panel of Figure 1, the CDS portfolio returns of the most negative stock quintile

[1] We conduct the strategy by pooling all firms together; This is only due to illustration purpose. All the assets are converted into U.S. dollar. The detail country by country analysis can be found in our latter section.

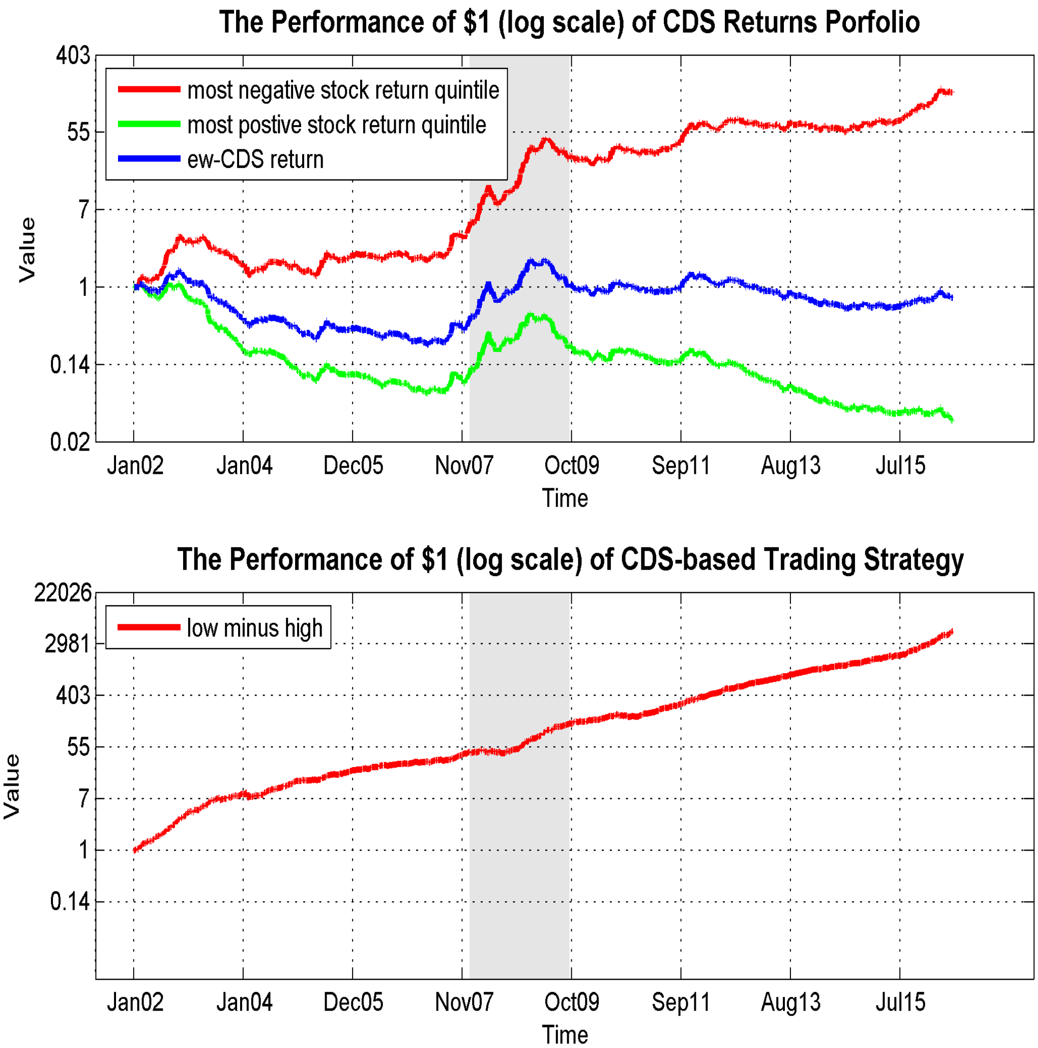

Figure 1

are significantly positive; the CDS portfolio returns of the most positive stock quintile are significantly negative. The return of the long-short portfolio (low minus high) is increasing over time. Consider equal-weighted CDS returns strategy as benchmark (blue line), we do not observe any significantly out-performance. In lower panel of Figure 1, we take a long-short portfolio between CDS portfolio with the most negative stock return quintile and the most positive stock return quintile. As we can see this strategy is very profitable, e.g.,$1 investment in 2002 Jan[2] will generate over $3000 in 2016 June. The monthly Sharpe ratio of this strategy is 1.21, which is eight times

[2]Our initial data sample starts from 2001. However, the number of firms are less in 2001 and not enough to form portfolios. Thus the sample of our analysis starts from 2002.

greater than the monthly SR of U.S. equity market index (Investing in S&P500 generates about SR 0.15 over the sample period.).

Next, we conduct a trading strategy in the stock market using past 1-day information of CDS returns that is similar to CDS-based trading strategy (we switch the position between stock to CDS). We term as stock-based trading strategy. We plot the accumulated return in Figure 2. Figure 2 presents the fact that even though stock-based trading strategy generates profit, the economics magnitude of the spread portfolio is far less than the CDS-based trading strategy.

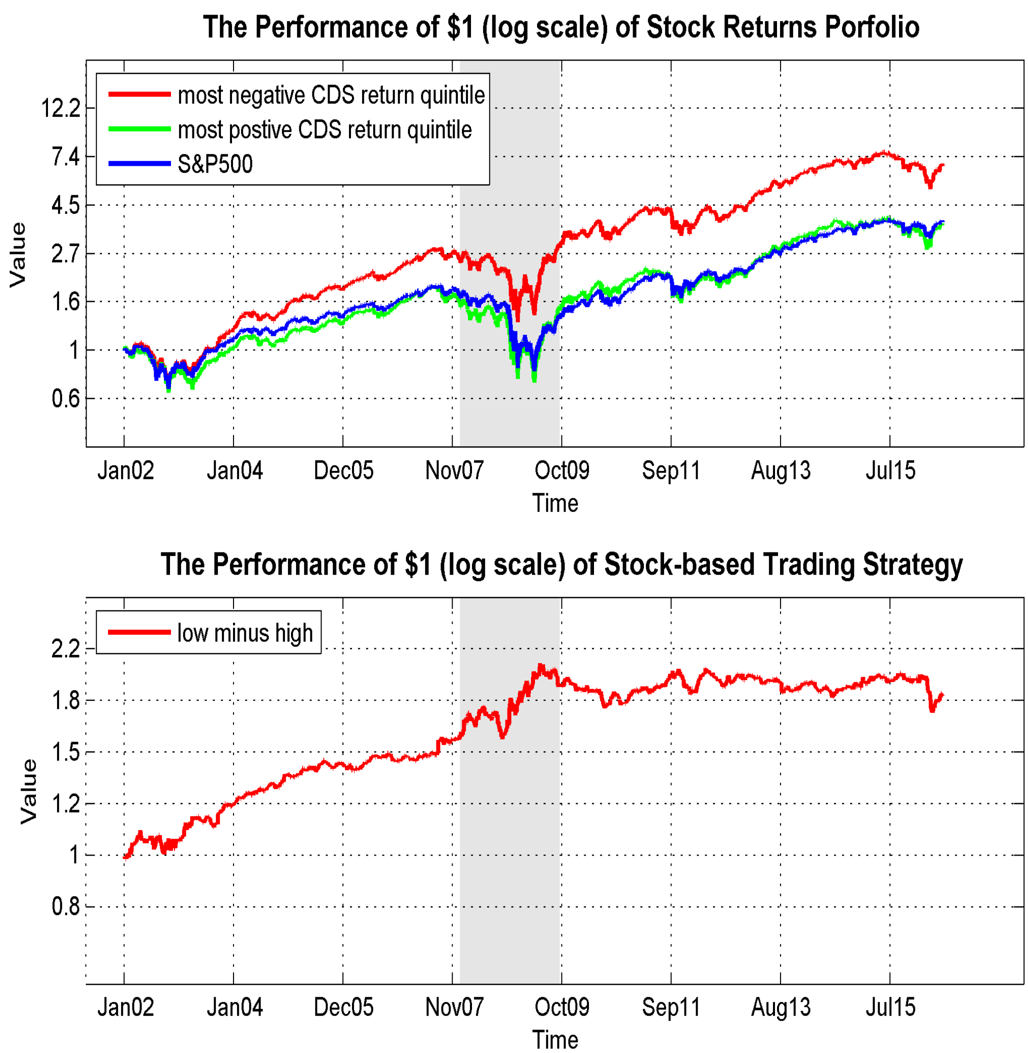

Figure 2

The economics question is where does such huge trading profit from CDS market based strategy come from? Specifically, we ask whether the profit stemming from trading CDS is only driven by nonsynchronous CDS price adjustment (In line with the prediction of Easley et al s' market selection theory). To test this, we use three proxies for liquidity in CDS market: number of quote counts, number of market makers and CDS 5-year bid-ask spread. If such huge profitability is due to lack of trading activity, we should expect that the profitability should ex-postly stronger for zero quote count, zero market marker and larger CDS bid-ask spread. We show the result from 2010-2016. [3].

However, as shown in Figure 3, the profitability stems from the most number of quote counts, the most number of dealers and the most liquid CDS spread; the CDS with lack trading activity cannot generate profit at all. Thus the degree of profitability in CDS market cannot be completely explained by Easley et al s' market selection theory.

There are three reasons why Easley, O'Hara, and Spinvas (1998) cannot fully explain the results. First, unlike equity market, both trades and order information are publicly reported through electronic platform, single-name CDS is traded in highly opaque over-the-counter (OTC) market. This might create incentive for dealers to speculate by restricting pre- and post-transaction price transparency (Bolton, Santos, and Scheinkman (2016), Monnet and Quintin (2017)). Thus if there exist uninformed hedgers in the CDS market with positive hedging demand, it should exist the opposite informed trade against hedgers (see, Duffie (2012) and Kelley and Tetlock (2013)). Second, CDS is not directly priced based on stocks. Correctly anticipate the default risk requires more advanced financial technology and more information. It imposes additional cost for uninformed hedgers becoming informed. As results, the strong empirical link might be omitted by some uninformed hedgers when they trade. Third, stock and CDS market are segmented. So it is less likely for all the informed investors in stock market to switch to CDS market to correct the mispricing, otherwise, we expect no profitability.

Hence we challenge this notion by proposing an market segmentation hypothesis based on informed speculation and partially informed hedging in segmented stock and CDS markets to explain the profitability. Essentially, we apply Goldstein, Li, and Yang (2013) s' theoretical framework.

[3]The liquidity data from Markit is only available from 2010. Thus we have to restrict our sample from 2010 onwards. In order verify the main test results are consistent using after 2010 sample, we repeat our panel regression analysis to confirm that remain is consistent using the smaller sample from 2010. Thus, we proceed our analysis using sample from 2010 to 2016 in the following analysis.

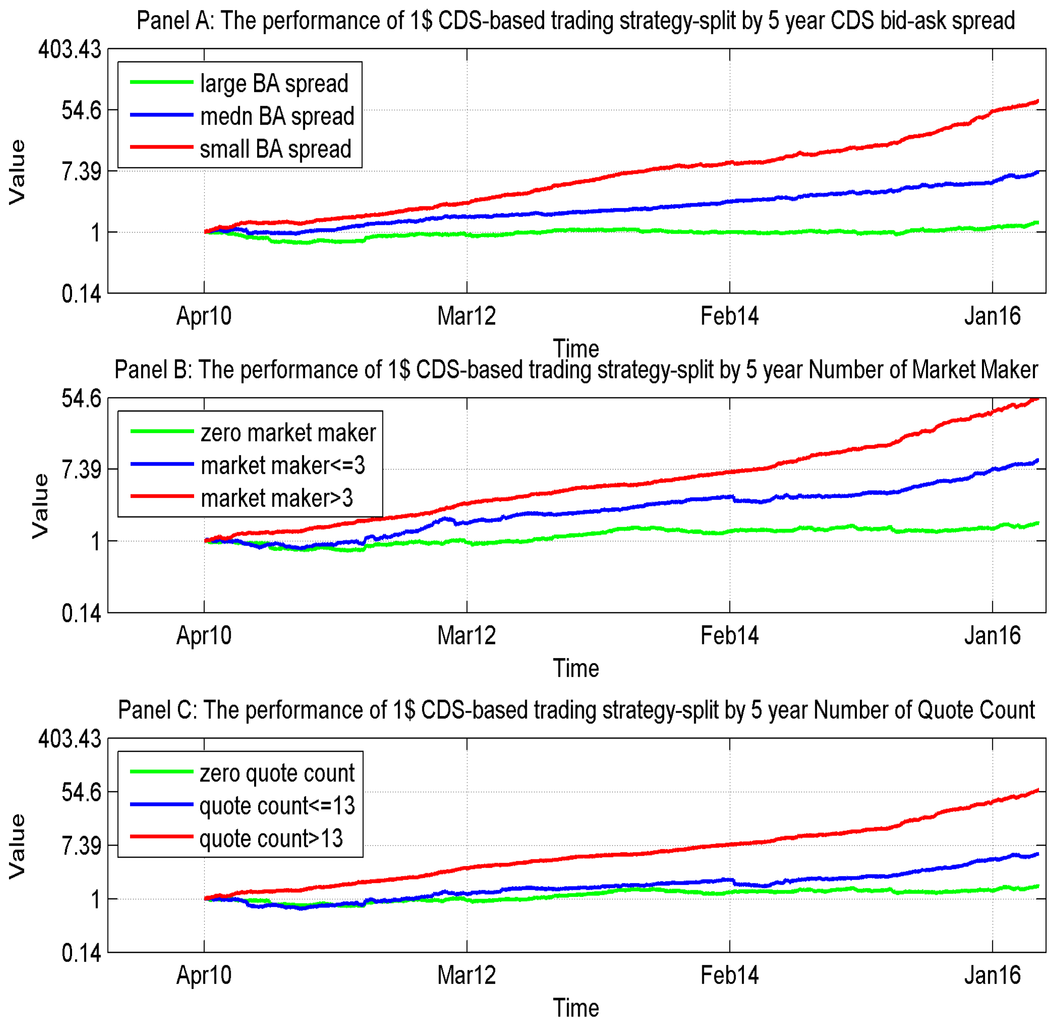

Figure 3

Consider informed speculators (e.g., hedge funds) with larger investment opportunity set that can trade in both stock and CDS markets; hedgers who pay for the learning cost to be informed with smaller investment opportunity set that can only trade in CDS market; uninformed hedgers restrict to the CDS market. In the first period, informed speculators simultaneously invest in stock and CDS market. Some hedgers in CDS market choose to be informed at period t. This two adverse informed forces make the CDS price less responsive to the information. Thus the stock market unconditionally leads the CDS market in first two periods. Consequently, the risk taking informed speculators hedge the credit risk exposure by trading stocks in third period thereby creates price pressure on stocks. Thus CDS leading stock is generally a follow up phenomena in last two periods. Overall, the theory has implication on the time series properties of equity returns of firms with debts and having an associated CDS market and implies that relative information inefficiency and market segmentation make credit risk transfer function more expensive in presence of informed investors.

We further develop three testable predictions according to the market segmentation hypothesis. If the market segmentation hypothesis is true, we expect (i) the time-series structure of CDS return exhibit positive series correlation; (ii) the CDS market underreact to stock market; (iii) the CDS market conditionally lead the stock market in terms of bad news for lower rating firms. See section 3 for detailed discussion. Empirically, we test our three predictions and find that they are not rejected by data. Therefore, the segmentation hypothesis not only complements to the existing market selection hypothesis but also better explain the huge empirical profitability of CDS market.

Lastly, we explore the asset pricing implication of CDS market using all common stocks in U.S.. According to our hypothesis, CDS-based trading strategy (CDSF hereafter) captures information asymmetric risk between the CDS market and the stock market. This essentially represents the distress risk. High CDSF indicates that the opportunity cost to conduct the credit risk transfer activity is high. Such friction reduces diversification benefit thus increase the risk of the overall stock system. Thus we investigate whether the return dynamic of CDSF can serve as risk factor for cross-sectional stock returns. Specifically, we test whether firms with high exposure or sensitivity on CDSF will earn high expected return. To empirically vertify our conjecture, we use all the stock return data in CRSP monthly file[4] from 2002-2016. We use CDS-based trading strategy return across U.S. speculative group as CDSF. We regress each stock on CDSF to obtain the sensitivity or CDS beta based on three year rolling window. Then we sort the stocks based on CDS beta, and we group stocks into five quintiles each month[5].

In Figure 4, we find that stock returns are increasing with CDS beta quintile. In particular, stocks with less exposure to CDSF earn less return; stock with largest exposure to CDSF earn higher return. The difference between the largest CDS beta quintile portfolio and smallest CDS beta quintile portfolio is 0.79% per month (t-stat=2.45). Additionally, we find that the distress

[4]with share code 10 and 11, in exchange 1, 2, 3 and share price greater than 5 dollar.

[5]Please refers to later session for more complete and detail analysis.

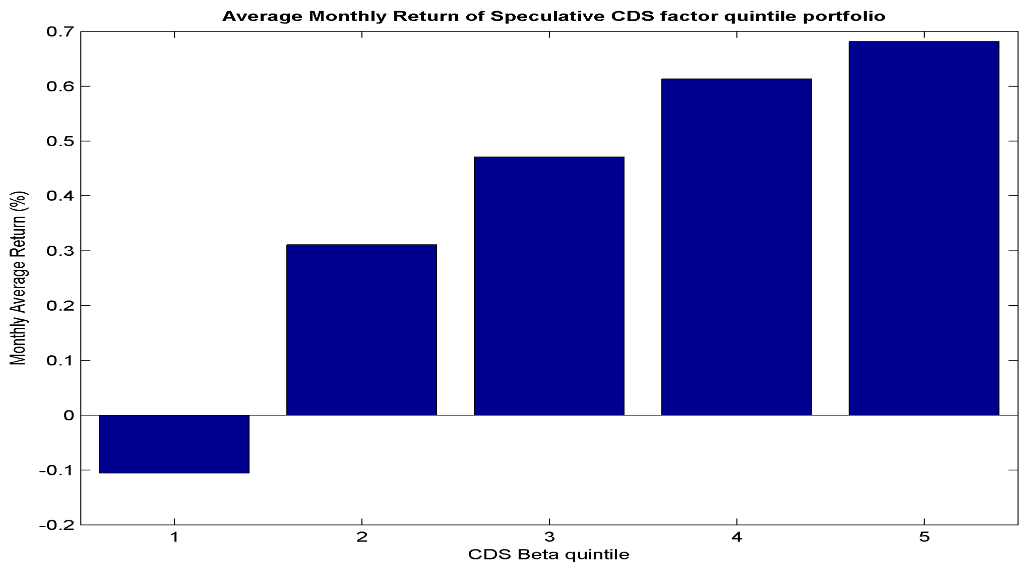

Figure 4

nature of firm is related to the recent momentum crashes (Daniel and Moskowitz (2015)). Specifically, we find that the winner and loser relationship flips during global financial crisis is because loser stocks bear more distress risk thus earn higher distress risk premium than winner stocks. Our asset pricing result sheds new light on distress risk puzzle and momentum crashes puzzle.

The rest of the paper is organized as follows. In section 2, we review the existing literature and demonstrate the differences and the contribution to the existing study. In section 3, we propose the market segmentation hypothesis and develop three testable prediction according to the hypothesis. The data sample and the summary statistics are discussed in Section 4. Section 5 replicates and extents HPW's empirical results. Section 6, we report the performance and the construction detail of the trading strategy. In addition to conduct the strategy using all firms, we conduct the country by country analysis to show that our findings work globally and across different rating groups. We also split the sample by CDS liquidity proxy in this section. Section 7 is the empirical results of the three testable prediction we developed in Section 3. The asset pricing implication is at Section 8. Section 9 concludes the paper.

2. Relation to the Existing Literature and Contribution

Our paper is related to three strands of literature. First, our paper relates to the literature about the relationship of stock and CDS price dynamic. Theoretically, the Merton (1974)'s structure framework implies two markets should be perfectly integrated without frictions. However, this is not true in the practice because there are frictions. For instance, frictions such as funding constraint (Shleifer and Vishny (1997), Gromb and Vayanos (2002), Mitchell, Pedersen, and Pulvino (2007), Duffie (2010) and Fuchs, Green, and Papanikolaou (2016)), price impact (Chen, Stanzl, and Watanabe (2002)), idiosyncratic uncertainty (Pontiff (2006)) or transaction costs (Kapadia and Pu (2009)) etc., should impose difficulty on the information processing process. Thus any observed discrepancy has implication on market friction thereby this is important to financial economists, practitioners, and policy makers. Some studies found that, under some particular conditions, CDS market leads equity market. For instance, Norden and Weber (2004) found that the CDS market reacts earlier to downgrades. Acharya and Johnson (2007) showed that CDS spreads of banking sector can predict its stock returns because banks are informed. Ni and Pan (2011) found that CDS leads stock markets during the period of U.S. short-sale ban, which suggests that CDS serves as additional trading venue to informed traders given bad news. Bai, Hu, Liu, and Zhu (2017) found that a firm's stock return synchronicity decreases after the commencement of CDS trading, which implies the firm-specific information transfer from CDS market to the stock market. However, most recently Hilscher, Pollet, and Wilson (2015) showed that stock market unconditionally leads CDS market based on U.S. sample. The explanation is that informed traders or arbitragers prefer to participate in only one trading venue in order to process their private information to minimize the transaction cost (Easley, O'Hara, and Srinivas (1998)). Thus it suggests that the empirical facts are largely explained by sluggish price adjustment of CDS market. Our paper extents this stream of literature in three ways. First, we transform the predictive regression into a profitable trading strategy to directly gauge the economics magnitude of the cross-market return predictability. Second, we show that the market selection theory by Easley, O'Hara, and Srinivas (1998) cannot fully explain the results because the profitability is mainly coming from most actively trading CDS. Third, we propose the market segmentation hypothesis to explain empirical results, which are not fully explained by the market selection theory.

Second, our paper relates to the literature about costly information of over-the-counter (OTC) market. As discussed by Ang, Shtauber, and Tetlock (2013), the stocks traded in OTC market behave very differently from those traded in listed markets. They found that information asymmetric nature (e.g. enable to hide orders and limited disclosure) of OTC market might serve as one of the important factor contributing to the difference. In addition, Bolton, Santos, and Scheinkman (2016), Monnet and Quintin (2017) theoretically argued that the OTC market enable institutional investors to retain the information thus generates the additional information rent. Empirically, Litvak (2009) found that the ”dark” firms’ prices departed significantly from semi-strong efficiency using pink sheets experiment. All of those papers points to the addition cost induced by the OTC market is due to opacity. Thus the profitability of the CDS-based trading strategy should include the cost of the degree of information asymmetry induced by the opaque nature of OTC market. Overall, our empirical evidence serves as an important support to this stream of literature.

Third, our paper relates to the asset pricing literature. First, our paper contributes to distress risk premium literature. In theory, if distress risk is priced in equity market, it should positive reflect on stock returns. However, the empirical evidence is mixed. For instance, some papers found that distress firms generate low return. Dichev (1998) and Griffin and Lemmon (2002) used Altman (1968) Z-score and the Ohlson (1980) O-score as measure distress risk and found the negative relationship. Campbell, Hilscher, and Szilagyi (2008) used a dynamic panel regression approach to incorporate both market data and accounting data and find the negative results. Some papers found the positive results. For instance, extracting the physical default probability using the Merton (1974) model, Vassalou and Xing (2004) found that distressed stocks earn higher returns. Chava and Purnanandam (2010) estimated the expected stock return using the implied cost of capital and found the positive relation to the distress risk. Most recently, Friewald, Wagner, and Zechner (2014) used Cochrane and Piazzesi (2005), and Pan and Singleton (2008) approach to extract the distress risk measure based on credit default swap term structure. They found the positive relation. In our paper, we use a simple and standard Fama-French (1993) portfolio approach to directly extract the distress risk exposure by regressing stock returns on the distress risk factor from CDS-based trading strategy. By sorting the stock returns based on the distress risk exposure, we find the positive relation. Thus our result is consistent with the theoretical prediction on distress risk and return relation. Second, our paper contributes to the momentum crashes literature. Daniel and Moskowitz (2015) documented the momentum strategy encounter a significant loss during the recession period. because winners become losers while losers become winners during post global financial crisis period. In this paper, we show that distress risk channel can explain the momentum crashes during the extreme risky episode. In particular, the winner and loser relationship flips during recent global financial crisis is because loser stocks bear more distress risk thus earn higher returns (or distress risk premium) than winner stocks. In sum, our asset pricing result sheds new light on distress risk puzzle and momentum crashes puzzle. Hence our paper has implication on asset pricing and financial risk management.

3. Price Informativeness in Segmented Markets

Goldstein, Li and, Yang (2013) (GLY hereafter) analyse a model in which traders have different trading opportunities in segmented market, which is defined as different investment opportunity sets by the ability of trading in different markets. The key prediction of their framework is that informed trading reduce price informativeness across any segmented markets sharing common information.

In a more specific context, we apply their theoretical framework to study the information integration between stock and CDS market. We consider informed speculators (e.g., hedge funds) with larger investment opportunity set that can trade in both stock and CDS markets; hedgers who pay for the learning cost to be informed with smaller investment opportunity set that can only trade in CDS market; uninformed hedgers restrict to the CDS market that can only infer the distress risk from observed CDS price.

We apply GLYs' framework to the stock and CDS market. We consider the true distress risk signal as θ with mean zero and variance σ_θ^2; the oberved stock price as p_s; the oberved CDS price as p_{CDS}; the true CDS price is $p^*_{CDS}(\theta)$; the variance of uninformed traders in both markets as σ^2_{nStock} and σ^2_{nCDS}. We borrow the price informativeness equation from GLY (Eqs. 23),

$$I = \frac{VAR(\theta)}{VAR(\theta|p_s, p_{CDS})} = 1 + k^2_{CDS}\frac{\sigma^2_\theta}{\sigma^2_{nCDS}} + k^2_{Stock}\frac{\sigma^2_\theta}{\sigma^2_{nStock}} \tag{1}$$

where the overall price informativeness of the system (the stock and CDS market) is defined as

$\frac{VAR(\theta)}{VAR(\theta|p_s,p_{CDS})}$. This construction is similar to Equation (14) in Grossman and Stiglitz (1980), which is common way to construct the overall equilibrium of the price system in modern finance literature. The ratio monotonically increases with efficiency bounds at 1 if there is no information asymmetry. k_{CDS} is the information injected in CDS market by the informed speculator with larger investment opportunity set and informed hedger with smaller investment opportunity set. Similarly, k_{Stock} is the information injected in stock market by informed speculator only. The key interest is k_{CDS}. This indicates the price efficiency in CDS market.

As show by GLY,

$$k_{CDS} = \lambda \delta_{CDS}^{\text{Informed Speculator}} + \mu \delta_{CDS}^{\text{Informed Hedger}} \tag{2}$$

where $\lambda \delta_{CDS}^{\text{Informed Speculator}}$ is the price informativeness contributed by informed speculator (λ, and μ are size of informed trader, and δ is information per unit of size). $\mu \delta_{CDS}^{\text{Informed Hedger}}$ is the price informativeness contributed by informed hedger.

The key result of GLY is

$$\text{cov}[\lambda \delta_{CDS}^{\text{Informed Speculator}}, \mu \delta_{CDS}^{\text{Informed Hedger}}] < 0 \tag{3}$$

Equation tells the story that since different traders trader in opposite directions due to different motivations, if they are both informed, it may reduce the price informativeness of the whole system through the segmented market (in our case this is CDS market). Other things equal (level of risk-aversion etc.), informed hedgers' hedging demand Q should be decreasing in the distance between observed CDS spread p_{CDS} and the theoretical CDS price $p^*_{CDS}(\theta)$. This means the CDS price will underreact to the distress risk when $|p_{CDS} - p^*_{CDS}(\theta)|$ become larger. Furthermore, since stock market incorporate all kinds of information, some information is not relevant to credit news θ. Therefore, some news revealing θ might be ignored by uninformed hedgers as they are not able to screen the θ apart from other news. Overall it suggests that the slow price response stems from information asymmetric in CDS market. It comes to our first hypothesis:

Hypothesis 1: CDS returns unconditionally underreact to the stock market shocks.

Our second hypothesis is followed by the first one:

Hypothesis 2: CDS returns are positive autocorrelated.

Hypothesis 2 suggests when $|p_{CDS} - p^*_{CDS}(\theta)|$ is high, there is not enough hedging demand Q to push the observed price p_{CDS} towards equilibrium price $p^*_{CDS}(\theta)$. So it takes time for observed price p_{CDS} toward $p^*_{CDS}(\theta)$ with same direction. This is different from the stock market. If stock is very actively traded, a larger fraction of the informed traders at t would need to close out their position at t+1 for given net supply or demand. Thus we usually observe return reversal at stock market.

Next we form our third hypothesis based on informed speculators' hedging demand:

Hypothesis 3: CDS return negatively leads stock return following a bad news. Such leading effect is stronger for speculative grade firms.

Informed speculators who sell CDS protection to hedgers are exposed to credit risk and would complete the other leg of the risky arbitrage by short-selling some stocks. This is because if default occurs, the speculators will not be totally exposed in their short credit position such as by AIG in 2009. When the next credit news hit or when stock prices reverse, informed speculators will then buy back the CDS and buy back the shares. It is important to note that this is not due to credit news first hitting the CDS market and then spillover to the stock market. It is due to perceived information premium by informed traders. This hedging behaviour of informed speculators create price pressure on stock with high distress risk and the impact should stronger for bad news rather than good news when informed speculators are risk averse.

4. Data Sample

The CDS data used in our study is from Markit[6]. The time period for our data is from January 2002 to June 2016. The spread of 5-year CDS contract is used in this study because these are the most widely traded and the most liquid ones. Our CDS data source is also used by Duarte, Longststaff and Yu (2007), Kapadia and Pu (2012), Hilscher, Pollet, and Wilson (2015), Marsh and Wagner (2016) and Han, Subrahmanyam, and Zhou (2017).

[6]Markit Group is a leading company who provides the credit derivatives real-time price information. Markit collects CDS quotes from market makers each day and applies a screening process to remove outliers,stale prices, and other inconsistent data. Then it computes the mean quoted price from those data, which pass the screening test.

We compute the 5 Year CDS daily return or credit protection return by percentage change in the credit spread. As notes by Hilscher, Pollet, and Wilson (2015), the credit protection return equals 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 well 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. The increase of credit protection return reflects the gain of the credit protection seller vice versa. We use an average of the Moody's and Standard & Poor's credit ratings by Markit as our credit rating criteria. Those are adjusted to the seniority of the instrument and rounded to not include the '+' and '-' levels.

We collect stock information from CRSP for U.S. sample and DataStream for UK, Japan, and Euro sample. It includes stock returns (all stock returns are adjusted for both share split and dividends), stock volumes, end-of-day (adjusted) stock prices, number of shares outstanding, and bid-ask spread. We then match the information of stock to information of CDS from Markit.

For U.S. sample, we match equity information to CDS information using first 6 digit CUSIP. The CUSIP for CDS sample is available at 'RED' reference entity file provided by Markit. In particular, we map out the CDS price information to the 'RED' file using 'REDCODE', which is unique identifier by Markit. For UK, Japan, and Euro, we conduct a manually search by matching companies' long legal name in DataStream terminal to 'long entity name' in 'RED' reference entity file provided by Markit given we cannot automatically generate the CUSIP number for the non-U.S. firms in DataStream because the majority of CUSIP in DataStream is available only for U.S. and Canadian entities. This gives us a final dataset of 2,136,200 firm-day observations for 1137 firms. Other variables used in this study include Fama-French factors, which are obtained from Ken French's website:http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data library.html; All exchange rate is obtained from the DataStream in order to adjust some variables (e.g., bid-ask spread, market cap and end-of day market share prices) into U.S. dolloar.

<u>Insert Table 1 about here</u>

Table 1 reports summary statistics. The sample average of full-sample CDS spread is 171.82 bps. Correspondingly, the sample average of full-sample share price is 48.73 dollar per share

(U.S. dollar). The sample average of protection return ΔCDS_t is around zero percent with standard deviation of 2.66 % per day. This is less profitable compared with investing in stock market with higher average daily return 0.04% per day and low standard deviation of 2.13 per day. We compare the liquidity of two markets by looking at the bid-spread. In order to make the spreads between stock market and CDS market directly comparable, we scale the bid-ask spread by each day's quoted price. Since the liquidity data of CDS is only available from 2010, the sample of the 5 year CDS bid-ask spread has to restrict from 2010 onwards.

We next partition our full data sample into three sub-samples. The first sub-sample contains firm with credit rating above or equal to BBB. These are considered as investment grade firms. As shown in our sample, the investment group contains the major observations (1386441 firm-day observations.). The second sub-sample contains firms with lower rating, which is below BBB. These are considered as speculative or high yield firms. It results 458215 firm-day observations. The last sub-sample contains firms without credit rating in our sample. There are 292685 firm-day observations. As expected, the mean of CDS_t in speculative group is 365.24 bps while that of investment grade group is three times smaller about 105.56 bps. Additionally, the investment group has lower stock volatility (1.87% per day) while speculative group has higher stock volatility (2.71% per day).

5. Replicate HPW

5.1. Stock returns predict CDS returns

We analyze the response of credit protection returns to equity returns of same firm in panel regression setting similar to HPW. We extend HPW in three dimensions. Firstly, we extend the sample to 2016. Secondly, we extend the sample to international sample including U.S., UK, European and Japan respectively. Thirdly, addition to follow HPW to include lag protection return as control, we further include control variables such as market factor, market size and equity bid-ask spread. In light of Marsh and Wagner (2016), market factor should be controlled because equity market's ability to incorporate common information plays an important role in explaining the predictive relation. Since the equity liquidity and market size play an important role in determining the daily stock return, it is also necessary to rule out the potential concern that result is driven by equity liquidity and market size. Thus we control for both. We test the hypothesis that equity returns unconditionally and negatively lead the CDS protection return. Particularly, we conduct the following specification:

$$\Delta CDS_{j,i,t} = a_0 + b_1 r_{j,i,t-1} + b_2 \Delta CDS_{j,i,t-1} + X_{j,i}\gamma_1' + \eta_j + e_{j,i,t} \tag{4}$$

where the dependent variable, $\Delta CDS_{j,i,t}$, is the credit protection return for firm i in country j over day t. The main variable of interest, $r_{j,i,t-1}$, is stock return for firm i in country j over day t-1. The alternative hypothesis for b_1 is $b_1 < 0$. The control variable includes $\Delta CDS_{j,i,t-1}$, the 1 day lag credit protection return to control for autocorrelation. The other control variables include market risk factor, market size (in \$US billion), and stock bid-ask spread (in \$US dollar). In addition, we control for firm fixed effect η_j. Standard errors are adjusted for heteroscedasticity and clustered by date. To control for outliers, all variables are winsorized at the 0.1% and 99.9% levels. Equation (5), (6), (7) (in the later section) follow the same specification as equation (4).

Insert Table 2 about here

Column (1) of Table 2 reports the full sample estimation of Eqs.(4). The magnitude of b_1 is comparable to HPW. In particular, the point estimate in our sample is -0.12, whereas HPW reports -0.16[7]. Both are statistically significant at 1% level. The coefficient is economics significant. It tells that increasing the equity return by 1% is associated with 1-day ahead change in the CDS return of 12bps. Furthermore, we partition our firms into investment sample and speculative sample. We find that the results are quantitatively similar across two sub-samples (Column (2) -(3) in Table 2). To examine whether the results are driven by various sample periods, we partition our sample into before 2007, 2007-2008 global financial crisis period (GFC hereafter), and post GFC period. We do not find the significant different results across the three samples (Column (4) -(6) in Table 2). Thus table 2 suggests that equity return robustly lead the protection return at daily frequency in a global sample.

[7]The main difference between our estimates are due to different sample selection. Our sample consists of 4 countries with long sample period whereas HPW only consider U.S. sample till 2007. This is the main reason why our point estimate is slightly smaller than that of HPW.

5.2. CDS returns predict stock returns

We next analyse the response of stock returns to 1-day lag credit protection returns by switching the dependent variable in the Eqs.(4) and the CDS returns becomes the independent variable. Addition to Eqs.(4), we include the 2 period lag equity return as control variable according to our 3 period trading model. The key variable of interest is b_2. Similar to Eqs.(4), we conduct the following specification:

$$r_{j,i,t} = a_0 + b_1 r_{j,i,t-1} + b_2 \Delta CDS_{j,i,t-1} + X_{j,i}\gamma_2 + \eta_j + e_{j,i,t} \tag{5}$$

Insert Table 3 about here

Column (1) of Table 3 reports the full sample estimation of Eqs.(5). Even though the estimates are statistically significant within 1% significant level, it does not economics significant. Specifically, increasing the CDS return by 1% is only associated with 1-day ahead change in the stock return of 0.08 bps. Additionally, in Column (2) -(3), the absolute magnitude of b_2 is larger for speculative grade than investment grade. The results remain robust to different sample periods (Column (4) -(6)). Using an international sample, we find that CDS returns significantly affect future stock returns. However, the economics magnitude is small. This is consistent with the findings by HPW.

In appendix A1, we use vector auto regression (VAR) to reproduce our results. Similar specifications are adopted by such as Norden and Weber (2009), Hilscher, Pollet, and Wilson (2015), Marsh and Wagner (2016) etc. Despite we use an international sample with longer time-series horizon, our VAR estimate result is consistent with the existing studies.

Insert Table A1 about here

6. Profitable Trading Strategy

6.1. Two-period Trading Strategy

In order to directly gauge the economics magnitude of HPW, we use the (out-of-sample) non-parametric portfolio approach to mimic the risk taking behavior of informed speculator. First we sort the credit protection returns into 5 portfolios based on their stock returns at t-2 and track 1-day post-formation equal-weighted quintile portfolio of protection returns. We term it CDS-based portfolio. Second, stocks are sorted into quintile portfolios based on their protection returns at t-1 and we track 1-day post-formation equal-weighted stock returns. We term it equity-based portfolio. Third, we combine the first and second steps portfolio returns by summing portfolios with most negative stock returns at t-2, e.g. 1-day post formation protection returns at t-1, and portfolios with most positive protection return at t-1, e.g. 1-day post formation stock returns at t-1. We denote it as 'Lowest'. We summing portfolios with second most negative stock returns at t-2 and portfolio with second most positive protection returns at t-1. We denote it as 'P2'. 'P3', 'P4' and 'Highest' portfolio can be constructed in a similar way. We expect 'Lowest' portfolio would generate most significant return. The strategy is free from look-ahead bias. When we conduct the country by country analysis, all assets are in local currency. When we pull all the firms across different countries together, we unify all the currency to US dollar. Since we do not have enough firms to conduct such strategy for speculative group of Japan and UK, we exclude Japan speculative case and UK speculative case from our country level analysis.

<u>Insert Table 4 about here</u>

Table 4 reports results of the two-period trading strategy by combining protection returns and stock returns for all firms as well as each of the U.S., UK, European countries and Japan. The first result in Table 4 is that portfolio with most negative past stock return and most positive protection return subsequently experience highest return according to our strategy for all countries. The portfolio returns are monotonically decreasing from 'Lowest' quintile, to 'Highest' quintile. Furthermore, by buying the 'Lowest' portfolio and selling the 'Highest' portfolio, it generates large and significant spread returns at daily level. Our results are strong in three dimensions. The average spread portfolio is statistically significant. For instance, average the long-short portfolio returns are positively and significantly different from zero for all cases except Investment grade firms for Japan. Second, It also economics significant. By looking at all firms' sample, the strategy generates 26.31 bps returns per day. For U.S., there are 25.8 bps per day for investment grade and 42.91 bps for speculative grade per day. For investment grade of UK and Japan, the daily the average returns are 14.70 bps and 6.90 bps respectively. For EU, the average returns are 17.91 bps and 19.53 bps respectively. Third, our strategy is very stable. This is because the daily Sharpe ratios are remarkably large. It suggests that the compensation of per unit of risk is large.

6.2. Decomposing Two-period Trading Strategy

We investigate whether the overwhelming strategy returns are stemming from CDS-based portfolio or equity-based portfolio. To examine this, we first decompose the two-period trading strategy returns into CDS-based portfolio and equity-based portfolio[8].

Insert Table 5A, 5B about here

Table 5A and 5B show that the magnificent performance of two-period trading strategy is mainly from CDS-based portfolio. Particularly, the average of equal-weighted portfolio return is highly statistically significant greater than zero for all countries/rating specifications except Japan investment grade. In contrast, the overall performance of equity-based portfolio is only significant within 5% level, which is much smaller than CDS-based portfolio. By zooming in country by country case, we find that the majority of average return is generated by U.S. firms.

6.3. Profitability in the Most Liquid CDS Contracts

We have shown that most of the profit of two period trading strategy is coming from CDS trading. We next ask question whether the profit stemming from CDS trading is due to nonsynchronous CDS price adjustment. In order to tackle this question, ideally we need to directly identify for

[8]The definition of CDS-based portfolio is: sort the credit protection returns into 5 portfolios based on their stock returns at t-2 and track 1-day post-formation equal-weighted quintile portfolio of protection returns. The definition of equity-based portfolio is: stocks are sorted into quintile portfolios based on their protection returns at t-1 and we track 1-day post-formation equal-weighted stock returns.

informed trading activity in CDS market. However, in presence of data constraint, we are not able to obtain the direct identification for informed trading. Nevertheless, we use three proxies for the likelihood of informed trading in CDS market. The first proxy is number quote counts for each single-name CDS each day. Second proxy is number of market makers for each CDS each day. The third proxy is the bid-ask spread of 5 year CDS spread. We expect the high likelihood of informed trading in CDS with more quote counts, more market makers and smaller bid-ask spread. The data is from Markit and is only available from 2010. Thus we have to restrict our sample from 2010 onwards. In order verify the main test results are consistent using after 2010 sample, we first repeat the panel regression analysis in Section 5 using data from 2010 onwards. The results remain consistent. Thus, we proceed our analysis using sample from 2010 to 2016 in the following analysis.

In order to obtain enough stocks in our portfolio, we pool all firms in the analysis. Specifically, at each day t, we partition CDS returns into three groups based on one informed trading proxy. Then we independently sort CDS returns into 5 quintiles based on their past 1-day stock return (stock return at day t-1). Lastly, we construct a spread portfolio by buying the portfolios with most negative day t-1 stock returns and selling the portfolio with most positive day t-1 stock returns within each informed trading group.

Insert Table 6 about here

Table 6 demonstrates the informed trading of CDS market. Panel A of Table 6 presents the double sort analysis using number of quote counts. We partition the total sample into three groups. First group contains the CDS with zero quote count at day t. If the profit is driven by sluggish CDS price adjustment, we expect to see that most of the results should concentrate on the group with zero quote count. However, the 'LML' spread or difference between 'Lowest' and 'Highest' is statistically insignificant (Average=4.06 pbs per day with 1.37 T-stats), which suggests that the sluggish price adjustment does not drive our results. Next, partition the sample by the median of quote according to our sample. We first look at firms with quote count ≤ 13 but not equal to zero. We find that the spread portfolio 'LMH' returns are statistically significant different from zero (Average=13.86 pbs per day with 3.53 T-stats). Second, the sample with quote count > 13 generates average return of 32.25 bps per day with T-stat 12.33. The evidence shows that the return of spread portfolio is monotonically increasing with the quote count, which proxies for informed trading activity. In Panel B, we conduct a reproduce the result of panel A by replacing number of quote by number of market makers. In Panel C, we sort the firms into tercile based on CDS-bid ask spread. Both Panels show the similar results.

Overall, the evidence suggests that the degree of profitability in CDS market cannot be completely explained by Easley et al s' market selection theory.

7. Three Testable Predictions

In this section, we test the three testable hypothesis developed in Section 3.

7.1. CDS Return Underreaction

We test Hypothesis 1, whether CDS market always underreact to stock market. We conduct a simple non-parametric sorting approach to test the hypothesis. We sort assets in one market based on the past 1-day performance from the other market. We form 5 quintile portfolios. We long the quintile with most negative past 1-day return and short the quintile with most positive past 1-day return. We conduct 26 buy-and-hold strategy from hold 1 day and rebalance (t=1) to hold 26 days and rebalance (t=26). If it takes few days for market to absorb the profit, this is evidence of short-term price underreaction.

First, we conduct the strategy in the CDS market. We plot the multiple days holding period ahead strategy in Figure 5. The x-axis is multiple days ahead holding period. The y-axis is daily portfolio returns in bps. In Figure 5, the CDS price underreacts for first 26 days then converges to the normal level. This is consistent for all countries sample across different rating group.

Second, we conduct the strategy in the stock market. We plot it in Figure 6. We do not observe the consistent stock return underreaction to CDS market except for U.S. speculative grade. It might because of the price pressure created by informed speculators who want to hedging the credit risk exposure among U.S. speculative firms. Overall the evidence consistent with our hypothesis 1.

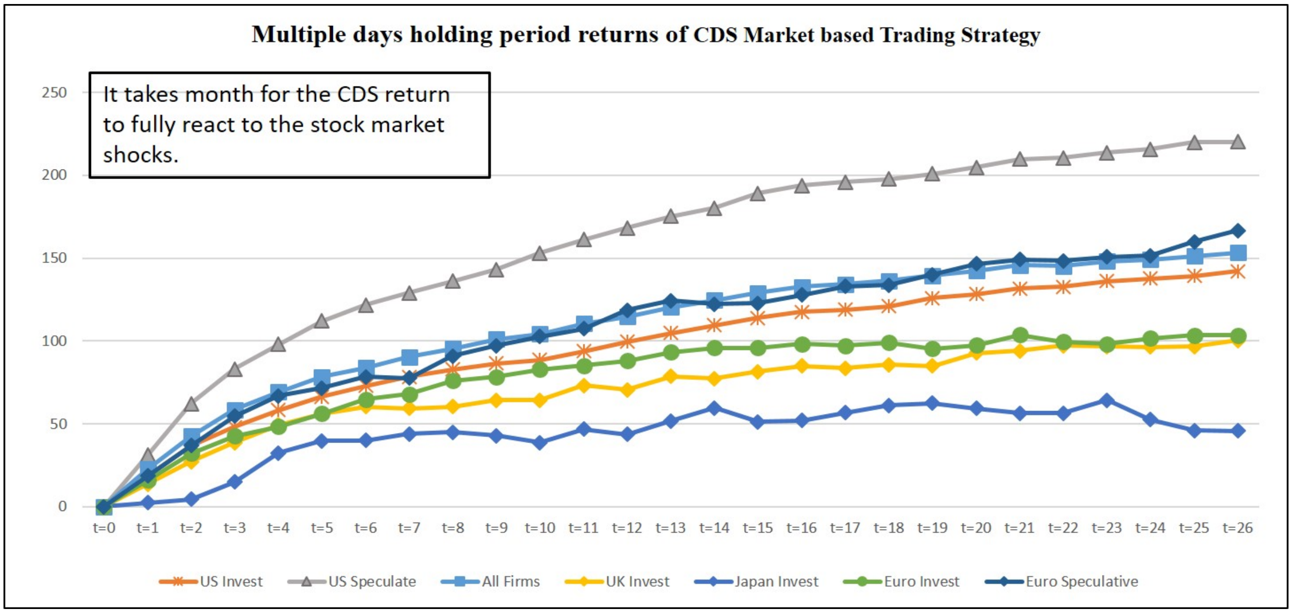

Figure 5

7.2. CDS Return Positive Autocorrelation

In this section, we empirically examine whether CDS return is positively autocorrelated (hypothesis 1). If informed hedgers' hedging demand Q is decreasing in the distance between observed CDS spread p_{CDS} and the theoretical CDS price $p^*_{CDS}(\theta)$, namely, $|p_{CDS} - p^*_{CDS}(\theta)|$, we should expect there is not enough hedging demand Q to push the observed price p_{CDS} towards equilibrium price $p^*_{CDS}(\theta)$ given credit news. So observed price p_{CDS} slowly but consistently adjust toward $p^*_{CDS}(\theta)$. Therefore, empirically, we should observe positive autoregressive structure of CDS returns.

We test this hypothesis based on regression approach. In fact, the results of our first approach has been reported in Table 3. In particular, consistent with Hypothesis 2, the slope coefficient of b_2 is positive across our 6 models in Table 2. It is statistically significant across all the specifications except 2007. Overall, CDS returns are positive autocorrelated is not rejected by data under regression approach.

7.2..1 Contingent on Credit Rating

We further examine the response of stock returns to 1-day lag CDS returns conditional on different rating group followed by our hypothesis 3. In particular, we expect the predictive effect from

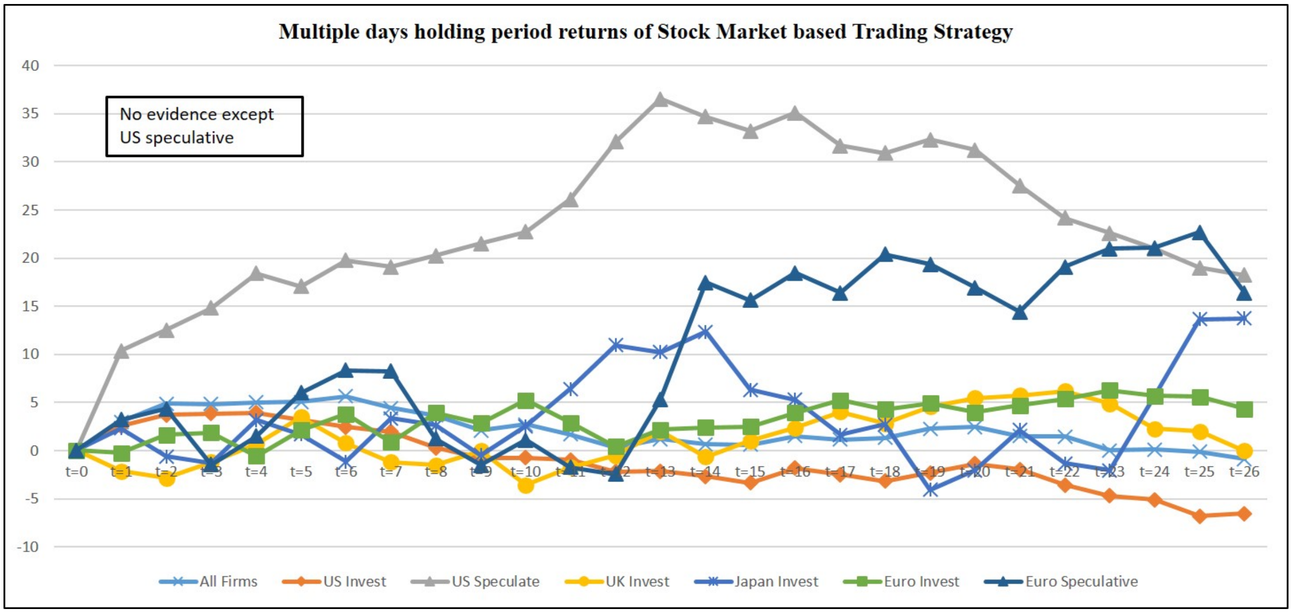

Figure 6

the CDS market to the stock market to be stronger for speculative grade firms than investment grade firm. When informed investor takes the credit risk of firms with high probability of default such as lower credit rating and if she is risk averse, we expect her to trade additional stocks to protect her position. In other words, such (informed trader's) hedging demand is expected to be more pronounced. Since the stock market might not be able to absorb all the additional hedging demand. Thus the additional hedging demand might spillover and create price pressure to next period stock return. To examine the hypothesis, we conduct following specification

$$r_{j,i,t} = a + \beta_1 * SPECU \times \Delta CDS_{j,i,t-1} + \beta_2 * SPECU + \beta_3 * \Delta CDS_{j,i,t-1} + \beta_4 * r_{j,i,t-1} + X_{j,i}\gamma_1' + \eta_j + e_{j,i,t} \tag{6}$$

where *SPECU* is dummy variable that equals to 1 if rating of reference entity is below BBB, zero otherwise. This is to test if hedging demand is high given the underlying reference entity with lower credit rating. If it is true, we expect to observe $\beta_1 < 0$. This suggests that informed investor has incentive to short stocks (This suggests $\beta_4 < 0$) by period t given the short position of credit protection to hedger by period t-1.

Insert Table 7 about here

Panel A of Table 7 reports the test result. Column (2) reports the full sample estimation. As we can see, the magnitude of point estimates of $SPECU \times \Delta CDS_{j,i,t-1}$ (β_1=-0.013) is about three times higher than that of $\Delta CDS_{j,i,t-1}$ (β_3=-0.005). This is consistent with our hypothesis. Furthermore, if our expectation is correct, we should observe the stronger result for GFC period and post GFC period because the risk hedging demand expect to be stronger for these two sub periods. Thus we partition our sample into before, within and after GFC. As expected in Column (2), we do not find the significant difference of credit effect between speculative grade and investment grade sample (β_1 is closed to β_3) before 2007. However, we find that the significant difference between speculative grade and investment grade sample during and after GFC in column (3)-(4). Overall, the empirical evidence is consistent with our conjecture.

7.2..2 **Contingent on Negative News**

Next, we expect that credit effect is stronger contingent on bad news rather than good news. This is also related to informed investor's hedging demand. If informed investor is risk averse, she might seek to hedge her credit positions using stocks. Such hedging demand is expecting to be strong to informed investor who is credit protection seller (or implies given negative news). Thus shorting stocks provide a channel to hedge the credit position. Similar to previews reasoning: since the stock market might not be able to absorb all the additional hedging demand, additional hedging demand (shorting stocks) might spillover and create price pressure to next period stock return. The asymmetric effect can be tested by following empirical specification

$$r_{j,i,t} = a + \beta_1 * SPECU \times \Delta CDS_{j,i,t-1} I[r_{j,i,t-2} < 0] + \beta_2 * SPECU \times \Delta CDS_{j,i,t-1} I[r_{j,i,t-2} \geq 0] + \beta_3 * SPECU + \beta_4 * \Delta CDS_{j,i,t-1} + \beta_5 * r_{j,i,t-1} + X_{j,i}\gamma_1' + \eta_j + e_{j,i,t} \quad (7)$$

In this specification, we split the $SPECU \times \Delta CDS_{j,i,t-1}$ by indicating variables $I[r_{j,i,t-2} < 0]$ and $I[r_{j,i,t-2} \geq 0]$. The proxy for bad credit news, $I[r_{j,i,t-2} < 0]$, indicates dummy variable that equals to 1 if stock return by day t-2 is negative. The proxy for good credit news,$I[r_{j,i,t-2} \geq 0]$, indicates dummy variable that equals to 1 if stock return by day t-2 is not negative. We expect the both magnitude and significance of β_1 is larger than that of β_2.

Panel B of Table 7 reports the test result. As expected, the credit effect is driven by negative news rather than positive news. This is consistent with our hypothesis 3.

8. Asset pricing implication

CDSF captures information asymmetric risk between the CDS market and the stock market. This essentially represents the distress risk. High CDSF indicates that the opportunity cost to conduct the credit risk transfer activity is high. Such friction reduces diversification benefit thus increase the risk of the overall stock system. Thus we investigate whether the return dynamic of CDSF can serve as risk factor to price cross-sectional stock returns.

Empirically, we form “ex-post” portfolios to test the conjecture. For each month t, we group stocks into 5 portfolios, based on realized OLS estimated betas over past three years. Within each portfolio, all stocks are equally weighted at the end of month t. While these portfolios are formed expostly and are not tradeable, they represent valid test assets to examine our hypothesis. That is, we test if the stock that has larger exposure to CDSF earns high return compared with those who has smaller exposure to CDSF that earn low return. We use all common stocks with share price greater than 5 dollars, and listed in NYSE, NASDAQ and AMEX with share code 10 and 11 and at least 30 months with non-missing returns to construct our testing sample. We use CDSF from speculative firms. We conduct our analysis in monthly frequency by converting to CDS risk factor to monthly frequency accordingly in order to align with asset pricing frequency.

Particularly, it includes two stages. In the first stage, we run time-series regression for each stock i based on past 3 years rolling window.

$$R_{i,t} = \alpha_i + \beta_i^{\tau} CDSF_t + e_{i,t} \tag{8}$$

where τ indexes for rolling estimated β_i. We collect all the $\hat{\beta}_i^{\tau}$. In the second stage, we group stocks into 5 quintile portfolio based on $\hat{\beta}_i^{\tau}$ each month. Table 8 reports the result.

Insert Table 8 about here

In Panel A of Table 8, stocks in the highest CDSF loading quintile earn equal-weighted average monthly returns 0.79% higher than stocks in the lowest CDSF loading quintile, with a t-statistics of 2.45 based on Newey-West standard errors using 18 lags. Average portfolio returns demonstrate a stable monotonic pattern that is increasing in CDSF sensitivity or distress risk. These findings are consistent with distress risk and return trade-off hypothesis. In Panel B of Table 8, we regress distress risk portfolios on Fama-French 5 factors, momentum factors, and liquidity factors (Pastor and Stambaugh (2003)). We find that the average return difference between high distress risk and low distress risk portfolio (HML portfolio) cannot be explained by those factors. Stocks with high distress risk tend to have lower market betas. It leads that the HML portfolio hedges the market risk (HML negatively loads on market factor with β_{mkt}=-0.18 with t-stats=-4.50.). It suggests the countercyclical behavior of distress risk portfolio yields positive risk premium during business downturns (e.g., U.S. stock market tanked during global financial).

Chan and Chen (1991) found that small firms are less likely to survive adverse throughout the bad economic conditions than large firms and hence size portfolio (small size firms minus large size firms) earn high average returns. We find that the distress risk portfolio significantly and positively loads on the size portfolio with β_{smb}=0.22, t-stats=4.05. Thus our finding is consistent with Chan and Chen (1991) that small size portfolio is more distressed. Additionally, Fama and French (1996) argued that distress risk is also the underlying cause of the value premium. However, we do not find the evidence that value portfolio significantly reflects distress risk in our data sample. Furthermore, we also find that distress risk portfolio is positively related to momentum factor and negatively related to investment factor and liquidity factor.

Next, we investigate whether our distress risk factor can explain momentum crashes. We find that the loading on momentum factor β_{mom}=0.14 with t-stats=1.92 is completely explained by including the momentum crashes dummy variable. Thus we conjecture that the failure of momentum strategy is due to loser stocks bear higher distress risk than winner stocks during the crashes period. To empirically examine this, we plot the momentum portfolios with y (hml portfolio from Table 8) in the Panel A of Figure 7; We plot the loser portfolio with the high distress risk portfolio (low CDS beta portfolio in Table 8) in the Panel B of Figure 7; We also plot the winner portfolio with the low distress risk portfolio (high CDS beta portfolio in Table 8) in the Panel C of Figure 7.

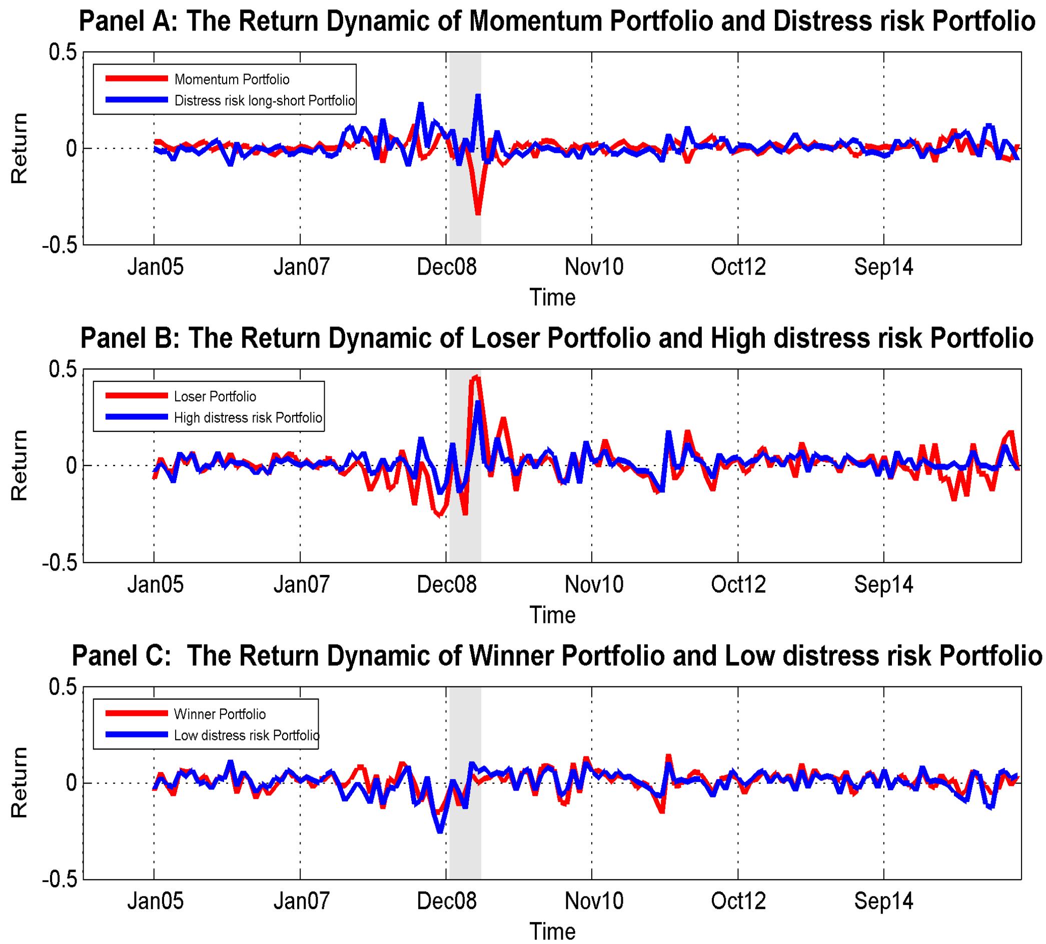

Figure 7

As shown from Panel B and Panel C, during the momentum crashes period (2009 Spring), the return dynamic of loser portfolio is highly correlated with high distress risk portfolio; the return dynamic of winner portfolio is highly correlated with low distress risk portfolio. This captures the out-performance of the loser portfolio during crashes period.

Insert Table 9 about here

We next move on to regression analysis. In the column (1)-(2) of Table 9, we regress loser portfolio and winner portfolio on the momentum crashes period (200812-200904). Consistent with the existing literature, the loser portfolio experience a significant rebounce (0.145%, t-stat=3.31) in the post global financial crisis period while the return of winner portfolio drops (-0.017, t-stat=-3.40). The magnitude of the loser rebounce is 8.59 (=0.145/0.017) times larger than that of winner portfolio. In the column (3)-(4), we regress the HighDistress(p5 is taken from Table 8. This is the portfolio with the most distress risk) on the interaction of loser portfolio and momentum crashes period. We find that HighDistress is significantly positive related to the rebounce of the loser portfolio (Loser$\times$MomCrashes=0.321, t-stat=3.30); while the LowDistress(p1 is taken from Table 8. This is the portfolio with the least distress risk) is also positively related to the dynamic of the winner portfolio. In the column (5)-(6), we show that our finding remains consistent after controlling for Fama-French 2015 risk factors. Overall, the result suggests that the reverse of loser portfolio is due to the high exposure to distress risk during the momentum crashes period. It shows that the momentum crashes can be essentially explained by the distress risk nature of firms.

9. Robustness

In this section, we conduct several further analyses to show the robustness of our findings. We first examine how the trading profits would look like if we incorporate the trading costs in CDS market? Since the strategy requires daily re-balancing, the abnormal return may decline quickly after taking into account transaction costs. Relatedly, we construct the strategy by replacing daily frequency sample into monthly frequency sample. Lastly, we examine whether the results are driven by the short-term fluctuation of the asset prices.

9.1. Does the profitability explain by transaction cost?

In the previous analysis, we do not impose transaction cost in the trading strategy. In this subsection, we explore how the trading profits would look like if the transaction costs are imposed. We follow DeMiguel, Nogales, and Uppal (2014) to measure the impact of proportional transactions costs on the performance of the strategy. Particularly, the portfolio returns net of transactions costs is defined as $r^p_{t+1} = (1 - c\sum_{j=1}^{N} |w_{j,t} - w_{j,t-1}|)w'_t r_{t+1}$ where $w_{j,t-1}$ is the portfolio weight in asset j at time t before rebalancing; $w_{j,t}$ is the portfolio weight at time t after rebalancing; c is the proportional transaction cost; w_t is the vector of portfolio weights; and r_{t+1} is the vector of returns. In our analysis, we mainly consider the equal-weighting aggregating rule (also term as native aggregation rule). We also restrict $w_{j,t-1} = 0$ in order to make our result more conservative. We consider the propositional trading cost as 1bps, 5bps, 10bps, 20bps, 30bps, 40bps, and 50bps.

<u>Insert Table 10 about here</u>

As shown in Table 10, the results are generally robust to impose transaction cost up to 50bps for each Single-name CDS across all firms. The average returns for the case of 40bps is about 12% p.a., which is significant at 1% level and reduces to zero when c=50bps. The performance of stock-based trading strategy is worse than the CDS-based trading strategy.

9.2. Can the profitability persist for the longer horizon?

In this subsection, we construct the strategy by replacing the daily frequency sample into monthly frequency sample.

<u>Insert Table 11A and 11B about here</u>

Table 11A and 11B report the robustness results. As shown in Table 11A, not surprisingly, the monthly rebalance CDS trading strategy yield smaller average returns than the corresponding daily rebalance CDS trading strategy in Table 5A because some of the profitability might average out across monthly horizon. Nevertheless, the majority of the long-short portfolios are still highly statistically significant with 1 percent significant level. In sharp contrast, all stock-based trading strategy portfolios are insignificant in monthly horizon (Table 11B). Overall, our monthly rebalance strategy results remain consistent to the daily rebalance strategy.

9.3. Does short-term price fluctuation drive the result?

In this subsection, we report the double sorting results by interacting daily protection returns with past 1-day protection returns as well as contemporaneous stock returns in order to control the temporal price fluctuation. At the beginning of each day t, we independently sort CDSs into five groups based on their last 1-day protection returns and five groups based on the stock returns at the day t, and construct CDS-based trading strategy by buying the lowest past stock quintile portfolio and selling the highest past stock quintile portfolio. Table 12 reports the average protection return of each portfolio and the associated Newey-West t-statistics with 18 lags.

Insert Table 12 about here

Panel A reports the double sorting results controlling for past 1-day protection returns. As we can see, the long-short portfolio (Lowest minus highest) generate the significantly positive return. In Panel B, we control for contemporaneous stock returns. For each quintile portfolio, the long-short portfolio of the CDS is consistently generate the significantly positive returns. Thus our finding cannot be explained by the short-term asset prices reversals.

10. Conclusion

This is the first paper to conduct the trading strategy using the price spillover effect from stock and CDS market and find remarkably large and persist trading profit in CDS market. The profitability, however, cannot explained by market selection hypothesis, which suggests the sluggish price adjustment of CDS market due to lack of informed trading generates the empirical finding. We address this issue by proposing an alternative market segmentation hypothesis to better explain the empirical finding. In addition, we propose three testable prediction based on the market segmentation hypothesis. We test them empirically and we show that proposed predictions are not rejected by data. Thus, our market segmentation hypothesis complements the disadvantage of market selection hypothesis. Lastly, we find that the return dynamic of CDS market based trading strategy is priced in the U.S. equity market. This is the direct evidence positive distress risk and return trade-off. Using U.S. stocks as test sample, we find that stocks with high sensitivity to the CDS risk factor earn higher return than stocks with low sensitivity to the CDS risk factor. Moreover, we find that the momentum crashes is because loser stocks bear more distress risk thus earn higher distress risk premium than winner stocks. Thus we shed new light on understanding the distress risk puzzle and momentum crashes puzzle.

More broadly, our analysis implies that CDS market needs to be more regulated and needs to be more standardized in order to reduce the information asymmetry between informed traders and hedgers. Of course, one of the most efficient solution to reduce the hedging cost is to establish the electronic platform for CDS market, yet it requires tremendously time, resources and effort. In this study, we provide an alternative way for the overall hedgers in CDS market to get sense of the fair value of CDS prices by looking at equity market under the same reference entity. It might serve as an alternative channel to reduce the information asymmetry thereby hedging cost.

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Table 1 reports the summary statistics of the sample used in our analysis.

(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Obs	Mean	S.D.	0.25 P	Mdn	0.75 P
Panel A: Full sample						
r_t	2137341	0.04	2.13	-0.96	0.00	1.02
ΔCDS_t	2137341	0.00	2.66	-0.66	0.00	0.49
P_t	2137341	48.73	67.58	18.38	35.26	57.4
$SIZE_t$ billion	2137341	1.84	1.51	0.92	1.93	2.9
CDS_t	2137341	171.82	308.12	42.5	83.1	180.37
STK BA Spread (%)	2137341	0.56	1.59	0.03	0.07	0.32
Panel B: Investment						
r_t	1386441	0.05	1.87	-0.86	0.03	0.96
ΔCDS_t	1386441	-0.01	2.59	-0.72	0.00	0.53
P_t	1386441	55.84	63.52	25.81	42.82	64.86
$SIZE_t$ billion	1386441	2.31	1.32	1.43	2.36	3.23
CDS_t	1386441	105.56	166.01	36.92	66.31	118.83
STK BA Spread (%)	1386441	0.47	1.46	0.02	0.05	0.19
Panel C: Speculative						
r_t	458215	0.02	2.71	-1.25	0.00	1.26
ΔCDS_t	458215	0.02	2.58	-0.62	0.00	0.51
P_t	458215	37.95	88.66	10.65	21.4	38.39
$SIZE_t$ billion	458215	1.07	1.27	0.21	1.05	1.96
CDS_t	458215	365.24	472.43	109.68	238.99	435.81
STK BA Spread (%)	458215	0.41	1.38	0.04	0.09	0.24
Panel D: No rating						
r_t	292685	0.02	2.26	-1.03	0.00	1.07
ΔCDS_t	292685	-0.01	3.04	-0.39	0.00	0.22
P_t	292685	31.9	35.0	9.96	21.83	41.89
$SIZE_t$ billion	292685	0.83	1.72	-0.01	1.12	2.02
CDS_t	292685	182.89	365.86	40.07	82.71	209.34
STK BA Spread (%)	292685	1.18	2.19	0.07	0.36	1.71

Table 2 reports following empirical specification:

$$\Delta CDS_{j,i,t} = a_0 + b_1 r_{j,i,t-1} + b_2 \Delta CDS_{j,i,t-1} + X_{j,i}\gamma_1' + \eta_j + e_{j,i,t}$$

where the dependent variable, $\Delta CDS_{j,i,t}$, is the credit protection return for firm i in country j over day t. The main variable of interest, $r_{j,i,t-1}$, is stock return for firm i in country j over day t-1. The alternative hypothesis for b_1 is $b_1 < 0$. The control variable includes $\Delta CDS_{j,i,t-1}$, the 1 day lag credit protection return to control for autocorrelation. The other control variables include market risk factor, market size (in $US billion), and stock bid-ask spread (in $US dollar). In addition, we control for firm fixed effect η_j (Our sample covers U.S., UK, Japan and Euro.). Standard errors are adjusted for heteroskedasticity and clusterd by date. To control for outliers, all variables are winsorized at the 0.1% and 99.9% levels. Column (1) is the full sample estimation from 2002 to 2016. Column (2) is sub-sample estimation by considering investment graded (rating above or equal BBB)firms. Column (3) is sub-sample estimation by considering investment graded firms (rating below BBB).Column (4)-(6) report the sub-sample estimation by spliting the sample into before 2007, 2007-2008 (GFC), and after 2008.

	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample	Invest	Speculative	< 2007	$2007, 2008$	> 2008
	$\Delta CDS_{j,i,t}$	$\Delta CDS_{j,i,t}$	$\Delta CDS_{j,i,t}$	$\Delta CDS_{j,i,t}$	$\Delta CDS_{j,i,t}$	$\Delta CDS_{j,i,t}$
$r_{j,i,t-1}$, (b_1)	-0.123***	-0.137***	-0.111***	-0.097***	-0.137***	-0.124***
	(0.005)	(0.006)	(0.004)	(0.006)	(0.014)	(0.005)
$\Delta CDS_{j,i,t-1}$, (b_2)	0.069***	0.082***	0.073***	0.002	0.163***	0.066***
	(0.005)	(0.006)	(0.006)	(0.006)	(0.015)	(0.007)
$r_{j,t}^{market factor}$, (γ_1)	-0.392***	-0.420***	-0.383***	-0.156***	-0.375***	-0.514***
	(0.017)	(0.019)	(0.019)	(0.019)	(0.035)	(0.022)
$SIZE_{j,i,t-1}$, (γ_2)	0.001**	0.001**	0.001	-0.001	-0.001	0.001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.003)	(0.001)
$BA_{j,i,t-1}$, (γ_3)	0.059***	0.056***	0.035	0.059***	0.012	0.011
	(0.016)	(0.018)	(0.022)	(0.020)	(0.043)	(0.016)
Constant, (a_0)	-0.016	-0.027	0.022	-0.058***	0.225***	-0.032
	(0.016)	(0.020)	(0.014)	(0.023)	(0.079)	(0.027)
Observations	2,136,200	1,385,853	457,950	749,346	340,842	1,046,012
R-squared	0.051	0.060	0.053	0.009	0.093	0.088
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Countries	All	All	All	All	All	All
Cluster	Yes	Yes	Yes	Yes	Yes	Yes

Table 3 reports following empirical specification:

$$r_{j,i,t} = a_0 + b_1 r_{j,i,t-1} + b_2 \Delta CDS_{j,i,t-1} + b_3 r_{j,i,t-2} + X_{j,i}\gamma_2 + \eta_j + e_{j,i,t}$$

where the dependent variable, $r_{j,i,t}$, is the stock return for firm i in country j over day t. The first variable of interest, $\Delta CDS_{j,i,t-1}$, is credit protection return for firm i in country j over day t-1. The alternative hypothesis to test informed investor's credit risk transfer effect is $b_2 < 0$. The second variable of interest is , $r_{j,i,t-1}$, the 1 period lag stock returns. This is to test the return reversal due to informed investor spillover from t to t+1 according to theory. The control variables include market risk factor, market size (in \$US billion), and stock bid-ask spread (in \$US dollar). In addition, we control for firm fixed effect η_j (Our sample covers U.S., UK, Japan and Euro.). Standard errors are adjusted for heteroskedasticity and clusterd by date. To control for outliers, all variables are winsorized at the 0.1% and 99.9% levels.Column (1) is the full sample estimation from 2002 to 2016. Column (2) is sub-sample estimation by considering investment graded (rating above or equal BBB)firms. Column (3) is sub-sample estimation by considering investment graded firms (rating below BBB).Column (4)-(6) report the sub-sample estimation by spliting the sample into before 2007, 2007-2008 (GFC), and after 2008.

	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample	Invest	Speculative	< 2007	$2007, 2008$	> 2008
	$r_{j,i,t}$	$r_{j,i,t}$	$r_{j,i,t}$	$r_{j,i,t}$	$r_{j,i,t}$	$r_{j,i,t}$
$\Delta CDS_{j,i,t-1}$,(b_2)	-0.008***	-0.005***	-0.014***	-0.005***	-0.008**	-0.008***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.004)	(0.002)
$r_{j,i,t-1}$,(b_1)	-0.009***	-0.021***	0.019***	-0.021***	-0.010	-0.003
	(0.003)	(0.003)	(0.004)	(0.004)	(0.008)	(0.004)
$r_{j,t}^{market factor}$,(γ_1)	0.917***	0.886***	1.055***	0.897***	0.820***	1.005***
	(0.013)	(0.011)	(0.022)	(0.008)	(0.025)	(0.006)
$SIZE_{j,i,t-1}$,(γ_2)	-0.001***	-0.001***	-0.001*	-0.003***	-0.002	-0.002***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
$BA_{j,i,t-1}$,(γ_3)	-0.025***	-0.027***	0.015	-0.013	-0.059**	-0.028***
	(0.008)	(0.008)	(0.020)	(0.012)	(0.024)	(0.009)
Constant,(a_0)	0.042***	0.062***	-0.007	0.089***	0.028	0.043***
	(0.007)	(0.007)	(0.011)	(0.010)	(0.040)	(0.010)
Observations	2,135,064	1,385,266	457,685	748,429	340,754	1,045,881
R-squared	0.305	0.346	0.276	0.217	0.349	0.338
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Countries	All	All	All	All	All	All
Cluster	YES	YES	YES	YES	YES	YES

Table 4 reports the profitability of two-period trading strategy. We first sort the protection returns into 5 portfolios based on their stock returns at t-2 and track 1-day post-formation equal-weighted quintile portfolio of protection returns. Second, stocks are sorted into quintile portfolios based on their protection returns at t-1 and we track 1-day post-formation equal-weighted stock returns. Third, we combine the first and second steps portfolio returns by summing portfolios with most negative stock returns at t-2, e.g. 1-day post formation protection returns at t-1, and portfolios with most positive protection return at t-1, e.g. 1-day post formation stock returns at t-1. We denote it as 'Lowest'. We summing portfolios with second most negative stock returns at t-2 and portfolio with second most positive protection returns at t-1. We denote it as 'P2'. 'P3', 'P4' and 'Highest' portfolio can be constructed in a similar way. We expect 'Lowest' portfolio would generate most significant return. As we can see from the construction, the strategy is free from look-ahead bias. US Invest indicates portfolio formed by US firms with credit rating above or equal BBB. US Speculate indicates portfolio formed by US firms with credit rating below BBB. It is similar to US, Japan, and Euro. Since we do not have enough firms to conduct such strategy for speculative group of Japan and UK, we remove them from the sample. The average portfolio returns are reported in daily basis point. We use ***, **, * to denote that the null of two tail Newly-West T-test with 18 lags is rejected at the 1%, 5%, and 10% level, respectively. SR indicates daily sharpe ratio.

	Lowest	P2	P3	P4	Highest	LMH
All firms						
Mean(bps)	18.77***	3.19	4.44	3.48	-7.54**	26.31***
T-stats	6.04	1.13	1.53	1.25	-2.57	13.26
SR	0.10	0.02	0.03	0.02	-0.04	0.27
US Invest						
Mean(bps)	19.47***	5.25*	4.75*	0.61	-6.22*	25.80***
T-stats	5.75	1.80	1.67	0.22	-1.97	10.91
SR	0.10	0.03	0.03	0.00	-0.03	0.25
US Speculate						
Mean(bps)	28.84***	8.08**	8.23**	0.55	-13.96***	42.91***
T-stats	7.28	2.48	2.49	0.17	-3.76	10.25
SR	0.11	0.04	0.04	0.00	-0.06	0.20
UK Invest						
Mean(bps)	13.83**	2.59	2.15	5.77	-0.93	14.70***
T-stats	2.53	0.54	0.44	1.12	-0.19	3.35
SR	0.05	0.01	0.01	0.02	0.00	0.06
Japan Invest						
Mean(bps)	2.38	-5.83	3.02	-2.35	-2.05	6.90
T-stats	0.34	-0.85	0.48	-0.36	-0.31	0.94
SR	0.01	-0.02	0.01	-0.01	-0.01	0.02
Euro Invest						
Mean(bps)	12.38***	7.33*	3.02	-0.35	-4.91	17.91***
T-stats	2.78	1.83	0.73	-0.09	-1.13	5.49
SR	0.05	0.03	0.01	0.00	-0.02	0.09
Euro Speculative						
Mean(bps)	7.32	3.32	-0.50	-1.60	-10.96**	19.53***
T-stats	1.28	0.64	-0.11	-0.31	-2.06	2.92
SR	0.02	0.01	0.00	0.00	-0.03	0.05

Table 5A is the performance of daily rebalanced CDS-based portfolio. Particular, we sort the credit protection returns into 5 portfolios based on their stock returns at t-2 and track 1-day post-formation equal-weighted quintile portfolio of protection returns. US Invest indicates portfolio formed by US firms with credit rating above or equal BBB. US Speculate indicates portfolio formed by US firms with credit rating below BBB. It is similar to U.S., Japan, and Euro. Since we do not have enough firms to conduct such strategy for speculative group of Japan and UK, we remove them from the sample. The average portfolio returns are reported in daily basis point. We use ***, **, * to denote that the null of two tail Newly-West T-test with 18 lags is rejected at the 1%, 5%, and 10% level, respectively. SR indicates daily sharpe ratio.

	Lowest	P2	P3	P4	Highest	LMH
All Firms						
Mean(bps)	13.49***	1.36	-1.38	-3.96	-9.21**	22.69***
T-stats	3.46	0.39	-0.41	-1.17	-2.50	13.61
SR	0.1	0.01	-0.01	-0.03	-0.07	0.26
US Invest						
Mean(bps)	7.65**	-2.29	-3.66	-6.73**	-10.6***	18.25***
T-stats	2.38	-0.76	-1.26	-2.30	-3.52	15.48
SR	0.07	-0.02	-0.04	-0.07	-0.10	0.30
US Speculate						
Mean(bps)	16.37***	1.53	-1.81	-6.19**	-14.62***	31.03***
T-stats	4.94	0.50	-0.62	-2.10	-4.67	17.47
SR	0.01	0.00	-0.01	-0.01	-0.02	0.06
UK Invest						
Mean(bps)	9.56	-0.54	0.64	-4.52	-6.78	13.61***
T-stats	1.74	-0.11	0.13	-0.89	-1.37	4.14
SR	0.01	0.00	-0.01	-0.01	-0.02	0.06
Japan Invest						
Mean(bps)	-5.88	-0.02	-1.12	-6.76	-10.65	2.28
T-stats	-0.83	0.00	-0.15	-0.90	-1.55	0.36
SR	0.01	0.00	-0.01	-0.01	-0.02	0.06
Euro Invest						
Mean(bps)	6.54	1.69	-2.51	-4.62	-9.57**	16.02***
T-stats	1.46	0.38	-0.57	-1.13	-2.22	7.82
SR	0.01	0.00	-0.01	-0.01	-0.02	0.06
Euro Speculative						
Mean(bps)	12.37**	6.96	-0.06	-3.40	-7.91*	18.47***
T-stats	2.39	1.45	-0.01	-0.67	-1.85	4.48
SR	0.01	0.00	-0.01	-0.01	-0.02	0.06

Table 5B is the performance of daily rebalance stock-based portfolio. Particularly, we sort stocks into quintile portfolios based on their protection returns at t-1 and we track 1-day post-formation equal-weighted stock returns. US Invest indicates portfolio formed by US firms with credit rating above or equal BBB. US Speculate indicates portfolio formed by US firms with credit rating below BBB. It is similar to U.S., Japan, and Euro. Since we do not have enough firms to conduct such strategy for speculative group of Japan and UK, we remove them from the sample. The average portfolio returns are reported in daily basis point. We use ***, **, * to denote that the null of two tail Newly-West T-test with 18 lags is rejected at the 1%, 5%, and 10% level, respectively. SR indicates daily sharpe ratio.

	Lowest	P2	P3	P4	Highest	LMH
All Firms						
Mean(bps)	5.10**	3.50	4.91**	5.75***	3.45	1.66**
T-stats	2.31	1.65	2.42	2.74	1.50	2.03
SR	0.18	0.13	0.19	0.21	0.12	0.17
US Invest						
Mean(bps)	7.09***	6.57***	5.93***	5.43***	4.53**	2.56***
T-stats	3.51	3.24	2.92	2.78	2.05	3.22
SR	0.05	0.05	0.04	0.04	0.03	0.05
US Speculate						
Mean(bps)	8.90**	6.66*	5.73*	3.46	-1.46	10.36***
T-stats	2.51	1.97	1.74	1.06	-0.38	4.40
SR	0.04	0.04	0.03	0.02	-0.01	0.08
UK Invest						
Mean(bps)	1.65	3.04	3.42	4.75**	4.53*	-2.15
T-stats	0.64	1.47	1.41	2.02	1.83	-0.89
SR	0.01	0.02	0.02	0.03	0.03	-0.01
Japan Invest						
Mean(bps)	6.18**	3.64	3.24	0.96	3.31	2.30
T-stats	2.02	1.24	1.00	0.29	1.01	0.77
SR	0.03	0.02	0.02	0.00	0.02	0.01
Euro Invest						
Mean(bps)	1.86	4.98**	4.22*	0.58	2.19	-0.24
T-stats	0.81	2.13	1.95	0.23	0.88	-0.15
SR	0.01	0.04	0.03	0.00	0.01	0.00
Euro Speculative						
Mean(bps)	-3.73	-2.29	-4.48	-4.99	-7.17*	3.20
T-stats	-0.93	-0.64	-1.42	-1.38	-1.83	0.85
SR	-0.02	-0.01	-0.02	-0.02	-0.03	0.01

Table 6:: We conduct bivariate portfolio analysis by controlling for number of quote counts, number of market makers, and 5 year CDS bid-ask spread respectively. In order to obtain enough stocks in our portfolio, we pool all firms in the analysis. Specifically, at each day t, we partition CDS returns into three groups based on one informed trading proxy. Then we independently sort CDS returns into 5 quintiles based on their past 1-day stock return (stock return at day t-1). Lastly, we construct a spread portfolio by buying the portfolios with most negative day t-1 stock returns and selling the portfolio with most positive day t-1 stock returns within each informed trading group. The average portfolio returns are reported in daily basis point. We use ***, **, * to denote that the null of two tail Newly-West T-test with 18 lags is rejected at the 1%, 5%, and 10% level, respectively. SR indicates daily sharpe ratio.

				Panel A:quote count				
	Lowest	P2	P3	P4	Highest	LMH	T-stats	SR
quote=0	3.64	0.33	-1.15	2.23	-0.42	4.06	1.37	0.04
quote$\leq$ 13	11.20	3.77	-1.08	1.67	-2.83	13.86***	3.53	0.11
quote$>$13	18.97	3.20	-1.51	-3.58	-12.64	32.25***	12.33	0.43
				Panel B:dealer count				
	Lowest	P2	P3	P4	Highest	LMH	T-stats	SR
market maker=0	3.66	0.49	-1.22	2.23	-0.67	4.32	1.46	0.04
market maker$\leq$3	15.41	4.25	1.18	1.68	-3.34	18.44***	5.00	0.16
market maker$>$3	17.77	2.96	-2.55	-4.03	-13.19	31.73***	12.14	0.43
				Panel C:CDS bid-ask spread				
	Lowest	P2	P3	P4	Highest	LMH	T-stats	SR
Least Liquid	-2.83	-3.67	-6.58	-2.99	-6.63	3.80	1.35	0.04
Med Liquid	10.60	2.85	-0.58	-1.44	-4.45	15.05***	6.44	0.18
Most Liquid	24.69	10.13	8.46	1.48	-8.93	33.63***	11.94	0.37

Table 7 reports that CDS leading effect is more pronounced contingent on poor credit rating and bad news. Panel A reports following empirical specification:

$$r_{j,i,t} = a + \beta_1 * SPECU \times \Delta CDS_{j,i,t-1} + \beta_2 * SPECU + \beta_3 * \Delta CDS_{j,i,t-1} + \beta_4 * r_{j,i,t-1} + \beta_5 * r_{j,i,t-2} + X_{j,i}\gamma_1' + \eta_j + e_{j,i,t}$$

where *SPECU* is dummy variable that equals to 1 if rating of reference entity is below BBB, zero otherwise.
Panel B reports following specification:

$$r_{j,i,t} = a + \beta_1 * SPECU \times \Delta CDS_{j,i,t-1} I[r_{j,i,t-2} < 0] + \beta_2 * SPECU \times \Delta CDS_{j,i,t-1} I[r_{j,i,t-2} \geq 0] + \beta_3 * SPECU + \beta_4 * \Delta CDS_{j,i,t-1} + \beta_5 * r_{j,i,t-1} + \beta_6 * r_{j,i,t-2} + X_{j,i}\gamma_1' + \eta_j + e_{j,i,t}$$

we partition the $SPECU \times \Delta CDS_{j,i,t-1}$ by indicating variables $I[r_{j,i,t-2} < 0]$ and $I[r_{j,i,t-2} \geq 0]$. The proxy for bad credit news, $I[r_{j,i,t-2} < 0]$, indicates dummy variable that equals to 1 if stock return by day t-2 is negative.The control variable includes $r_{j,i,t-2}$, the 2 day lag stock return to control for autocorrelation. The other control variables include market risk factor, market size(in $US billion), and stock bid-ask spread(in $US dollar). We control for firm fixed effect η_j (Our sample covers U.S., UK, Japan and Euro.). Standard errors are adjusted for heteroskedasticity and clusterd by date. To control for outliers, all variables are winsorized at the 0.1% and 99.9% levels. Column (1) is the full sample estimation from 2002 to 2016.Column (4)-(6) report the sub-sample estimation by spliting the sample into before 2007, 2007-2008 (GFC), and after 2008 respectively.

	(1) Full Sample $r_{j,i,t}$	(2) < 2007 $r_{j,i,t}$	(3) $2007, 2008$ $r_{j,i,t}$	(4) > 2008 $r_{j,i,t}$
Panel A:				
$SPECU \times \Delta CDS_{j,i,t-1}$,($\beta_1$)	-0.013***	-0.005**	-0.015***	-0.016***
	(0.002)	(0.003)	(0.005)	(0.003)
$\Delta CDS_{j,i,t-1}$,(β_2)	-0.005***	-0.004***	-0.005	-0.005***
	(0.001)	(0.001)	(0.003)	(0.002)
Observations	2,135,064	748,429	340,754	1,045,881
R-squared	0.305	0.217	0.349	0.338
Countrols and Constant	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Countries	All	All	All	All
Cluster	Yes	Yes	Yes	Yes
Panel B:				
$SPECU \times \Delta CDS_{j,i,t-1} \times I[r_{j,i,t-2} < 0]$,($\beta_1$)	-0.018***	-0.009**	-0.020***	-0.019***
	(0.003)	(0.003)	(0.006)	(0.005)
$SPECU \times \Delta CDS_{j,i,t-1} \times I[r_{j,i,t-2} \geq 0]$,($\beta_2$)	-0.008***	-0.001	-0.007	-0.012***
	(0.003)	(0.003)	(0.007)	(0.004)
$\Delta CDS_{j,i,t-1}$	-0.005***	-0.004***	-0.005	-0.005***
	(0.001)	(0.001)	(0.003)	(0.002)
Observations	2,135,064	748,429	340,754	1,045,881
R-squared	0.305	0.217	0.349	0.338
Countrols and Constant	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Countries	All	All	All	All
Cluster	Yes	Yes	Yes	Yes

Table 8: We run time-series regression for each stock i based on past 5 years rolling window from 2002-2016.

$$R_{i,t} = \alpha_i + \beta_i^{\tau} CDSF_t + e_{i,t}$$

where τ indexes for rolling estimated β_i. $CDSF_t$ is return dynamic of CDS-based trading strategy compuated across US speculative grade firms. We collect all the $\hat{\beta}_i^{\tau}$. Next we group stocks into 5 quintile portfolio based on $\hat{\beta}_i^{\tau}$ each month. The sample average return (Ave.Ret) and T-statistics (T-stat) are reported in the first row and second row of the table respectively. We also report the equal-weighted CDS beta in the last row of the table. 'low' is the lowest quintile CDS beta portfolio. 'p2' is the second lowest quintile CDS beta portfolio so on so forth. hml is the long short portfolio between high and low. In Panel B, we regress portfolios from Panel A on Fama-French 5 factors, momentum factors, and liquidity factors. Factor loadings and alphas are reported respectively. Newly-West T-test with 18 lags is reported in the brackets.

Panel A: Raw returns						
	Low	P2	P3	P4	High	HML
Ave.Ret (%)	-0.11	0.31	0.47	0.61	0.68	0.79
T-stat	-(0.18)	(0.66)	(1.15)	(1.52)	(1.37)	(2.45)
CDS beta	-0.58	-0.17	-0.02	0.13	0.56	
Panel B: Alpha						
	Low	P2	P3	P4	High	HML
α	-0.14	0.31	0.53	0.77	0.89	1.03
	-(0.21)	(0.58)	(1.25)	(2.38)	(2.18)	(2.22)
β_{mkt}	0.34	0.27	0.18	0.14	0.17	-0.18
	(1.92)	(1.58)	(1.19)	(0.97)	(0.97)	-(4.50)
β_{smb}	-0.50	-0.40	-0.31	-0.28	-0.28	0.22
	-(2.38)	-(2.14)	-(2.24)	-(2.80)	-(3.04)	(4.05)
β_{hml}	-0.26	-0.25	-0.20	-0.18	-0.22	0.05
	-(2.14)	-(1.91)	-(1.53)	-(1.62)	-(1.63)	(0.82)
β_{rmw}	-0.39	-0.31	-0.32	-0.44	-0.46	-0.07
	-(0.98)	-(0.96)	-(1.08)	-(1.54)	-(1.41)	-(0.38)
β_{cma}	0.13	0.08	-0.04	-0.17	-0.31	-0.44
	(0.42)	(0.31)	-(0.17)	-(0.67)	-(0.98)	-(2.93)
β_{mom}	-0.22	-0.16	-0.12	-0.10	-0.08	0.14
	-(5.43)	-(3.51)	-(3.77)	-(4.36)	-(2.82)	(1.92)
β_{liq}	-0.07	-0.10	-0.13	-0.21	-0.32	-0.25
	-(0.82)	-(1.20)	-(1.65)	-(2.01)	-(2.30)	-(3.14)
R-square	14.0%	13.1%	10.6%	11.3%	10.5%	11.8%

Table 9 reports the momentum crashes test result. HighDistress is the portfolio with largest CDS beta ('High') taken from Table 8. LowDistress is the portfolio with smallest CDS beta ('Low') from Table8. Loser is the loser portfolio of the momentum strategy. Winner is the winner portfolio of the momentum strategy. In the column (1) and (2), we regress loser and winner portfolio on the momentum crashes period (includes 200812-200904). In the column (3)-(4) we regress high distress risk portfolio and low distress risk portfolio on Loser × MomCrashes and Winner × MomCrashes respectively. In the column (5)-(6), we include Fama-French 5 factors as controls. Alpha indicates the abnormal return. Our sample period is from 200501 to 201605. ***, **, and * indicates the significance level at 1%, 5%, and 10% respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Loser	Winner	HighDistress	LowDistress	HighDistress	LowDistress
Alpha	-0.002	0.000	0.005	-0.004	0.007	-0.003
	(-0.27)	(0.00)	(1.10)	(-0.75)	(1.34)	(-0.63)
MomCrashes	0.145***	-0.017***	-0.011	0.049**	-0.019	0.044*
	(3.31)	(-3.40)	(-0.45)	(2.02)	(-0.70)	(1.67)
Loser×MomCrashes			0.321***		0.367***	
			(3.30)		(3.55)	
Winner×MomCrashes				0.849**		0.650
				(2.11)		(1.50)
Loser			0.030		0.053	
			(0.59)		(0.61)	
Winner				0.135		-0.022
				(1.57)		(-0.13)
MKT					-0.016	0.370
					(-0.09)	(1.58)
SMB					-0.376	-0.534**
					(-1.64)	(-2.11)
HML					-0.154	-0.007
					(-1.11)	(-0.05)
RMW					-0.646*	-0.413
					(-1.76)	(-1.12)
CMA					0.106	0.209
					(0.27)	(0.51)
N	137	137	137	137	137	137
R-sq	0.075	0.079	0.140	0.073	0.183	0.140
adj. R-sq	0.068	0.072	0.120	0.052	0.131	0.086

Table 10: We follow DeMiguel, Nogales and Uppal (2014) to measure the impact of proportional transactions costs on the performance of the strategy. Particularly, the portfolio returns net of transactions costs is defined as $r_{t+1}^{p} = (1 - c\sum_{j=1}^{N}|w_{j,t} - w_{j,t-1}|)w_t' r_{t+1}$ where $w_{j,t-1}$ is the portfolio weight in asset j at time t before rebalancing; $w_{j,t}$ is the portfolio weight at time t after rebalancing; c is the proportional transaction cost; w_t is the vector of portfolio weights; and r_{t+1} is the vector of returns. In our analysis, we mainly consider the equal-weighting aggregating rule (also term as native aggregation rule). We also restrict $w_{j,t-1} = 0$ in order to make our result more conservative. We consider the propositional trading cost as 1bps, 5bps, 10bps, 20bps, 30bps, 40bps, and 50bps. Panel A is the CDS-based trading strategy and Panel B is the stock-based trading strategy.

Panel A:CDS-based trading strategy						
	Lowest	P2	P3	P4	Highest	LMH(bps)
c=1bps	13.35	1.35	-1.37	-3.92	-9.12	22.24
c=5bps	12.81	1.29	-1.31	-3.76	-8.75	20.43
c=10bps	12.14	1.22	-1.24	-3.57	-8.29	18.16
c=20bps	10.79	0.56	-1.11	-3.17	-7.37	13.62
c=30bps	9.44	0.49	-0.97	-2.77	-6.45	9.08
c=40bps	8.09	0.42	-0.83	-2.38	-5.52	4.54
c=50bps	6.74	0.35	-0.69	-1.98	-4.60	0.00
Panel B:Stock-based trading strategy						
	Lowest	P2	P3	P4	Highest	LMH(bps)
c=1bps	5.05	3.46	4.86	5.70	3.42	1.63
c=5bps	4.84	3.32	4.66	5.47	3.28	1.49
c=10bps	4.59	3.15	4.42	5.18	3.11	1.33
c=20bps	4.08	2.80	3.93	4.60	2.76	1.00
c=30bps	3.57	2.45	3.44	4.03	2.42	0.66
c=40bps	3.06	2.10	2.94	3.45	2.07	0.33
c=50bps	2.55	1.75	2.45	2.88	1.73	0.00

Table 11A is the performance of monthly rebalanced CDS-based portfolio. Particular, we sort the credit protection returns into 5 portfolios based on their stock returns at t-2 and track 1-day post-formation equal-weighted quintile portfolio of protection returns. US Invest indicates portfolio formed by US firms with credit rating above or equal BBB. US Speculate indicates portfolio formed by US firms with credit rating below BBB. It is similar to U.S., Japan, and Euro. Since we do not have enough firms to conduct such strategy for speculative group of Japan and UK, we remove them from the sample. The average portfolio returns are reported in daily basis point. We use ***, **, * to denote that the null of two tail Newly-West T-test with 18 lags is rejected at the 1%, 5%, and 10% level, respectively. SR indicates monthly sharpe ratio.

All firms	Lowest	P2	P3	P4	Highest	LMH
Mean(%)	1.208	0.046	-0.538	-0.963	-1.761	2.746
T-stats	1.994	0.066	-0.724	-1.610	-2.786	6.705
SR	0.170	0.007	-0.076	-0.145	-0.262	0.588
US Invest						
Mean(%)	-0.277	-0.691	-0.962	-0.961	-1.505	1.253
T-stats	-0.772	-1.868	-2.345	-2.673	-4.019	8.125
SR	-0.071	-0.169	-0.239	-0.245	-0.385	0.555
US Speculate						
Mean(%)	0.315	-0.045	-0.701	-1.058	-1.448	1.776
T-stats	1.184	-0.125	-1.726	-2.731	-3.009	5.326
SR	0.074	-0.010	-0.164	-0.243	-0.315	0.474
UK Invest						
Mean(%)	-0.155	-0.942	-1.534	-0.994	-1.430	1.152
T-stats	-0.319	-1.843	-4.045	-2.246	-3.134	2.677
SR	-0.021	-0.135	-0.226	-0.135	-0.211	0.199
Japan Invest						
Mean(%)	-0.103	-1.329	-1.679	-1.280	-1.783	1.699
T-stats	-0.157	-2.575	-3.199	-1.626	-2.161	2.940
SR	-0.011	-0.175	-0.214	-0.169	-0.220	0.209
Euro Invest						
Mean(%)	-0.655	-0.890	-1.298	-1.230	-1.034	0.385
T-stats	-1.651	-1.560	-2.802	-2.686	-2.515	1.140
SR	-0.107	-0.143	-0.220	-0.206	-0.174	0.084
Euro Speculative						
Mean(%)	0.667	-0.742	-0.706	-0.790	-2.196	2.695
T-stats	1.320	-1.130	-0.858	-1.464	-3.656	3.942
SR	0.091	-0.101	-0.095	-0.105	-0.308	0.332

Table 11B is the performance of monthly rebalanced stock-based portfolio. Particular, we sort the credit protection returns into 5 portfolios based on their stock returns at t-2 and track 1-day post-formation equal-weighted quintile portfolio of protection returns. US Invest indicates portfolio formed by US firms with credit rating above or equal BBB. US Speculate indicates portfolio formed by US firms with credit rating below BBB. It is similar to U.S., Japan, and Euro. Since we do not have enough firms to conduct such strategy for speculative group of Japan and UK, we remove them from the sample. The average portfolio returns are reported in daily basis point. We use ***, **, * to denote that the null of two tail Newly-West T-test with 18 lags is rejected at the 1%, 5%, and 10% level, respectively. SR indicates monthly sharpe ratio.

All firms	Lowest	P2	P3	P4	Highest	LMH
Mean(%)	0.723	0.826	0.813	0.849	0.784	-0.078
T-stats	1.827	2.420	2.215	2.369	1.791	-0.301
SR	0.149	0.181	0.185	0.170	0.136	-0.031
US Invest						
Mean(%)	1.001	1.021	1.116	1.140	1.160	-0.158
T-stats	2.961	3.357	3.609	3.625	3.489	-0.839
SR	0.231	0.229	0.261	0.246	0.225	-0.066
US Speculate						
Mean(%)	1.128	0.764	0.607	0.636	0.344	0.423
T-stats	2.609	1.530	1.111	1.224	0.523	1.061
SR	0.160	0.120	0.094	0.092	0.049	0.074
UK Invest						
Mean(%)	0.562	0.580	0.611	0.732	0.660	-0.084
T-stats	1.192	1.459	1.938	1.842	1.890	-0.180
SR	0.110	0.135	0.122	0.158	0.132	-0.015
Japan Invest						
Mean(%)	0.488	0.992	-0.381	0.902	0.463	0.006
T-stats	0.853	2.169	-0.977	1.978	0.845	0.013
SR	0.063	0.141	-0.059	0.133	0.064	0.001
Euro Invest						
Mean(%)	0.239	0.421	0.498	0.502	0.400	-0.291
T-stats	0.456	0.894	1.092	1.041	0.862	-0.965
SR	0.042	0.081	0.089	0.085	0.072	-0.073
Euro Speculative						
Mean(%)	0.069	0.033	-0.561	-0.314	-0.628	0.532
T-stats	0.112	0.090	-0.794	-0.491	-1.076	1.123
SR	0.009	0.005	-0.075	-0.045	-0.087	0.066

Table 12 is the double sorting results by interacting daily protection returns with past 1-day protection returns as well as contemporaneous stock returns in order to control the temporal price fluctuation. At the beginning of each day t, we independently sort CDSs into five groups based on their last 1-day protection returns and five groups based on the stock returns at the day t, and construct CDS-based trading strategy by buying the lowest past stock quintile portfolio and selling the highest past stock quintile portfolio. Table 12 reports the average protection return of each portfolio and the associated Newey-West t-statistics with 18 lags. Panel A controls for ΔCDS_t; Panel B controls for R_t.

Panel A :Control for ΔCDS_t							
		P1	P2	P3	P4	P5	LMH
P1 ΔCDS_t	Mean(bps)	-2.40	-7.68	-7.36	-8.07	-14.35	15.60
	T-stats	-1.00	-3.35	-3.08	-3.38	-5.78	12.68
P2 ΔCDS_t	Mean(bps)	-12.95	-15.93	-15.90	-16.40	-15.78	5.52
	T-stats	-6.43	-7.92	-8.41	-8.26	-7.54	6.63
P3 ΔCDS_t	Mean(bps)	0.81	-3.32	-4.10	-3.19	-3.30	5.27
	T-stats	0.43	-1.85	-2.30	-1.81	-1.86	6.30
P4 ΔCDS_t	Mean(bps)	13.85	6.79	8.34	7.70	5.95	8.66
	T-stats	6.64	3.44	4.05	3.89	2.98	9.11
P5 ΔCDS_t	Mean(bps)	17.68	-0.34	-3.48	-4.26	-2.13	20.84
	T-stats	6.81	-0.14	-1.44	-1.79	-0.89	16.13
Panel B :Control for R_t							
		P1	P2	P3	P4	P5	LMH
P1 R_t	Mean(bps)	21.42	8.37	7.51	6.67	3.15	19.60
	T-stats	8.73	3.81	3.41	3.04	1.42	16.63
P2 R_t	Mean(bps)	2.23	-4.60	-3.72	-5.17	-6.39	9.96
	T-stats	1.08	-2.30	-1.91	-2.56	-3.23	10.15
P3 R_t	Mean(bps)	0.62	-5.81	-5.43	-6.52	-6.90	9.15
	T-stats	0.30	-2.96	-2.72	-3.22	-3.27	8.77
P4 R_t	Mean(bps)	0.42	-6.25	-5.49	-7.31	-8.20	10.65
	T-stats	0.20	-3.15	-2.77	-3.69	-3.90	10.34
P5 R_t	Mean(bps)	-1.79	-8.75	-8.93	-10.21	-12.60	13.10
	T-stats	-0.85	-4.63	-4.46	-4.81	-6.26	12.70

Table A1 reports the standard VAR system of lag order 1 is specified as following

$$r_{j,i,t} = \alpha_{0,j,i} + \alpha_{1,j,i} r_{j,i} + \alpha_{2,i} \Delta CDS_{j,i,t-1} + X_{j,i,t-1}\gamma_1' + e_{j,i,t}$$
$$\Delta CDS_{j,i,t} = \beta_{0,j,i} + \beta_{1,j,i} r_{j,i,t-1} + \beta_{2,i} \Delta CDS_{j,i,t-1} + X_{j,i}\gamma_2' + \varepsilon_{j,i,t}$$

where $r_{j,i,t}$ is stock return and $\Delta CDS_{j,i,t}$ is CDS protection return for firm i in country j at day t. t is the daily time subscript. The residuals for each firm i are checked to be stationary or I(0). $X_{j,i}$ is control variables including bid-ask spread(in $US dollar), market size(in $US billion) and market risk factor. Then we apply the VAR model on all firms in our sample. The null hypothesis is $\alpha_{1,j,i} = 0$ and $\beta_{1,j,i} = 0$ against alternative hypothesis where $\alpha_{1,j,i} < 0$ and $\beta_{1,j,i} < 0$. $\alpha_{1,j,i} < 0$ indicates that stock return negatively leads protection return. $\beta_{1,j,i} < 0$ indicates that protection return negatively leads stock return. Column (2) reports the average slope coefficient of first equation of VAR. Column (3) reports percentage cases that are 95% significant and positive. Column (4) reports percentage cases that are 95% significant and negative. Column (5) reports sum between column (3) and column (4). Column (6)-(9) are similar to column (2)-(5). Panel A reports the sub-sample estimates for investment group. Panel B reports the sub-sample estimates for speculative group.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Invest								
	r_t				$\Delta CDS_{j,i,t}$			
	Ave.Coef	Pos.Sig	Neg.Sig	Total	Ave.Coef	Pos.Sig	Neg.Sig	Total
r_{t-1}	α_1: -0.0236	13.57%	35.00%	48.57%	β_1: -0.1226	2.14%	64.46%	66.61%
$\Delta CDS_{j,i,t-1}$	α_2: -0.0021	7.50%	12.68%	20.18%	β_2: -0.0248	38.75%	40.89%	79.64%
Controls:								
$SIZE_{t-1}$	0.0022				0.0056			
$BA_{j,i,t-1}$	-0.0003				0.0097			
$r_{j,t}^{market factor}$	0.0038				-0.0046			
Rsquare	36.22%				8.99%			
Panel B: Speculative								
	r_t				$\Delta CDS_{j,i,t}$			
	Ave.Coef	Pos.Sig	Neg.Sig	Total	Ave.Coef	Pos.Sig	Neg.Sig	Total
r_{t-1}	α_1: 0.0129	23.97%	11.57%	35.54%	β_1: -0.1042	3.31%	54.55%	57.85%
$\Delta CDS_{j,i,t-1}$	α_2: -0.0094	4.96%	15.70%	20.66%	β_2: -0.0540	30.17%	45.87%	76.03%
Controls:								
$SIZE_{t-1}$	0.0023				-0.0027			
$BA_{j,i,t-1}$	-0.0012				0.0125			
$r_{j,t}^{market factor}$	0.0382				-0.0038			
Rsquare	28.29%				9.30%			