Transmigration across price discovery categories: Evidence from the U.S. CDS and equity markets

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October 22, 2011

Abstract

We examine credit risk price discovery between the equity market's implied credit default spreads (using RiskMetrics CreditGrade model) and credit default swap (CDS) spreads for 174 U.S. non-financial investment-grade firms between Jan 2005 and Dec 2009. Using Gonzalo-Granger (1995) and Hasbrouck (1995) measures, we sort firms into five categories of credit risk price discovery. When we forward-shift the estimation window, we uncover an interesting transmigration pattern. From Jan 2005 to Jun 2007, the CDS market influences price discovery for 92 firms. From Jan 2006 to Jun 2008, with the onset of the GFC, that number increases to 159 firms. As we move away from the height of the GFC, the number of CDS-influenced firms is reduced, but remains high compared to the pre-GFC period. Using CDS spreads as trading signals, a conditional portfolio strategy which updates the list of CDS-influenced firms produce a significant alpha against Fama-French factors. It also outperforms buy-and-hold, momentum and dividend yield strategies. Our empirical finding is consistent with theoretical arguments by Keynes (1923) and Working (1953) about the risk-sharing role of a derivative market. During the credit crunch induced GFC, risk-averse hedgers are willing to pay a larger premium for default protection. The substantially higher and volatile spreads present informed speculators with attractive trading opportunities in the CDS market that were not available before the GFC.

Keywords: Price discovery; CDS; Credit risk; Trading strategy.

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1 Introduction

The fundamental economic role of a derivative market is to facilitate risk-sharing and price discovery. As Working (1953) argues, robust trading interactions between hedgers and more informed speculators constitute a successful and liquid derivative market. This can be said for derivative markets operating under normal circumstances, for example, index futures markets before the October 1987 crash, as well as the credit default swap (CDS) market before the 2008 global financial crisis (GFC). Blanco et al (2005) find that the CDS market is more efficient than the bond market in reflecting credit risk information. Acharya and Johnson (2007) document that negative private information is first revealed in the CDS market before it is transmitted to the stock market.

An interesting question is whether such a role of derivative markets ceases to function properly during extreme events. For example, during the crash of October 1987, the price discovery mechanism of index futures markets were severely affected by the lack of liquidity and market-making to facilitate the trading process. Trade prices were few and far between, and they were extremely volatile. Quote prices factored in a huge premium for immediacy. During the GFC when financial markets were gripped with a systemic credit crunch, we naturally expect CDS spreads to be higher and more volatile as well. A time-series plot of the cross-sectional average CDS spread for our firm sample in Figure 1 shows that this is indeed the case. Accordingly, one may draw an analogy between the two financial crises and expect the U.S. CDS market's risk sharing and price discovery mechanism to be similarly impaired during the GFC.

INSERT FIGURE 1

In our study, we document a strikingly different picture regarding the price discovery mechanism of the U.S. CDS market during the course of the GFC. We find that, with the onset of the GFC, the CDS market took over price discovery leadership from the underlying equity market for nearly our entire sample of 174 firms. Although the equity market subsequently regained its price discovery leadership for some firms in the aftermath of the GFC, it remains less important than the CDS market in performing credit risk price discovery.

Why is the experience of the CDS market during the GFC evidently different from what was observed during the crash of October 1987? We argue that there is a crucial difference between the two crashes. During the crash of 1987, market participants experienced a liquidity crisis, which could not be hedged with index futures contracts. Merton Miller chaired a blue ribbon commission established by CME and CBOT to investigate the events surrounding October 1987. Grossman and Miller (1988) explain that, regardlessly of the cause, what was experienced during the October 1987 crash is essentially a liquidity crisis[1].

In contrast, the GFC is a credit crisis, and credit risk can be hedged with CDS contracts. Like all derivative markets, the CDS market facilitates risk-sharing. Keynes (1923) argues that risk averse hedgers will pay a premium to take positions against more informed speculators. Prior to mid-2007, when CDS spreads were low and tranquil, we argue that trading in the CDS market consisted mainly of commercial banks, pension funds and insurance firms through their uncorrelated hedging demand associated with idiosyncratic lending and investing activities. With the onset of the GFC, credit risk became a prime concern. Hedgers increased their demand for risk-sharing and were willing to pay a higher premium

[1] Before trading commenced on 19th October 1987, both spot and futures markets were simultaneously hit with massive sell-orders. Differences in opening procedures between NYSE and CME had caused a temporary breakdown in the spot-futures linkage, although it was restored at around 11AM New York time. However, efforts to absorb huge sell orders have sapped NYSE specialists and CME locals of their market-making resources. When the second wave of sell orders hit later that day, the crash was underway. In the aftermath of the crash, regulatory restrictions were imposed on program trading. Grossman and Miller (1988) argue that this cuts "the normal arbitrage linkage between the market makers in the spot and futures markets." By taking near simultaneous offsetting positions across both markets, arbitragers are able to transmit some the initial order imbalance over to be absorbed by the other market.

for protection against default. And it is the higher and more volatile spreads during the GFC that makes the CDS market attractive to informed speculators. Keynes's argument is also consistent with the observation that index futures markets did not attract sufficient informed speculators during the 1987 crash. Since liquidity risk was the main concern during that crash, it was not clear to informed speculators that the demand for hedging market risk would increase. Conversely, the main concern during the GFC was credit risk, and Keynes (1923) implies that a surge in demand and price offered by hedgers for credit risk-sharing during the GFC will attract more informed speculators into the CDS market.

Our main objective in this paper is to provide an empirical test of Keynes's proposition and examine whether the CDS market's price discovery ability is actually enhanced during the course of the GFC. By doing so, we offer a better understanding of the time-varying nature of cross-market credit risk information flow between the U.S. CDS market and equity market before, during and after the GFC. We note that our paper is not merely testing whether the GFC has imposed some structural break on cross-market credit-risk price discovery. Rather, our paper offers an insight into the nature of the structural break itself.

Our daily sample consists of 174 U.S. non-financial investment-grade firms between Jan 2005 and Dec 2009, which we sort into five price discovery categories using Gonzalo-Granger (1995) and Hasbrouck (1995) measures. We document a strong transmigration pattern, with firms moving into categories for which the CDS market influences price discovery. For the initial estimation window Jan 2005 to Jun 2007, the CDS market provides price leadership for 92 firms. For estimation windows that ended with Jun 2008 and Sep 2008, that number has increased to 159 and 156 firms respectively. As the estimation window moves away from 2008, the number of CDS-influenced firms decline, but remains high compared to the pre-GFC period. Our documented transmigration pattern suggests that, in the midst of the GFC, the CDS market has taken over credit risk price leadership from the equity market for nearly the entire firm sample. Trading strategies which take advantage of the price discovery ability of the CDS market to form portfolios in underlying stocks produce significant alpha against Fama-French factors and outperform other benchmark portfolio strategies. Our main findings are generated from a four-stage empirical analysis.

First, we use the RiskMetrics CreditGrade Model to extract a time series of implied credit default spreads (ICDS_{it}) from the stock prices of Firm $i = 1, 2, ..., 174$. This is aligned with the time series of corresponding observable CDS spreads (CDS_{it}). Conceptually, ICDS_{it} and CDS_{it} represent the price of credit risk. Empirically, ICDS_{it} and CDS_{it} are cointegrated.

Second, we apply both Gonzalo-Granger (1995) common-factor-weight (GG) and Hasbrouck (1995) information-share (HAS) measures to determine the credit risk price discovery contributions from the CDS and equity markets. We sort firms into five price discovery categories {C1,...,C5}. The latter represent a spectrum of cross-market price discovery status. As we move from C1 to C5, the price discovery contribution shifts from the CDS market to the equity market.

Third, we forward shift the estimation window on a quarterly basis to re-compute GG and HAS measures. This allows us to re-categorize firms across {C1,...,C5}. Over 11 rolling-window estimations, we are able to track the transmigration patterns of firms across {C1,...,C5} as we approach and move away from the height of the GFC. Our documented findings on transmigration patterns across price discovery categories can only come from measuring and updating GG and HAS measures on a quarterly basis for a large firm sample.

Fourth, we ascertain economic significance with five portfolio strategies {PS1,...,PS5}, all of which draw trading signals from the CDS market to trade corresponding stocks. These five strategies are designed to analyze the incremental profit/loss from identifying and updating the list of CDS-influenced firms during the test period, net of transaction cost. We evaluate profitability against two sets of benchmarks. First, we test the significance of each strategy's risk-adjusted realized return using Jensen's alpha (α_j) against Fama-French factors. Second, we benchmark our strategies against other proven portfolio strategies that are implemented using our firm sample over the same trading period, including buy-and-hold (B&H), momentum and dividend yield strategies.

We find strong evidence of cointegration between CDS_{it} and ICDS_{it} for 173 firms based on full sample estimation. Pre-GFC and GFC sub-sample testing confirms that the cointegrating relation remains for more than 160 firms during the GFC. This strongly suggests that the long-run credit risk pricing equilibrium between CDS_{it} and ICDS_{it} prevails for the majority of firms throughout the sample period. We attribute this to our improved calibration to extract ICDS_{it}. The presence of cointegration allows us to utilize GG and HAS measures to sort firms into price discovery categories.

We implement {PS1,...,PS5} using a threshold portfolio approach. Every Wednesday, we set a long (short) position in Firm i if, on Tuesday, we observe that the weekly $\Delta\text{CDS}_{it} < -20\%$ ($> 20\%$). The portfolio is liquidated next Wednesday, and a new portfolio is formed. PS2 and PS3 are the only two strategies that display substantial profitability with returns (Sharpe Ratios) of 14.44%pa (0.299) and 15.64%pa (0.363) respectively. Compared to PS2, PS3 has a higher return and lower volatility, which accounts for its higher Sharpe Ratio. PS1 generates 2.05%pa return and a Sharpe Ratio of 0.048. In terms of risk-adjusted net realized returns against Fama-French factors, PS2 and PS3 are the only two strategies that produce a significant alpha, with p-values of 0.08 and 0.022 respectively.

From the second set of bench-marking, the buy-and-hold strategy led to a realized loss of 0.85%pa. The 6-month rank and 1-month hold, or 6-1 momentum portfolio produces an even greater loss at 32%pa. We expand the momentum benchmark to a six-by-six rank-hold permutation matrix of 36 momentum strategies. Only four momentum portfolios generate positive returns. The two largest realized returns of 11.34%pa and 11.30%pa come from the 1-1 and 1-3 strategies, which are lower than the returns of PS2 and PS3. We implement two dividend-yield strategies: i) Dow-Dogs, which ranks Dow-Jones stocks, and ii) CDS-Dogs, which ranks our entire firm sample. We consider annual, quarterly, monthly and weekly re-balancing, which gives eight variant dividend-yield strategies. All Dow-Dogs produce negative returns. In contrast, three CDS-Dogs produce positive returns. The quarterly CDS-Dog strategy exhibits the highest Sharpe Ratio at 0.217. While it manages to outperform PS1, the best CDS-Dog's Sharpe Ratio is still lower than that of PS2 (0.299) and PS3 (0.363).

Our paper proceeds as follow. We discuss institutional details and sampling in section 2. The empirical methodology and in-sample statistical results are outlined in section 3. Section 4 presents out-of-sample profit/loss results. Section 5 concludes.

2 Prior studies, sample and calibration

Conceived in the early 1990s, the CDS market gained prominence around 2002. Accordingly, academic research on the CDS market is still in its infancy. Ericsson et al (2009) and Greatrex (2009) investigate the determinants of CDS spreads. Blanco et al (2005) examine credit risk dynamics between the CDS and bond markets for 16 U.S. investment-grade firms over 18 months. They document an evident cross-market credit risk pricing relation, which confirms the theoretical relation derived by Duffie (1999). Specifically, Blanco et al (2005) find that the CDS market is more efficient than the bond market in reflecting credit risk information.

Comparatively fewer studies have examined CDS and equity markets. An economic link exists between the two markets since equity holders own residual claims on a firm upon default. Hence, credit risk matters to equity holders as well, and stock returns should reflect information relating to the credit worthiness of the firm. Theoretically, the seminal work of

Merton (1974) establishes a link between equity value and credit risk under structural credit risk pricing[2].

Norden and Weber (2004) focus on the impact of credit-rating changes on a firm's credit risk. However, they did not obtain conclusive evidence on whether the equity or CDS market is more informative. Acharya and Johnson (2007) find that negative private information is first revealed in the CDS market through insider trading before it is transmitted over to the stock market. However, their two-stage least-square approach does not allow for possible two-way information flow between the two markets. In contrast, Norden and Weber (2009) use VAR estimation and find that stock returns lead ΔCDS_{it}. Forte and Pena (2009) conduct a similar study using bond spreads, CDS spreads and implied spreads from stock prices. They also find that, more often, it is stock returns that lead ΔCDS_{it}.

Compared to prior studies, our paper covers a larger firm sample over a longer and more recent period that encompasses the GFC. This allows us to investigate the time-varying nature of cross-market credit risk price discovery associated with a credit-crunch induced financial crisis. Since stock prices also respond to non-credit related information, we extract ICDS_{it} embedded in stock prices using the CreditGrade model. Our improved calibration involves less ad-hoc parameter setting and more frequent updating of parameters to reflect new balance-sheet information, which allows us to extract a clean measure of ICDS_{it}. This is supported by the fact that we find cointegration between ICDS_{it} and CDS_{it} for more than 95% of our firm sample for the GFC sub-sample. More importantly, it allows us to apply GG and HAS measures to analyze cross-market price discovery.

We outline basic institutional details and background information to provide a better

[2] Equity-holders are able to retire debt at maturity and claim firm ownership. This is akin to holding a call option against debt-holders on firm assets, with the face-value of debt as the strike price. Accordingly, the probability of non-exercise is analogous to the probability of default. Any information that affects a firm's credit worthiness will affect the value of equity-holders' embedded call options, hence its stock price.

understanding on how we obtain CDS_{it} and ICDS_{it}. Our study requires a comprehensive database that includes daily observations for CDS spreads, stock price, historical volatility, common shares outstanding and quarterly figure of total liabilities. To avoid anomalous results due to the GFC, our firm sample includes only investment-grade non-financial firms with S&P long term debt-rating better than BBB-[3]. After matching data availability between the CDS and equity markets, our final sample contains 174 firms[4] over a five year period between 03-Jan-2005 to 31-Dec-2009, or 1,259 daily observations per firm. For preliminary analysis, we examine a pre-GFC sample period from Jan 2005 to Jun 2007. The GFC sub-sample runs from Jul 2007 to Dec 2009,

INSERT TABLE 1

Table 1 shows the industry classifications and credit ratings of our firm sample. Our firm sample covers 7 industry sectors. Consumer Non-cyclical, Consumer Cyclical and Industrial each contains 44, 35 and 33 firms respectively. Next are Energy and Basic Materials firms with 27 and 22 firms. Lastly, there are 7 firms in Technology and 6 Communication firms. In terms of firm distribution across rating classes, there are 99 BBB firms and 65 A-rated firms. Lastly, there are 13 AA firms and 5 AAA firms in our sample.

2.1 The CDS market

The U.S. CDS market has been exhibiting remarkable growth since 2002. The British Bankers Association (BBA) credit derivatives report (2006) states that one-third of CDS contracts are used by banks to hedge credit risk exposure. The rest are mainly investors and speculators who use the CDS market to fulfil their credit risk trading demand. The payoff from a

[3]Three companies are further excluded as their maximum CDS spreads are greater than 10000bps. This implies paying more than $100 to insure a debt with a $100 face value. These companies are Fortune Brand, Ford Motor and American Axle.

[4].The full list of companies is available upon request.

CDS is triggered by a default event, such that the CDS market allows a firm's credit risk to be tradable at observable prices. In contrast, credit spreads from bond yields are not directly observable. Furthermore, bond yields are also affected by liquidity effects and investor clienteles, which are not necessarily credit-related. CDS is a derivative contract, so traders are not required to own any underlying assets. This enhances the liquidity of the CDS market.

Over the years, the CDS spread is increasingly being regarded as a benchmark indicator of the underlying reference entity's credit risk[5]. Hull et al. (2004) discuss the advantages of CDS spreads over bond yield spreads as a measure of credit risk. Following prior studies, we examine USD 10 million five-year CDS contracts written on senior unsecured debt issued by U.S. firms. Our CDS data is provided by CMA, a leading data provider in credit derivatives markets. When constructing our final sample, we cross-reference CDS data from both Bloomberg and Datastream to check for consistency.

2.2 The CreditGrade Model and ICDS

We utilize the RiskMetrics CreditGrade model[6] (Finger et al, 2002) to extract the implied CDS spread ICDS_{it} embedded in Firm i stock price. The CreditGrade model provides a simple analytical approach for structural credit risk pricing and has a closed form solution. CreditGrade models a firm's default as the first time when its assets value falls below a default barrier. By allowing default barrier to follow a stochastic process, the probability of asset value hitting the default barrier is also increased. This addresses the underpricing problem common in other structural models. As a result, the short-term default probability and credit spreads implied by the CreditGrade model are more realistic. We provide a technical outline

[5] See Longstaff et al. (2005), Blanco et al. (2005), Yu (2006) and Acharya and Johnson (2007) for a discussion on CDS spreads as a measure of credit risk.

[6] The CreditGrade model is jointly developed by four leading financial institutions in the credit market. They are RiskMetrics, JP-Morgan, Goldman Sachs and Deutsche Bank. In Finger et al. (2002, p.5), the purpose of the CreditGrade model is to establish a robust but simple framework linking the credit and equity market.

of the CreditGrade model in the appendix.

Bystrom (2006) and Yu (2006) confirm that the CreditGrade model can capture the time-series dynamics of credit risk. Given it is easy to implement, the CreditGrade model has become a standard benchmark model to extract implied credit risk information that is widely used by practitioners[7]. Bystrom (2006) uses the CreditGrade model to examine the relation between the CDS iTraxx index[8] and its constituent equity index. The author finds that equity-implied CDS index has predictive power over the spreads of the CDS iTraxx index. Unlike Bystrom (2006), we analyze credit risk dynamics at the firm-level, where the inherent $\text{CDS}_{it}, \text{ICDS}_{it}$ linkage would be less impaired by market frictions associated with having to trade in the index constituents.

The CreditGrade model requires the following input parameters: stock price s_{it}, stock return volatility (σ_{it}), debt per share (D), risk-free rate (r_f), mean ($\bar{L}$) and volatility (λ) of the expected global recover rate and the recovery rate of reference bond (R). For s_{it}, we use the CRSP daily stock files[9] to match firms against the reference entities in the CDS sample. After matching, we download the CRSP daily closing prices. For σ_{it}, we compute the one-year historical volatility using CRSP adjusted daily returns. Cao et al (2010) find that option-implied volatility gives a more accurate measure of ICDS_{it} compared to historical volatility. Our main objective is to analyze credit-risk information flow between the equity and CDS markets. By using implied volatility, the information content of ICDS_{it} spans both equity and option markets. This would contaminate the interpretation of our main results.

Blanco et al (2005) confirm that the 5-year swap rate is a better proxy of r_f for credit

[7] See Yu (2006) and Cao et al (2010).

[8] iTraxx CDS Europe index consists of 125 equally weighted CDS contracts with European investment-grade reference entity. The underlying CDS contracts are selected based on trading volume over the previous six months.

[9] Since the CDS contracts are denominated into US dollar, we use share code 10 and 11 to pull out those firms with common shares traded on U.S. exchanges.

risk pricing. We download the daily 5-year swap rate from Datastream. Following Yu (2006), we define debt-per-share (D) as Total Liabilities divided by Common Shares Outstanding. We search Total Liabilities of the matched firms in Compustat North America files.[10]. These quarterly figures are lagged one month from the end of the corresponding quarter to avoid any look-ahead bias. However, it is sub-optimal to use quarterly D figures to extract a daily time-series of ICDS_{it}, especially when capital structure events e.g stock splits[11] occur during the extraction window. To construct a daily measure of D, we download daily Common Shares Outstanding data from CRSP, which has been adjusted for corporate events.

The mean and volatility of the expected global recovery rate $(\bar{L}, \lambda)$, as well as the recovery rate of reference bond R are not directly observable. Following Hull and White (2004) and Yu (2006), we set R=0.5. This is based on an industry rule-of-thumb that is consistent with Moodys statistics on historical corporate bond recovery rate[12]. However, there are no industry guidelines for setting both $(\bar{L}, \lambda)$. We calibrate $(\bar{L}, \lambda)$ to minimize the sum of squared difference between CDS_{it} and ICDS_{it} in equation (1). After $(\bar{L}, \lambda)$ are calibrated, they are applied over the next 30 days to extract ICDS_{it}.

$$[\bar{L}, \lambda] = \underbrace{argmin}_{\bar{L},\lambda\in[0,1]} \sum_{t=1}^{30} (\text{ICDS}_{it} - \text{CDS}_{it})^2 \tag{1}$$

We improve on previous calibration approaches in three regards. First, we calibrate both $(\bar{L}, \lambda)$. Yu (2006) assumes $\lambda = 0.3$ and calibrates the model with respect to $\bar{L}$. Our ICDS_{it} should contain less bias associated with the ad-hoc setting of λ. Second, Bystrom (2006) and Yu (2006) both calibrate the model once using 10 daily observations, then apply the

[10]In that regard, there are various problems with calculating the liability figures for banking and financial service firms. Furthermore, our sample period encompasses the GFC, which has an anomalous impact on financial firms. That is why we focus on high quality investment-grade non-financial firms in our paper

[11]On the stock-split day, the share price will drop by around 50%, but the quarterly number of shares remains unchanged. This will cause the per-share debt/equity (D/E) ratio to double. The D/E ratio is a key input parameter to determine probability of default and back out ICDS_{it}.

[12]See Moody's Investor's Service Historical Default Rates of Corporate Bond Issuers, 1920-1999 (January 2000).

calibrated parameters for the rest of the entire sample. We recalibrate $(\bar{L}, \lambda)$ every 30 days[13]. Third, Leland (1994) and Leland and Toft (1996) argue that the recovery process depends on a firm's capital structure fundamental. If new accounting information on Total Liabilities is released during any 30-day extraction window, we immediately use the new accounting figures to update D and re-calibrate $(\bar{L}, \lambda)$ using the prior 30 days of data. The updated recovery rate parameters are then used for the remainder of that extraction window. We ensure that both the calibration and extraction of ICDS_{it} utilizes only past information to avoid introducing any look-ahead biases.

INSERT FIGURE 2

To ascertain the claimed improvements, we replicate Yu (2006) to extract ICDS^*_{it}, which we contrast against ICDS_{it} to examine their ability to track CDS_{it}. Figure 2A and 2B plots the time series of the cross-sectional averages of $\text{ICDS}^*_{it}, \text{ICDS}_{it}$ and CDS_{it} for the pre-crisis and crisis sub-samples respectively. Figure 2A clearly shows that ICDS_{it} tracks CDS_{it} better than ICDS^*_{it}. The difference in tracking ability is further exemplified in Figure 2B, where the gap between CDS_{it} and ICDS^*_{it} widens substantially from Oct 2008 onwards.

$$AAPE_i = \frac{1}{N} \sum_{t=1}^{N} |\text{ICDS}_{it} - \text{CDS}_{it}| \tag{2}$$

In addition, we compute the Average Absolute Pricing Error (AAPE) for the two competing implied CDS spread measures in equation (2), using CDS_{it} as the benchmark. The results across both sub-samples confirm that our ICDS_{it} measure is superior to ICDS^*_{it} in tracking CDS_{it}. Due to space constraint, we exclude the table of results from this paper[14].

[13] See Bakshi et al (1997) for a discussion on the benefits of frequent calibration on option pricing model.
[14] They are readily available upon request.

3 Methodology and Statistical Results

Our empirical analysis has three stages. First, we test for cointegration between CDS_{it} and ICDS_{it}. Second, we use both Gonzalo-Granger (1995) and Hasbrouck (1995) measures of cross-market price discovery contribution by $(\text{CDS}_{it}, \text{ICDS}_{it})$ to sort our firm sample into one of five price discovery categories. Third, we track the transmigration of firms across price discovery categories between the pre-GFC and GFC sub-samples.

3.1 Long-run credit risk pricing equilibrium

Augmented Dickey-Fuller (ADF) tests confirm that ICDS_{it} and CDS_{it} are I(1) processes for every firm. The results are consistent across pre-GFC and GFC sub-samples. If ICDS_{it} and CDS_{it} share a long-run credit-risk pricing equilibrium, they should be cointegrated. We apply Johansen's cointegration test to each firm's $(\text{ICDS}_{it}, \text{CDS}_{it})$. We present the summary results in Table 2. Panel A provides cointegration results for the full sample, pre-GFC and GFC sub-samples. Panel B provides a further partitioning base on credit-ratings.

INSERT TABLE 2

In Table 2 Panel A, the $(\text{ICDS}_{it}, \text{CDS}_{it})$ of 173 firms are cointegrated at the 95% level for the full sample period. In the pre-GFC sub-sample, the $(\text{ICDS}_{it}, \text{CDS}_{it})$ of only 2 firms are not cointegrated at the 95% level. While this increases to 9 firms in the GFC sub-sample, it is evident that an information linkage between the CDS and equity markets exists. Furthermore, it prevails for the majority of investment-grade U.S firms during the GFC. This is despite investors' negative sentiment about credit risk and regulatory intervention e.g. rescue packages and short-selling restrictions etc. The results strongly suggest the presence of prevailing cross-market credit risk pricing equilibrium between the CDS and equity markets.

Panel B does not reveal any systematic patterns of cointegration across credit-ratings. It shows the loss of cointegration in 7 additional firms in the GFC sample are all rated BBB. Intuitively, if the GFC is expected to disrupt the credit risk pricing equilibrium between the CDS and equity markets, this is more likely to occur in BBB rather than AA firms.

3.2 Price discovery contribution by CDS and equity markets

The presence of cointegration for the majority of our firm sample allows us to model cross-market dynamics between ICDS_{it} and CDS_{it} as a bivariate VECM in equation (3). The estimates allow us to compute Gonzalo-Granger (GG) and Hasbrouck (HAS) price discovery contribution measures for each firm. The model assumes $E(\varepsilon_{1t}) = E(\varepsilon_{2t}) = 0$, $E(\varepsilon_{1t}^2) = \sigma_1^2, E(\varepsilon_{2t}^2) = \sigma_2^2$ and $E(\varepsilon_{1t}\varepsilon_{2t}) = \sigma_{12}$. We use the Schwarz Information Criterion (SIC) to determine the VECM's optimal lag specification S on a firm-by-firm basis.

$$
\begin{aligned}
\Delta CDS_t &= \alpha_{10} + \sum_{s=1}^{S}(\alpha_{1s}\Delta CDS_{t-s} + \beta_{1s}\Delta ICDS_{t-s}) + \lambda_1(\tau_0 + CDS_{t-1} - \tau_1 ICDS_{t-1}) + \varepsilon_{1t} \\
\Delta ICDS_t &= \alpha_{20} + \sum_{s=1}^{S}(\alpha_{2s}\Delta CDS_{t-s} + \beta_{2s}\Delta ICDS_{t-s}) + \lambda_2(\tau_0 + CDS_{t-1} - \tau_1 ICDS_{t-1}) + \varepsilon_{2t}
\end{aligned} \tag{3}
$$

In equation (3), the long-run credit risk pricing equilibrium is manifested in the error-correction variable $(\tau_0 + CDS_{t-1} - \tau_1 ICDS_{t-1})$. The latter prevents any short-run deviations between CDS_{it} and ICDS_{it} to persist in the long-run, with τ_1 as the normalization coefficient. τ_0 allows the error-correction variable to have a non-zero mean, which account for dissimilar institutional and microstructural effects on CDS_{it} and ICDS_{it}. The key parameters to ascertain the cross-market price discovery mechanism between the two markets are the error-correction coefficients λ_1 and λ_2. If only $\lambda_1 < 0$ ($\lambda_2 > 0$) is significant, it suggests only ΔCDS_{it} (ΔICDS_{it}) relies on the error-correction variable to adjust for temporal deviations from the equilibrium pricing relation. This implies that the equity (CDS) market dominates price discovery.

If both $\lambda_1 < 0, \lambda_2 > 0$ are significant, this implies both CDS and equity markets contribute to credit risk price discovery. We compute GG and HAS measures of price discovery contribution. The GG measures for CDS and equity markets calculated as $\frac{-\lambda_1}{\lambda_2-\lambda_1}$ and $\frac{\lambda_2}{\lambda_2-\lambda_1}$ respectively. If the GG measure for one market exceeds 0.5, this translates to greater price discovery contribution. The HAS measure defines an upper (HAS_U) and lower bound (HAS_L) for each markets price discovery contribution. Outlined in equation (4), HAS_U and HAS_L for the CDS market are calculated using λ_1, λ_2 as well as the variance-covariance matrix of $\varepsilon_{1t}, \varepsilon_{2t}$.

$$\text{HAS}_U = \frac{(\lambda_2\sigma_1 - \lambda_1\frac{\sigma_{12}}{\sigma_1})^2}{(\lambda_2\sigma_1)^2 + (\lambda_1\sigma_2)^2 - 2\lambda_1\lambda_2\sigma_{12}} \qquad \text{HAS}_L = \frac{\lambda_2^2(\sigma_1^2 - \frac{\sigma_{12}^2}{\sigma_2^2})}{(\lambda_2\sigma_1)^2 + (\lambda_1\sigma_2)^2 - 2\lambda_1\lambda_2\sigma_{12}} \tag{4}$$

Following Baillie et al. (2002) and Blanco et al (2005), when $\frac{1}{2}(\text{HAS}_U + \text{HAS}_L) > 0.5$ and $\frac{-\lambda_1}{\lambda_2-\lambda_1} > 0.5$, this indicates that the CDS market has a larger price discovery contribution than the equity market, and vice versa. However, if there is no consensus between GG and HAS measures, we regard the CDS and equity markets as contributing similarly to credit risk price discovery. This is a reasonable compromise between the two standard measures of cross-market price discovery. Furthermore, for trading purposes, our interest lies on firms where one market drives the other.

The preceding discussion naturally implies five mutually exclusive price discovery categories {C1,...,C5}. C1 (Category 1) and C5 (Category 5) contain firms where the CDS and equity market dominates price discovery respectively. Firms where both GG and HAS measures indicate the CDS (equity) market contributes more to price discovery are allocated in C2 (C4). Lastly, firms for which the two measures do not share a consensus are assigned to C3. Hence {C1,...,C5} can be viewed as a price discovery spectrum with the CDS market dominating price discovery at one end, while the equity market dominates at the other end.

INSERT TABLE 3

In Table 3, we present results for the full sample period in Panel A, whereas Panels B and C results correspond to pre-GFC and GFC sub-samples. Panel A shows that 131 firms, or 76% of the firm sample, are categorized as either C1 or C2, where the CDS market either dominates or leads the price discovery mechanism. However, the equity market is not entirely irrelevant with 28 C4 and C5 firms, which constitutes around 17% of the firm sample. Most of these firms have comparatively lower credit-ratings of A and BBB.

The results across Panels B and C reveal an interesting dissimilarity in the categorization results, which implies that Panel A is indeed an averaging of the pre-GFC and GFC sub-samples. In Panel B, 92 firms or 53% of the firm sample belong to either C1 or C2. The equity market holds its own with 62 firms or 36% belonging to either C4 or C5. In stark contrast, Panel C shows the CDS market influences credit risk price discovery during the credit-crunch induced GFC, with 118 firms or 71.5% categorized as either C1 or C2 firms[15]. To follow, the number of C4 and C5 firms have dropped from 62 to 34 firms. This suggests that the CDS market has actually become more efficient than the equity market at incorporating credit risk information during the GFC. With the heightened awareness of credit risk, the market for trading credit risk becomes all the more pertinent.

Our results, which are based on a cleaner measure of ICDS_{it}, suggests that the CDS market possess informational efficiency. Prior studies by Norden and Weber (2004, 2009) and Bystrom (2006) offer inconclusive findings on this issue. Acharya and Johnson (2007) find that the CDS market is more efficient at revealing negative private information. Our results show that this is also the case for a market-wide credit-crunch. Blanco et al (2005) confirm that the CDS market is more efficient than the corporate bond market in reflecting

[15]We lost 7 additional firms when we move from Panel B to Panel C as their CDS_{it} and ICDS_{it} are not cointegrated in the GFC sub-sample.

credit risk information. Our results show that the CDS market performs more credit risk price discovery than the equity market.

We make a further comparison between Panels B and C. The number of firms in each category is unstable going from the pre-GFC to GFC sample. For example, the number of C1 firms jumped from 52 to 90. C5 firms increase slightly from 15 to 23. However the number of C4 firms dropped from 47 to 11. C2 firms are also reduced from 40 to 28. This suggests a shift in the price discovery mechanism towards C1 and C5 i.e. the ends of the spectrum, where either the CDS or equity market dominates credit risk price discovery. Our findings thus far indicate possible transmigration of firms across price discovery categories as the sample progresses towards and away from the GFC. This motivates us to perform a more detailed analysis of firm categorization in the next section.

3.3 Transmigration patterns across price discovery categories

We report details on the number and percentage of firms that migrate from one category to another in Table 4 Panels A and B respectively. In both panels, the column headings are for the pre-GFC sample and the row headings represent the GFC sample. For example, in Panel A, at the intersection of pre-GFC C2 and GFC C1, 17 firms have migrated from C2 to C1 price discovery going from the pre-GFC to GFC sample. We include C6, which represents firms for which no cointegration exists between CDS_{it} and ICDS_{it}.

INSERT TABLE 4

We discuss key findings from Panel B, which expresses the number of firms as a percentage of total firms in each category for the pre-GFC sample. The diagonal figures indicate that 67% of C1 firms remain in C1 when we move from the pre-GFC to GFC sub-sample. In stark contrast, for the other price discovery categories, less than 20% of firms remain. For example, 16.67% of C3 firms remain in C3. Instead, 66.67% of C3 firms have migrated to C1 in the GFC-sample. Indeed, Panel B clearly shows a large proportion of firms have shifted from other categories into GFC-C1 when we move from the pre-GFC to GFC sub-sample. Specifically, GFC-C1 has absorbed 42.5% of C2 firms, 66.67% of C3 firms, 42.55% of C4 firms and 26.67% of C5 firms in the GFC-sample. C1 and C2 have jointly attracted more than half the entire firm sample. Specifically, 77.78% of pre-GFC C3 firms, 63.83% of pre-GFC C4 firms and 66.67% of pre-GFC C5 firms have migrated to either GFC C1 or C2. Table 4 confirms the presence of time-varying price discovery between the CDS and equity market and the heightened price discovery role of the CDS market for an increasing number of firms during the GFC.

The results in Table 4 indicate a structural break in credit risk dynamics for a large number of firms. However, since the results are based on a pre-GFC versus GFC sub-samples, they do not provide a clear picture of transmigration patterns during the course of the GFC. In Table 5, we report the number of firms in {C1,...,C5} base on 11 quarterly rolling window estimations {RW1,...,RW11} of GG and HAS measures. Rolling-window 1 (RW1) is simply the pre-GFC sub-sample. RW2 ranges from 01-Apr-2005 to 30-Sep-2007, and so on. Lastly, RW11 covers from 01-Jul-2007 to 31-Dec-2009 i.e. GFC sub-sample. In other words, we update the price discovery categorization for each of the 174 firms on a quarterly basis.

INSERT TABLE 5

Table 5 provides a more fluent perception of price discovery transmigration patterns as we shift our estimation window towards and away from the midst of the GFC. There is an evident migration of price discovery towards the CDS market, with the number of C1 and C2 firms increasing sharply from 92 in RW1 to 159 in RW5. The latter constitutes the onset of the GFC. From RW7 onwards, the number of C1 and C2 firms decrease substantially, but remains high compared to RW1 i.e. pre-GFC sample period.

INSERT FIGURE 3

In Figure 3, we plot the number of C1 and C2 firms across {RW1,...,RW11}. The figures shows that the CDS market is gradually taking over price discovery leadership from the equity market as we move towards the GFC. Even as we move away from the height of the GFC, the heightened awareness of credit risk implies that the number of C1 and C2 firms in RW11 (118) remains high relative to RW1 (92).

4 Portfolio strategies and economic significance

Gonzalo and Granger (1995) and Hasbrouck (1995) both measure the summary informativeness of CDS_{it} versus ICDS_{it}. This allows us to ascertain the direction of credit-risk information flow between the two markets for each firm in order to allocate them into price discovery categories {C1,...,C5}. For C1 and C2 firms, CDS_{it} will respond to credit-related shocks before ICDS_{it}, due to a delayed response by equity prices. Accordingly, a natural test of the economic significance of the price discovery statistical results is to examine the profitability of trading stocks based on fluctuations in CDS spreads.

The aim of this section is to ascertain the economic significance of i) identifying the direction of credit risk information flow and ii) updating the time-varying nature of credit risk price discovery dynamics between the CDS and equity market. We implement five portfolio strategies {PS1,...,PS5}, all of which draw trading signals from CDS_{it} to set positions in the corresponding stocks. The key difference among {PS1,...,PS5} lies in the list of candidate firms that are being considered for trading.

PS1 is an unconditional strategy that trades from the entire firm sample. To demonstrate the economic significance of information flow from the CDS to equity market, PS2 considers only the 52 C1 firms and 40 C2 firms in Table 5 under RW1, for which the CDS market has price leadership. The firm list for PS2 is static, such that we do not update the list of C1 and C2 firms during the trading period. In contrast, PS3 trades from a list of C1 and C2 firms that is updated on a quarterly basis. Once the list of C1 and C2 firms are updated, they are then used by PS3 in the next quarter. The profit/loss comparison between PS2 and PS3 brings out the incremental value of tracking firm transmigration patterns in and out of C1, C2. Lastly, PS4 and PS5 trade exclusively in non-C1 and non-C2 firms i.e. firms that are mutually exclusive to PS2 and PS3 respectively.

PS4 and PS5 serve three purposes. First, the two pairwise comparisons PS2 versus PS4, and PS3 versus PS5, further brings out the importance of identifying the direction of credit risk information flow. Second, they provide a robustness check. If PS2 and PS3 both out-perform PS1 because they trade exclusively in C1, C2 firms, then PS4 and PS5 should both under-perform PS1 as they trade exclusively in non-C1 and non-C2 firms. Third, during part of the test period, the number of C1 and C2 firms increases to nearly 160. This implies the list of candidate firms for PS1 and PS3 are become increasingly similar, at least during part of the test period. PS5 provides another comparison for PS3.

The estimation period runs from 03-Jan-2005 to 30-Jun-2007. The remainder of the sample is used for out-of-sample testing. Any categorization of C1 and C2 firms is based only on past observation, such that anchoring {PS1,...,PS5} on CDS_{it} does not evoke a look-ahead bias. All five strategies are designed to share a similar trading methodology e.g. trading signal, holding period, re-balancing frequency etc. This is to ensure that any discrepancy in profit/loss performance is not due to features of the trading process.

The SEC recommended a short-sale ban list on US equity firms. The ban list is reviewed, revised and imposed by U.S. stock exchanges between 19-Sep-2008 to 08-Oct-2008. We cross-reference the short-sale ban list and find that 10 firms in our sample are on that ban list. As our study is based on high-quality investment-grade firms, the short-sale ban applies to only 5.75% of our firm sample. We have marked these 10 firms and imposed short-sale constraints on all portfolio strategies during the banned period. Our profit/loss results are adjusted for regulatory short-sale constraints imposed during the GFC.

4.1 Threshold portfolio approach

GG and HAS are measures of summary informativeness. For a C1 or C2 firm, the measures indicate, on average over the estimation window, that the CDS market is more responsive than the equity market. However, the measures do not explicitly stipulate the extent of delay in the equity market's response. Furthermore, such delays are likely to vary across firms. As such, it is an awkward task to set an optimal holding period, if any.

To address this issue, we hold portfolios for one week, even though the price discovery measures are based on daily price adjustments. Indeed, if a weekly holding period is deemed too long, it simply implies we are too late in closing out stock positions. This can only make findings of economic significance stronger. Moreover, our main objective is to demonstrate the incremental profits by sequentially moving from PS1 to PS3.

We apply a long-short threshold portfolio approach across {PS1,...,PS5}. Candidate firms are sorted base on weekly changes in CDS spreads. We impose a threshold weekly change of $\pm$20% as a signal that the underlying firm's credit risk profile has changed. Put differently, we trade stocks whose weekly change CDS spreads are large, both in absolute terms as well as relative to other stocks. As CDS spreads are quoted in basis points, a CDS contract trading at 100bps subjected to a 20% threshold translates to a weekly change of 20bps. We can confirm that the relative ranking among {PS1,...,PS5} is robust to threshold values ranging from 5% to 30%[16]. The cross-sectional average CDS spread for our firm sample is around 250bp. A ±20% threshold translates to a weekly change of 50bps. We argue that our threshold is more conservative than the 50bps daily change threshold dummy variable used in Acharya and Johnson (2007).

Under the threshold approach, the number of firms in the long and short portfolios are not necessarily balanced. However, we maintain a zero-cost portfolio by committing equal dollar value exposure to both sides. However, if the threshold is triggered only at the top (bottom) end of the sorted firm list, our portfolio position would only be short (long). This is designed from the perspective of hedge funds or proprietary trading desks, which are endowed with initial investment capital. Other aspects, however, are similar to a standard long-short portfolio approach[17]. Each week, we form a portfolio that is subsequently closed out one week later. The realized annual return is based on the cumulative return of a given portfolio strategy over the trading period.

INSERT TABLE 6

We report profit/loss results in Table 6, including basic statistics of realized returns, features of the portfolio, annualized return/risk ratio etc. On average, the ratio of long to short positions across {PS1,...,PS5} is around 3:7. The number of weekly portfolios traded range from 98 for PS2 to 119 for PS1. In other words, there are 32 (11) weeks where no trading is warranted for PS2 (PS1), due to the lack of tangible credit signals from the CDS market. Similarly, the average number of firms traded ranges from 5.76 for PS2 to 16.62 for PS1. Even with a dynamically updated list of C1 and C2 firms, PS3 forms 103 weekly portfolios with an average of 10.83 firms for each traded weekly portfolio.

[16]Results for other threshold values are not included, but are readily available upon request.

[17]For example, change in CDS spreads are sorted every Tuesday; Positions are taken up the next trading day to form an equally-weighted portfolio; Transaction cost of 10bps per stock etc.

Only PS1, PS2 and PS3 exhibit positive realized cumulative returns over the 2.5 year trading period. PS4 is the worst performer with an annualized return of -12.61%pa. While PS1 manages a modest return of 2.05%pa, it is clearly overshadowed by the realized returns of PS2 and PS3 at 14.44%pa and 15.64%pa respectively. This clearly brings out the non-trivial economic significance for portfolio strategies that draw trading signals from the CDS market to be conditioned on firms that actually rely on the CDS market for price discovery in the first place. Interestingly, PS3 has both a higher return and lower volatility than PS2, such that it has a more impressive Sharpe Ratio of 0.363 compared to PS2's 0.299. In addition, the proportion of weekly portfolios that generate positive weekly returns is 58.25% for PS3. This is higher than the 52.04% for PS2.

It is interesting to note that PS5, which trades in firms that are mutually exclusive to PS3, actually performs better than PS4. Since the list of candidate firms for PS2 is fixed, the mutually exclusive list for PS4, which comprises 82 firms, is also fixed. As the firm list for PS4 is longer than PS5, there is a greater tendency for PS4 to trade firms under the 20% threshold approach[18]. Indeed, PS4 trades 50% more firms on average (12.19) compared to PS5 (8.30). But for PS4 and PS5, more trading implies greater expected loss simply because we are forming portfolios using ΔCDS_{it} as signals, but for firms that do not actually rely on the CDS market for price discovery. Hence PS5's better profit/loss performance can attributed to its abstinence from trading.

4.2 Profit/loss evaluation against proven portfolio strategies

The preceding profit/loss results allow us to ascertain the relative profit rankings among {PS1,...,PS5 }. While they clearly bring out the incremental profitability of PS2 and PS3 over PS1, PS4 and PS5, they are not formally compared against other proven portfolio strategies.

[18]For rolling windows 5 and 6, there are only 15 and 18 companies for PS5 to consider.

In this section, we evaluate if the profit performances of the five strategies, especially PS2 and PS3, are economically significant when compared against other well-established portfolio strategies. We consider two sets of benchmarks.

4.2.1 Jensen's alpha against Fama-French Factors

To evaluate the economic significance of risk-adjusted net returns, we compute Jensen's alpha (α_j) by regressing weekly excess return from PS$_j$, $j = 1, 2, ..., 5$, against weekly Fama-French market risk premium (MRP_t), size (SMB_t) and book-to-market (HML_t) factor returns[19]. Table 7 Panel A shows that PS2 and PS3 possess substantially higher α_j and lower p-values compared to PS1, PS4 and PS5. However, all α_j coefficients are insignificant. In fact, all the coefficient estimates in Panel A are insignificant.

INSERT TABLE 7

When we plot the weekly residual returns ε_{jt} for each of the five portfolio strategies, we observe volatility clustering effects, especially for PS1, PS2 and PS3. Subsequent diagnostic tests using the Godfrey (1978) and Breusch and Pagan (1979) procedures confirm the presence of heteroskedasticity in ε_{jt} for all portfolio strategies. The finding suggests that that the least-square estimates in Panel A, which ignore GARCH effects, are inefficient. This would explain why all least-square coefficients are statistically insignificant.

We explore various lag dynamics for the conditional variance equation, and find that a GARCH(2,3) specification has the lowest Akaike Information Criterion (AIC) across portfolio strategies[20]. In equation (5), we re-estimate the Fama-French return equation, allowing $\varepsilon_{jt} \sim$

[19] These factor portfolio returns are downloaded from Kenneth French's website.

[20] While the Schwartz Information Criterion (SIC) suggests slightly different GARCH specifications for each of the five portfolio strategies, the main results are not sensitive to whether we use AIC or SIC to specify the GARCH process.

$N(0, \sigma_{jt}^2)$ by fitting a GARCH(2,3) specification to σ_{jt}^2. We report estimates for both the mean and variance equations in Table 7 Panel B. The results show that the majority of AR and MA terms in the conditional variance equation are significant across {PS1,...,PS5}. This reaffirms the presence of GARCH effects in ε_{jt}.

More importantly, the results also show that PS2 and PS3 are the only two strategies that produce a significant weekly alpha against Fama-French factors. For PS3, $\alpha_3 = 0.0041$, which is larger than $\alpha_2 = 0.0034$. The p-values indicate that α_2 is significant at the 10% level, while α_3 is significant at the 5% level. These results support the presence of incremental profits from conditioning and dynamically updating the list of C1 and C2 firms during the course of the trading period.

$$r_{jt} - r_{ft} = \alpha_j + b_j(MRP_t) + s_j(SMB_t) + h_j(HML_t) + \varepsilon_{jt}$$

$$\sigma_{jt}^2 = c + \phi_{1j}\varepsilon_{jt-1}^2 + \phi_{2j}\varepsilon_{jt-2}^2 + \gamma_{1i}\sigma_{jt-1}^2 + \gamma_{2j}\sigma_{jt-2}^2 + \gamma_{3j}\sigma_{jt-3}^2 \tag{5}$$

Interestingly, {PS1,...,PS5} all exhibit negative market beta across Panels A and B. This could be simply due to the overall poor performance of the market during the GFC. Furthermore, while it is standard procedure to evaluate risk-adjusted returns against priced factors, one may question the validity of bench-marking against priced factors for a trading period that encompasses a disequilibrium event such as the GFC.

4.2.2 Buy-and-Hold, Momentum and Dividend-Yield

To address the preceding concern, we implement a second set of benchmarks, including buy-and-hold (B&H), momentum and dividend yield. Our aim is simple. If we apply the same firms over the same trading period using proven portfolio strategies, can we produce profit results similar to those achieved by PS2 and PS3? We report profit/loss results in Table 8

Panel A for the B&H, Panel B for a 6-month rank; 1-month hold (6-1) momentum strategy, and two variant dividend-yield strategies in Panels C and D. For all strategies, we impose 10bps per traded stock as transaction cost, which is consistent with {PS1,...,PS5}.

INSERT TABLE 8

First, we analyze the risk-return performance from a B&H strategy in an equally-weighted portfolio formed using the entire firm sample. This is a more convincing benchmark than MRP_t, which plunged during the GFC. On the 5-July-2007, which corresponds to the first Wednesday of the trading period, we form an equally-weighted long portfolio in all 174 stocks. We reinvest all dividends back into the portfolio during the holding period, which is liquidated on 30-December-2009. The latter corresponds to the last Wednesday of the trading period. The B&H strategy produces a cumulative net return of -2.11%, or a -0.85%pa annualized return with a Sharpe Ratio (SR) of -0.033.

Second, to ensure that our profit results are not driven by market trend, we implement a 6-1 momentum strategy using our firm sample. Given our earlier concerns on evaluating risk-adjusted returns using priced factors, there is limited incremental value in generating Jensen's α_j using Carhart (1997) factors rather than Fama-French factors. Our benchmark is not the momentum factor per se, but rather, momentum as a portfolio strategy.

At the start of the trading period, we sort firms base on their past 6 months' return. We go long in the bottom (winner) decile portfolio and short-sell the top (loser) decile portfolio. There are 17 stocks in each of the winner and loser portfolios. The momentum profit/loss results correspond to the equally-weighted winner-minus-loser (WML) portfolio comprising 34 stocks. The WML portfolio is liquidated at the end of the month, with 10bps deducted from the realized return for each traded stock. The process is repeated. In Panel B, the WML portfolio produced an annualized return of -32%pa with an annualized volatility of

51.68%pa. However, there may be an optimal rank-hold configuration for the WML portfolio which corresponds to our firm sample and trading period. We will address this issue shortly.

Our last benchmark is a simple but popular strategy on Wall-Street. Coined Dow-Dogs, the strategy goes long in the top ten dividend-yielding Dow-Jones Industrial Average (DJIA) stocks. This strategy is intuitively appealing. It stipulates buying stocks with high dividend payout that have been potentially oversold relative to other stocks[21], resulting in excessively high dividend yields. The subsequent price recovery translates into capital gain. And while waiting for the price recovery to eventuate, the investor benefits from generous dividend payments. Dow-Dogs investors argue that the dividend-price ratio is more informative than earnings-price ratio in reflecting a firm's future earning ability. This is simply because earnings can be "managed" to a certain extent, but the same cannot be said for dividends[22].

We implement two similar strategies using the top ten dividend-yielding stocks from i) the DJIA (Dow-Dogs[23]), and ii) our sample of 174 firms (CDS-Dogs). For each of the two strategies, we consider yearly, quarterly, monthly and weekly re-balancing intervals, which gives us eight variant portfolios[24]. The profit/loss results for the Dow-Dog and CDS-Dog strategies are reported in Table 8 Panels C and D respectively. Panel C shows that none of the four re-balancing intervals for Dow-Dogs manage to produce any profits[25]. In contrast,

[21]On Wall Street, these stocks are called 'Fallen Angels'. We believe that a dividend yield strategy is a meaningful benchmark for our paper since it has been proven to outperform the market during times of financial crisis. With the associated economic downturn, government stimulus through loosening monetary policy suppresses Treasury bond yields. This makes a high dividend-yielding portfolio appealing.

[22]If a 50 cents dividend is declared, it has to be paid, whether in cash or new shares.

[23]We match the CRSP dividend announcement data file against the price file for DJIA firms and our firm sample. In addition, we track and update the list of DJIA component stocks during the trading period.

[24]For weekly re-balancing, we sort firms every Tuesday based on dividend yield. The next trading day, we form an equally-weighted portfolio in the top ten dividend yielding firms. This portfolio is liquidated next Tuesday. For monthly re-balancing, we sort firms on the first trading day of each month. The portfolio is formed the next trading day, and is subsequently liquidated on the last trading day of the month. For quarterly re-balancing, we sort firms on the first trading day of each of the March, June, September and December quarter. We form a long portfolio the next trading day, which is subsequently liquidated on the last trading day of each quarter.

[25]The 21%pa realized return for 2010 documented on that Wall Street Journal article is at least partially attributed to the substantial recovery of the US stock market. Our test period ends in 2009.

Panel D shows that three CDS-Dog portfolios are profitable. The weekly CDS-Dog portfolio has a higher return (7.46%pa) and lower volatility (42.03%) compared to the monthly CDS-Dog portfolio. However, it is the CDS-Dog portfolio with quarterly re-balancing that is the best performer with a 13.79%pa annualized return and SR of 0.217. All the three CDS-Dog portfolios manage to produce SRs that are higher than PS1. However, in terms of both annualized return and SR, the best CDS-Dog portfolio under-performs PS2 (14.44%pa; 0.299) and PS3 (15.64%pa; 0.363).

INSERT TABLE 9

Our benchmark momentum strategy will be more convincing if we consider more than one rank-hold configuration. In Table 9, we present WML portfolio return and SR for a six-by-six permutation matrix of momentum strategies, using the same trading procedure as previously described. The results show that 4 out of 36 WML portfolios are profitable, with the 1-1 and 1-3 portfolios being the two most outstanding. Both portfolios produce an annualized return of around 11.3%pa. This remains lower than the annualized return of PS2 (14.44%pa) and PS3 (15.64%pa). However, the 1-1 and 1-3 portfolios exhibit impressive SRs. The 1-1 WML portfolio has a SR of 0.356. This is higher than PS2 (0.299) but lower than PS3 (0.363). The 1-3 WML portfolio has a SR of 0.516.

In sum, we have considered a total of (1+8+36)=45 benchmark portfolio strategies against PS2 and PS3. The best of the 45 strategies is the 1-3 WML portfolio. It possesses a SR higher than both PS2 and PS3. The 1-3 WML portfolio comes from 'cherry-picking' the best benchmark portfolio from Tables 11 and 12. However, its 11.3%pa return is lower than PS2 and PS3. Furthermore, PS2 and PS3 are evaluated based on weekly returns, while momentum is evaluated based on monthly returns. The difference in return frequency could partially explain a higher annualized volatility, hence lower SR, for PS2 and PS3 relative to the 1-3 WML portfolio. Just as importantly, our prime focus is to demonstrate the economic significance from conditioning portfolio strategies, which draw trading signals from the CDS market, on firms that actually depend on the CDS market for credit risk price discovery. Both conditional PS2 and PS3 substantially outperform the unconditional PS1 as well their mutually exclusive counterparts PS4 and PS5 respectively.

4.2.3 Further discussions on the profit/loss results

We design {PS1,...,PS5} to demonstrate the economic value for portfolio strategies (that draws trading signals from the CDS market) to be conditional on cross-market price discovery dynamics between each firm's CDS and equity markets. PS1 is the unconditional strategy that is based on our entire firm sample. PS2 trades from a conditional but static list of CDS-influenced C1 and C2 firms, while PS3 trades from a conditional and dynamically updated list of CDS-influenced C1 and C2 firms, which incorporates transmigration patterns documented in this paper. We address five potential issues when interpreting the profit/loss results.

First, it is possible that the Credit Grade model-implied ICDS_{it} becomes noisier during the GFC. If so, this could partially explain the price discovery dominance of the directly observable CDS_{it} over ICDS_{it} during the GFC. We test for cointegration with the coefficient restriction $\tau_0 = c, \tau_1 = 1$[26] Blanco et al (2005) suggest that, if $\mathrm{CDS}_{it}, \mathrm{ICDS}_{it}$ do not cointegrate with the imposed restrictions, it is possible that at least one of the two variables is measured with a time-varying non-transient error. However, we show that even during the GFC sub-sample, $\mathrm{CDS}_{it}, \mathrm{ICDS}_{it}$ are cointegrated for more than 95% of our entire firm sample. If ICDS_{it} does become too noisy for some firms, they would be categorized as C6 firms and excluded from the analysis for the corresponding rolling window(s).

Second, while {PS1,...,PS5} take advantage of credit signals from the CDS market to set

[26]Conceptually, $\tau_0 = 0$. Since our risk-free rate is a proxy, we allow for $\tau_0 = c$.

both short and long positions, our documented profit results could be driven simply by short-selling distressed stocks during the GFC. If so, the findings may have limited generalization to other states of the world. Figure 1 shows that, during the trading period, the cross-sectional average CDS spread did increase sharply, but it dropped substantially as well. Near the bottom of Table 6, we report the average number of stocks traded every week for {PS1,...,PS5}, as well as the proportion of long and short positions. Across the five strategies, the ratio of long-to-short stock positions is around 3:7. This implies that a reasonable portion of our profit results are driven by long positions. And since the 3:7 long-short ratio is quite stable across {PS1,...,PS5}, the incremental profitability shown by PS2 and PS3 over PS1, PS4 and PS5 cannot be simply explained by the short-selling of financially distressed firms.

Third, our portfolio strategies are executed during a trading period when corporate distress and credit constraints dominate the financial media. As such, a strategy that takes advantage of credit-related information has a natural advantage over other non credit-risk driven portfolio strategies. Paradoxically, that is what we set out to demonstrate in terms of ascertaining the economic significance of the heightened importance of the CDS market to credit risk price discovery during a period of heightened sensitivity to credit risk.

Fourth, our firm sample contains financially distressed firms that survived the GFC. Firm that did not survive would have been excluded from our sample, such that our profit results may be potentially laced with survivorship bias. Our firm sample covers the entire population of investment-grade firms in 2005. These 174 firms are high-quality non-financial companies that survive throughout our sample period. Indeed, that is why we focus on investment-grade firms in the first place. We exclude a small number of firms during the trading period due to the absence of cointegration between CDS_{it} and ICDS_{it}. Furthermore, if survivorship bias exists, this implies our portfolio strategies would only short-sell financially distressed firms that eventually recovered. This can only strengthen the validity of our profit/loss results.

Fifth, if we extend our trading period to include 2010 data, when there is substantial market recovery, the benchmark B&H, momentum and dividend-yield strategies are likely to perform better. In addition, the number of C1 and C2 firms may reduce further, such that PS2 and PS3 may not be as profitable compared to results in the current paper. If that is the case, it is entirely consistent with the core implication of our main finding, which is the fact that the CDS market takes over credit risk price discovery when credit risk is a binding concern for firms and investors alike.

5 Concluding remarks

In this paper, we analyze cross-market credit risk information flow between the CDS and equity markets for a sample of 174 U.S. investment-grade firms. Our improved calibration of the CreditGrade model in RiskMetrics allows us to extract ICDS_{it}, which is a cleaner indicator of the price of credit risk implied by the equity market. ICDS_{it} and the CDS market's observable CDS_{it} are cointegrated for nearly the entire firm sample and the results are robust across sub-samples. We use Gonzalo-Granger (1995) and Hasbrouck (1995) measures to sort firms into one of five price discovery categories. When we forward shift the estimation window on a quarterly basis to update GG and HAS measures, we find strong evidence of time-varying credit risk price discovery contribution between the CDS and equity markets for the majority of our firm sample.

While we expect to find time-varying price discovery process for a sample period that encompasses the GFC, it is the direction of the transmigration pattern that constitutes our most interesting finding. One would instinctively expect the price discovery mechanism of any credit-related market to cease functioning properly during a systemic credit-crunch, including, and especially, the U.S. CDS market. This would be manifested in firms migrating out of C1 into other price discovery categories.

What we have documented is the exact opposite. The U.S. CDS market has taken over price discovery leadership from the equity market during the GFC. Between April 2006 and September 2008, the number of CDS-influenced C1 and C2 firms constitute nearly the entire firm sample. And as we move away from the height of the GFC, firms gradually migrate out of C1 and C2 into other categories. But the number of C1 and C2 firms remain high compared to the pre-GFC period. Profit/loss evaluation confirms that, using information conveyed by the CDS market, the portfolio strategy conditional on identifying and updating the list of CDS-influenced firms generates a significant alpha against Fama-French factors. It also outperforms other proven portfolio strategies that utilize our firm sample, including buy-and-hold, momentum and dividend yield.

Our main finding is consistent with an insightful observation by Hong and Sraer (2011) "A Taxonomy of Bubbles". The authors argue that, unlike the Dot-Com bubble, the lead-up to the credit bubble is described by a credit binge, which led to financial markets exhibiting high prices but low volatility. Indeed, Figure 1 shows that CDS spreads are especially low and tranquil pre mid-2007. To informed speculators, the CDS market offers modest profit when credit is cheap and in abundance. It is during a credit-crunch induced financial crisis when the market for trading credit risk becomes exciting to informed speculators.

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Appendix: Technical Notes on the CreditGrade Model

The CreditGrade model assumes that a firm's asset value V_t follows a geometric Brownian motion without drift $\frac{dV_t}{V_t} = \sigma dW_t$. A zero-drift assumption is consistent with evidence of stationary leverage ratios documented by Collin-Dufresne and Goldstein (2001). In the event of default, debt-holders receive a recovery amount LD, where L is the global average recovery rate and D is debt per share. Denote $E(L) = \bar{L}$. In CreditGrade, the recovery amount upon default LD is defined as the default barrier and is assumed to follow a stochastic process. The model assumes that L follows a log-normal distribution with $Log(L) \sim N(\mu, \lambda^2)$, such that LD can be expressed as equation (6), where $Z \sim N(0,1)$. Since $\bar{L} = e^{(\mu+\frac{\lambda^2}{2})}$, hence $\bar{L} \cdot e^{(\lambda Z - \frac{\lambda^2}{2})} = e^{(\mu+\lambda Z)}$. As $Z \sim N(0,1)$, $log(e^{\mu+\lambda Z}) \sim N(\mu, \lambda^2)$. Hence $LD = e^{(\mu+\lambda Z)}D = \bar{L}D \cdot e^{(\lambda Z - \frac{\lambda^2}{2})}$.

$$LD = \bar{L}D \cdot e^{(\lambda Z - \frac{\lambda^2}{2})} \tag{6}$$

A default event is triggered by $V_t < LD$. Using Ito's Lemma and given the initial asset value V_0, the firm will exist as long as equation (7) is satisfied.

$$V_0 \cdot e^{(\sigma W_t - \frac{1}{2}\sigma^2 t)} > \bar{L}D \cdot e^{(\lambda Z - \frac{\lambda^2}{2})}$$
$$\sigma W_t - \frac{1}{2}\sigma^2 t - \lambda Z + \frac{\lambda^2}{2} > log(\frac{\bar{L}D}{V_0}) \tag{7}$$

Denote $X_t = \sigma W_t - \frac{1}{2}\sigma^2 t - \lambda Z + \frac{\lambda^2}{2}$. It can be shown that $X_t \sim N[(-\frac{\sigma^2}{2}(t+\frac{\lambda^2}{\sigma^2})), \sigma^2(t+\frac{\lambda^2}{\sigma^2})]$. Then X_t can be approximated by a time-shift Brownian motion $\hat{X}_t$ that starts at $t_0 = -\frac{\lambda^2}{\sigma^2}$[27]. Default is triggered by $\hat{X}_t \leq (log(\frac{\bar{L}D}{V_0}) - \lambda^2)$. The survival probability is the cumulative probability before $\hat{X}_t$ hits and falls below a certain level of $(log(\frac{\bar{L}D}{V_0}) - \lambda^2)$ for the first time. Applying distributions for the first-time hitting of $\hat{X}_t$, the CreditGrade model provides a closed-form solution in equation (8) to calculate the survival probability $P_{(t)}$ up to time t[28].

$$P_{(t)} = \phi(-\frac{A_t}{2} + \frac{log(d)}{A_t}) - d\phi(-\frac{A_t}{2} - \frac{log(d)}{A_t})$$
$$d = \frac{V_0 \cdot e^{\lambda^2}}{\bar{L}}; A_t^2 = \sigma^2 t + \lambda^2 \tag{8}$$

[27] Define a time-shift Brownian motion $\hat{W}_t$ that starts at $\hat{t}_0$. Then $\frac{d\hat{X}_t}{\hat{X}_t} = -\frac{\sigma^2}{2}d\hat{t} + \sigma d\hat{W}_t$ also follows time-shift Brownian motion with $\hat{X}_{\hat{t}_0} = 0; E(\hat{X}) = -\frac{\sigma^2}{2}(t + \frac{\lambda^2}{\sigma^2}); Var(\hat{X}) = \sigma^2(t + \frac{\lambda^2}{\sigma^2})$.

[28] The general formula for the probability of a Brownian motion is $Y_t = at + bW_t > y, \forall s < t$ is $P[Y_s > y] = \phi(\frac{at-y}{b\sqrt{t}} - e^{\frac{2ay}{b^2}}\phi(\frac{at+y}{b\sqrt{t}}))$, where $\phi(\cdot)$ is the cumulative probability distribution function. The CreditGrade model focuses on the Brownian motion probability $\hat{X}_t = -\frac{\sigma^2}{\hat{t}} + \sigma\hat{W}_t$ exceeding the fixed level of $log(\frac{\bar{L}D}{V_0}) - \lambda^2$.

$P_{(t)}$ allows us to specify the implied credit default spread ICDS. Denote R as recovery rate for underlying debt[29], $f(t)$ as the default density function and r as the risk-free rate. The present values of expected compensation and expected CDS spread payments due to a default event are given by equations (9) and (10) respectively.

$$(1-R)[1-P_{(0)}+\int_0^t f(s)\cdot e^{-rs}ds] \tag{9}$$

$$cds\int_0^t P_{(s)}\cdot e^{-rs}ds \tag{10}$$

The day τ value of a CDS contract M_τ for the protection buyer is the difference between present values of expected compensation and expected spreads payments in equation (11).

$$M_\tau=(1-R)[1-P_{(0)}+\int_0^t f(s)\cdot e^{-rs}ds]-cds\int_0^t P_{(s)}\cdot e^{-rs}ds \tag{11}$$

Since $\int_0^t P_{(s)}\cdot e^{-rs}ds=\frac{1}{r}(P_{(0)}-P_{(t)}\cdot e^{-rt})-\frac{1}{r}\int_0^t f(s)\cdot e^{-rs}ds$, then equation (11) can be re-expressed as equation (12).

$$M_\tau=(1-R)[1-P_{(0)}-\frac{cds}{r}(P_{(0)}-P_{(t)}\cdot e^{-rt})+(1-R+\frac{cds}{r})\int_0^t f(s)\cdot e^{-rs}ds \tag{12}$$

Using equation(13), we rewrite equation(12) as equation(14), where $\xi=\frac{\lambda^2}{\sigma^2}$; $z=\sqrt{\frac{1}{4}+\frac{2r}{\sigma^2}}$.

$$\int_0^t f(s)\cdot e^{-rs}ds=e^{r\frac{\lambda^2}{\sigma^2}}[G(t+\frac{\lambda^2}{\sigma^2})-G(\frac{\lambda^2}{\sigma^2})]$$

$$G(t)=d^{z+\frac{1}{2}}\phi(-\frac{log(d)}{\sigma\sqrt{t}}-z\sigma\sqrt{t})+d^{-z+\frac{1}{2}}\phi(-\frac{log(d)}{\sigma\sqrt{t}}+z\sigma\sqrt{t}) \tag{13}$$

$$M_\tau=(1-R)[1-P_{(0)}-\frac{cds}{r}(P_{(0)}-P_{(t)}\cdot e^{-rt})+(1-R+\frac{cds}{r})e^{r\xi}(G(t+\xi)-G(\xi)) \tag{14}$$

Finally, by setting $M_\tau=0$, we obtain the close-form solution for ICDS in equation (15). Since it uses only stock prices and balance sheet information, ICDS is the CDS spread implied by the equity market.

$$ICDS=r(1-R)[\frac{1-P_{(0)}+e^{r\xi}(G(t+\xi)-G(\xi))}{P_{(0)}-P_{(t)}\cdot e^{rt}-e^{r\xi}(G(t+\xi)-G(\xi))}] \tag{15}$$

[29] R is different from $\bar{L}$. R is the expected recovery rate for specific debt covered by the CDS contract, whereas $\bar{L}$ is the expected global recovery rate i.e. expected average recovery rate for all debt of the firm. Base on $P_{(t)}$, the risk neutral probability of the default density function can be defined as $f(t)=-\frac{dP_{(t)}}{dt}$.

Figure 1: Cross sectional average CDS spreads and ICDS estimates for full sample period

Figure 2A: Cross sectional average CDS spreads and ICDS for pre-GFC sub-sample

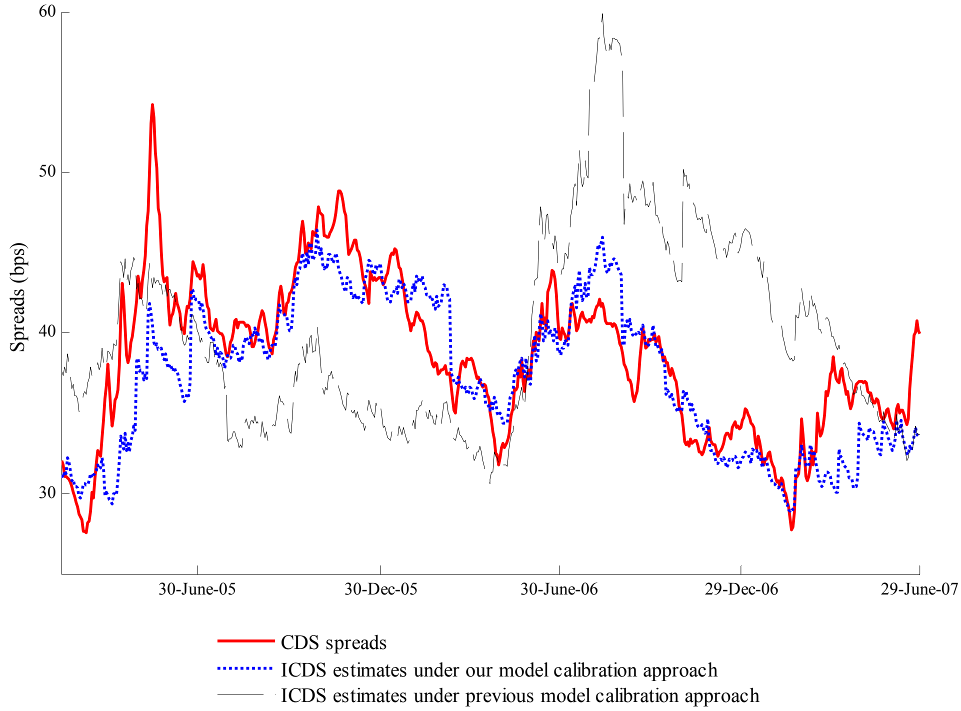

Figure 2B: Cross sectional average CDS spreads and ICDS estimates for GFC sub-sample

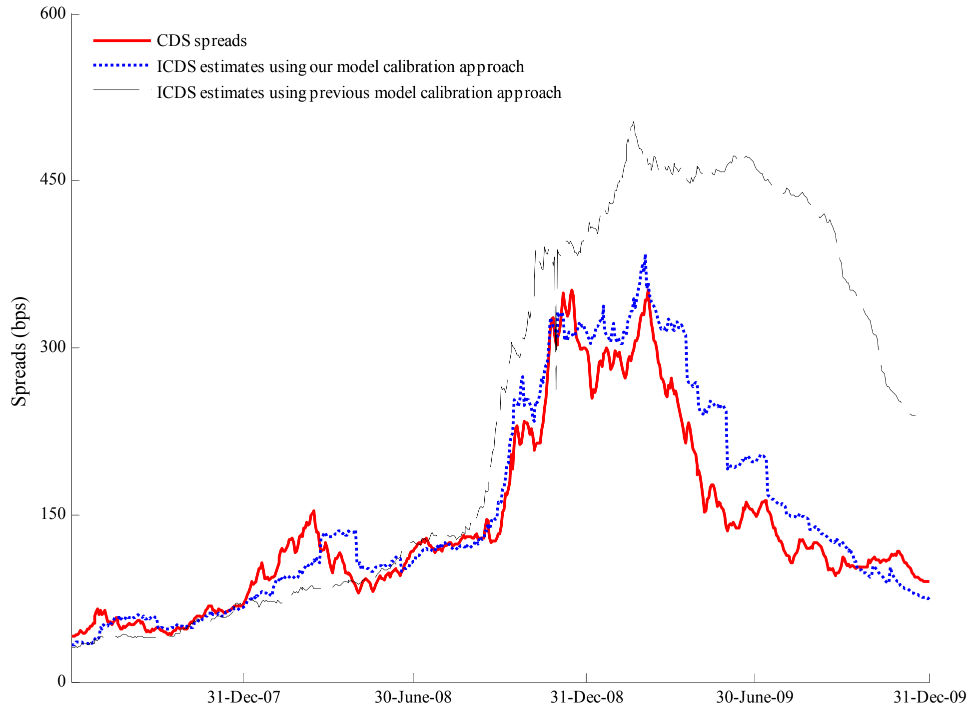

Figure 3: Number of C1 and C2 firms across eleven rolling windows (RW)

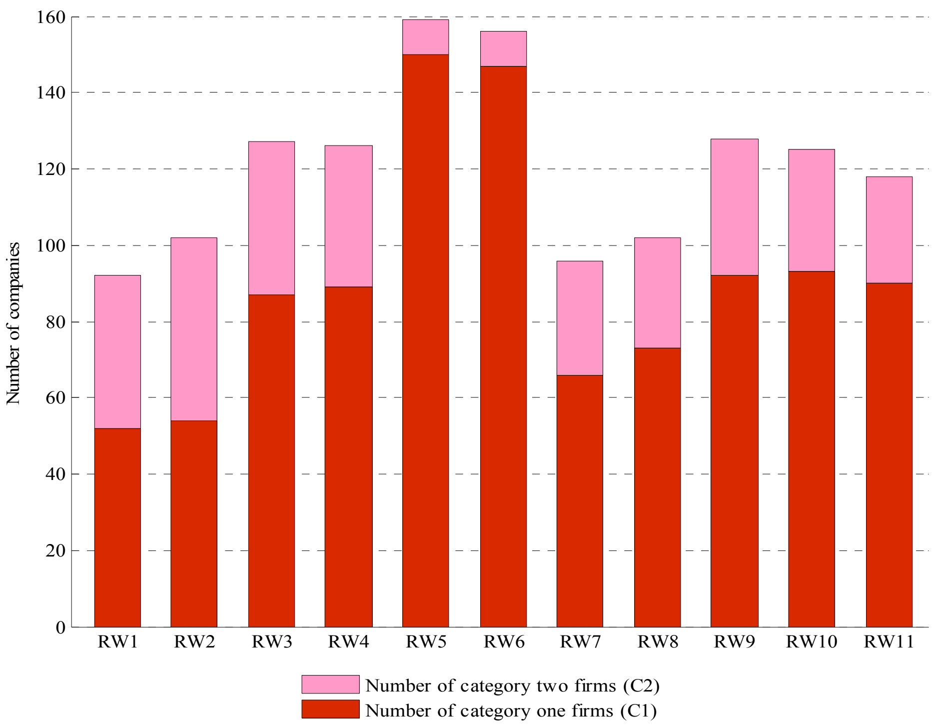

Table 1: Industry Classification and Rating Groups

This table shows industry classifications and credit ratings of our firm sample, which covers 7 industry sectors: basic materials, communications, consumer non-cyclical, consumer cyclical, energy, industrial and technology. We use S&P long term debt rating to classify firms into credit rating groups. AA group includes firms with ratings AA+, AA and AA-, A group includes firms with ratings A+, A and A- and BBB group includes firms with BBB+, BBB and BBB- ratings.

	Number of Companies
Whole Sample	174
AAA	5
AA	13
A	65
BBB	91
Basic Materials	22
Communications	7
Consumer Cyclical	35
Consumer Non-Cyclical	44
Energy	27
Industrial	33
Technology	6

Table 2: Long-run Credit Risk Pricing Equilibrium across CDS and Equity Markets

We apply Johansen' cointegration test to each firm's ($CDS_{i,t}$ and $ICDS_{i,t}$). Panel A provides cointegration outcomes for the full sample, pre-GFC sub-sample of Jan 2005 to Jun 2007 and GFC sub-samples of Jul 2007 to Dec 2009. Panel B provides a further partitioning based on credit-ratings.

	Total Number of Companies	Cointegrated at 5% level	Not cointegrated at 5% level
Panel A: Full and Sub-sample Periods			
Full Sample Period	174	173	1
Pre-GFC Sub-Sample Period	174	172	2
GFC Sub-Sample Period	174	165	9
Panel B: Rating Group			
Full Sample Period AAA Firms	5	5	0
Full Sample Period AA Firms	13	13	0
Full Sample Period A Firms	65	64	1
Full Sample Period BBB Firms	91	91	0
Pre-GFC Sample Period AAA Firms	5	5	0
Pre-GFC Sample Period AA Firms	13	12	1
Pre-GFC Sample Period A Firms	65	64	1
Pre-GFC Sample Period BBB Firms	91	91	0
GFC Sample Period AAA Firms	5	5	0
GFC Sample Period AA Firms	13	12	1
GFC Sample Period A Firms	65	64	1
GFC Sample Period BBB Firms	91	84	7

Table 3: Credit Risk Price Discovery across CDS and Equity Markets

We present results of credit risk price discovery across CDS and equity market. In equation (3), if only $\lambda_1 < 0$ ($\lambda_2 > 0$) is significant, it suggest equity (CDS) market dominates credit risk price discovery process. If both $\lambda_1 < 0, \lambda_2 > 0$ are significant, this implies equity and CDS market both contribute to credit risk price discovery. We compute Gonzalo-Granger (GG) and Hasbrouck (HAS) measures of price discovery contribution. The GG measure for CDS market is calculated as $\frac{-\lambda_1}{\lambda_2-\lambda_1}$. HAS measure defines an upper $\mathrm{HAS_U}$ and lower bound $\mathrm{HAS_U}$ and lower bound $\mathrm{HAS_L}$ for each market price discovery contribution. $\mathrm{HAS_U}$ and $\mathrm{HAS_L}$ for the CDS market are calculated as equation (4). When $\frac{1}{2}(\mathrm{HAS_U} + \mathrm{HAS_L}) > 0.5$ and $\frac{-\lambda_1}{\lambda_2-\lambda_1} > 0.5$, this indicates that the CDS market has larger price discovery contribution than the equity market and vice versa. However, if there is no consensus between GG and HAS measures, we regard CDS and equity market as contributing similarly to credit risk price discovery. The preceding discussion implies five mutually exclusive price discovery categories {C1,…,C5}. C1 (Category 1) and C5 (Category 5) contain firms where the CDS and equity market dominates price discovery respectively. Firms where both GG and HAS measures indicate the CDS (equity) market contributes more price discovery are allocated in C2 (C4). Lastly, firms for which the two measures do not share a consensus are assigned to C3. Hence {C1,…,C5} can be viewed as a price discovery spectrum with the CDS market dominating price discovery at one end, while the equity market dominates at the other end. The results for the full sample period are presented in Panel A, whereas Panels B and C results correspond to pre-GFC and GFC sub-samples.

	Category 1 (C1)	Category 2 (C2)	Category 3 (C3)	Category 4 (C4)	Category 5 (C5)	Total
Panel A: Whole Sample Period						
All Firms	74	57	14	16	12	173
AAA	2	3	0	0	0	5
AA	8	2	1	1	1	13
A	24	23	4	6	7	64
BBB	40	29	9	9	4	91
Panel B: Pre-GFC Sample Period						
All Firms	52	40	18	47	15	172
AAA	1	0	0	4	0	5
AA	1	2	2	7	0	12
A	19	10	8	22	5	64
BBB	31	28	8	14	10	91
Panel C: GFC Sample Period						
All Firms	90	28	13	11	23	165
AAA	4	1	0	0	0	5
AA	8	1	0	1	2	12
A	34	12	3	3	12	64
BBB	44	14	10	7	9	84

Table 4: Transition of Firms between Price Discovery Categories

This table reports relevant details on the number and percentage of firms that migrate from one category into another in Panels A and B respectively. In both panels, the column headings are for the pre-GFC sample and row headings represent the GFC sample. For completeness, we include C6, which represents firms for which no cointegration exists between $CDS_{i,t}$, $ICDS_{i,t}$.

Panel A: Number of Firms	Pre-GFC C1	Pre-GFC C2	Pre-GFC C3	Pre-GFC C4	Pre-GFC C5	Pre-GFC C6	Total
GFC C1	**35**	17	12	20	4	2	90
GFC C2	4	**6**	2	10	6	0	28
GFC C3	3	6	**3**	1	0	0	13
GFC C4	2	4	0	**4**	1	0	11
GFC C5	6	5	0	10	**2**	0	23
GFC C6	2	2	1	2	2	**0**	9
Total	52	40	18	47	15	2	174

Panel B: Percentage of firms in Pre-GFC Category	Pre-GFC C1	Pre-GFC C2	Pre-GFC C3	Pre-GFC C4	Pre-GFC C5	Pre-GFC C6
GFC C1	**67.31%**	42.50%	66.67%	42.55%	26.67%	100.00%
GFC C2	7.69%	**15.00%**	11.11%	21.28%	40.00%	0.00%
GFC C3	5.77%	15.00%	**16.67%**	2.13%	0.00%	0.00%
GFC C4	3.85%	10.00%	0.00%	**8.51%**	6.67%	0.00%
GFC C5	11.54%	12.50%	0.00%	21.28%	**13.33%**	0.00%
GFC C6	3.85%	5.00%	5.56%	4.26%	13.33%	**0.00%**
Total	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%

Table 5: Rolling Window Credit Risk Price Discovery

We report the number of firms in {C1,…, C5} base on 11 quarterly rolling window estimations {RW1,…, RW11} of GG and HAS measures. Rolling-window 1 (RW1) is simply the pre-GFC sub-sample. RW2 ranges from 01-Apr-2005 to 30-Sep-2007, and so on. The last rolling window RW11 covers from 01-Jul-2007 to 31-Dec-2009 i.e. GFC sub-sample. In other words, we update the price discovery categorization for each of the 174 firms on a quarterly basis.

	RW1	RW2	RW3	RW4	RW5	RW6	RW7	RW8	RW9	RW10	RW11
Starting Date	2005/1/1	2005/4/1	2005/7/1	2005/10/1	2006/1/1	2006/4/1	2006/7/1	2006/10/1	2007/1/1	2007/4/1	2007/7/1
Ending Date	2007/6/30	2007/9/30	2007/12/31	2008/3/31	2008/6/30	2008/9/30	2008/12/31	2009/3/31	2009/6/30	2009/9/30	2009/12/31
C1 Firms	52	54	87	89	150	147	66	73	92	93	90
C2 Firms	40	48	40	37	9	9	30	29	36	32	28
C3 Firms	18	23	23	8	3	2	13	20	14	18	13
C4 Firms	47	37	20	12	1	2	17	20	12	10	11
C5 Firms	15	9	0	12	6	6	39	25	15	16	23
C6 Firms	2	3	4	16	5	8	9	7	5	5	9
Total	174	174	174	174	174	174	174	174	174	174	174

Table 6: Profit/loss results of the threshold portfolio approach

We set a threshold of $\pm 20\%$ change in weekly CDS spreads as a signal that the underlying firm's credit risk profile has changed. Ever Tuesday, we sort candidate firms according to the weekly percentage change in CDS spreads ΔCDS%. Next trading day, an equally-weighted portfolio is created by short-selling (buying) firms for which $\Delta CDS\% > 20\%$ ($\Delta CDS\% < -20\%$). The portfolio is held for one week, after which it is liquidated. Other aspects are similar to the long-short portfolio approach. We report profit/loss results, including basic statistics of realised returns, features of the portfolio, annualised return/risk ratio etc.

	PS1	PS2	PS3	PS4	PS5
Min	-12.61%	-15.05%	-13.37%	-23.16%	-14.48%
Max	21.18%	23.60%	21.59%	28.07%	20.37%
Median	0.12%	0.31%	0.72%	-0.13%	-0.12%
Mean	0.18%	0.56%	0.52%	-0.12%	0.06%
Standard Deviation	5.26%	6.57%	5.88%	5.8%	4.89%
Percentage of Portfolios Generating Positive Returns	52.94%	52.04%	58.25%	47.41%	47.12%
Cumulative Returns	5.21%	40.10%	43.81%	-28.62%	-5.33%
Annualised Return	2.05%	14.44%	15.64%	-12.61%	-2.17%
Annualised Standard Deviation	37.91%	47.41%	42.41%	41.84%	35.29%
Sharpe Ratio	0.0475	0.2993	0.3629	-0.3074	-0.0686
Number of Portfolios	119	98	103	116	104
Average Number of Stocks Included in the Portfolio	16.62	5.76	10.83	12.19	8.30
Average Number of Long Stocks in the Portfolio	5.01	1.66	2.83	3.72	2.91
Average Number of Short Stocks in the Portfolio	11.61	4.11	8.01	8.5	5.38
Standard Deviation of Number of Stocks Included in the Portfolio	22.22	6.47	15.79	16.56	10.39

Table 7: Weekly estimation results on Jensen's Alpha

We present weekly estimation results for Jensen's alpha against Fama-French factors. We present least-square estimates in Panel A. The residual returns in Figure 4 exhibit possible GARCH-effects in the time-series. Subsequent diagnostic tests using the Godfrey (1978) and Breusch and Pagan (1979) procedures confirm the presence of heteroskedasticity in residual returns. In Panel B, we fit a GARCH (2, 3) process to re-estimate Jensen's alpha.

Panel A: Least-square estimation

Variables	**PS1**	**PS2**	**PS3**	**PS4**	**PS5**
α_i	0.0014	0.0039	0.0038	-0.0012	0.0005
	(0.751)	(0.439)	(0.403)	(0.796)	(0.887)
MRP_{it}	-0.1885	-0.0474	-0.2919	-0.1783	-0.0768
	(0.494)	(0.840)	(0.268)	(0.602)	(0.791)
SMB_{it}	-0.0510	-0.3691	-0.1298	-0.0313	0.2777
	(0.919)	(0.496)	(0.811)	(0.954)	(0.617)
HML_{it}	-0.0528	-0.2341	0.0169	0.0506	-0.1284
	(0.904)	(0.673)	(0.970)	(0.922)	(0.756)

Panel B: GARCH (2,3) estimation

Variables	**PS1**	**PS2**	**PS3**	**PS4**	**PS5**
α_i	0.0026	0.0034	0.0041	0.0018	0.0007
	(0.178)	(0.080)*	(0.022)**	(0.539)	(0.759)
MRP_{it}	-0.2823	-0.3635	-0.4380	-0.1608	-0.1512
	(0.154)	(0.001)**	(0.000)**	(0.300)	(0.443)
SMB_{it}	-0.0898	-0.9092	-0.6309	-0.2491	-0.0504
	(0.742)	(0.001)**	(0.012)**	(0.292)	(0.854)
HML_{it}	0.0491	0.8044	0.1977	0.2116	-0.0446
	(0.845)	(0.000)**	(0.375)	(0.412)	(0.850)
ε^2_{it-1}	0.2832	0.3528	0.4439	0.3811	0.5670
	(0.028)**	(0.000)**	(0.000)**	(0.009)**	(0.055)*
ε^2_{it-2}	0.2317	0.1289	-0.1770	-0.4251	-0.5008
	(0.026)**	(0.204)	(0.018)**	(0.002)**	(0.058)*
σ^2_{it-1}	0.1441	0.1773	0.3331	1.1625	1.1292
	(0.206)	(0.022)**	(0.003)**	(0.000)**	(0.000)**
σ^2_{it-2}	-0.4051	-0.2951	-0.2273	0.2511	-0.2318
	(0.000)**	(0.000)**	(0.001)**	(0.310)	(0.438)
σ^2_{it-3}	0.6618	0.6404	0.5698	-0.3747	0.0286
	(0.000)**	(0.000)**	(0.000)**	(0.005)**	(0.834)

[a] p-values in parentheses

** indicate 5% or less significance level

* indicates 10% or less significance level

Table 8: Profit/loss results from the second set of bench-marking

We present profit/loss results from other proven portfolio strategies that we apply using our firm sample. This includes a buy-and-hold strategy in Panel A, a 6-months rank and 1-month hold, or 6-1 momentum strategy in Panel B and a high dividend-yield portfolio strategy that we apply on Dow-Jones stocks (Dow-Dogs) in Panel C, and our firm sample (CDS-Dogs) in Panel D. For the latter two, we consider yearly, quarterly, monthly and weekly rebalancing intervals.

	Panel A: Buy & Hold	*Panel B: Momentum*	*Panel C: Dow-Dogs*				*Panel D: CDS-Dogs*			
Rebalancing frequency	*N.A*	*Rank 6-Hold 1*	*Yearly*	*Quarterly*	*Monthly*	*Weekly*	*Yearly*	*Quarterly*	*Monthly*	*Weekly*
Cumulative return	-2.11%	-79.98%	-40.39%	-32.64%	-40.66%	-44.02%	-25.35%	38.12%	11.81%	19.70%
Annualized return	-0.85%	-31.99%	-22.79%	-14.12%	-18.84%	-20.71%	-13.60%	13.79%	4.57%	7.46%
Annualized standard deviation	33.50%	51.68%	3.49%	31.12%	37.21%	38.74%	2.4%	62.29%	49.52%	42.03%
Sharpe Ratio	-0.033	-0.619	-6.601	-0.478	-0.513	-0.541	-5.763	0.217	0.087	0.172
Number of trading portfolios	1	30	2	10	30	130	2	10	30	130

Table 9: Profit/loss results from a six-by-six month rank-hold permutation matrix of momentum portfolios

We report the annualised returns and Sharpe Ratios (in parentheses) for 36 momentum portfolios over a six months rank-hold permutation matrix. The first column represents the number of ranking months, while the first row represents the number of holding months. We sort firms based on their past k months returns. We go long in the bottom (winner) decile portfolio and short-sell the top (loser) decile portfolio to form our winner-minus-loser portfolio. Accordingly, each momentum portfolio consists of 34 stocks in total. Every momentum portfolio is formed using the same firm sample. The strategies are implemented over the same trading period. Momentum portfolios that generate positive returns are highlighted in bold.

Holding Month Ranking Month	1	2	3	4	5	6
1	**11.34%** **(0.356)**	-3.90% (-0.206)	**11.30%** **(0.516)**	-7.27% (-0.441)	**3.30%** **(0.200)**	-7.91% (-0.823)
2	-0.86% (-0.033)	-1.95% (-0.078)	-1.62% (-0.117)	-9.54% (-0.403)	-6.58% (-0.382)	-9.45% (-0.785)
3	-17.32% (-0.212)	**9.26%** **(0.116)**	-22.55% (-0.401)	-11.08% (-0.218)	-6.96% (-0.218)	-9.93% (-0.201)
4	-9.63% (-0.122)	-13.14% (-0.206)	-12.59% (-0.257)	-19.26% (-0.390)	-21.77% (-0.576)	-11.22% (-0.252)
5	-20.26% (-0.417)	-3.42% (-0.123)	-32.61% (-0.877)	-13.36% (-0.541)	-6.10% (-0.331)	-10.80% (-0.668)
6	-31.99% (-0.619)	-7.30% (-0.286)	-35.02% (-0.846)	-14.97% (-0.724)	-3.78% (-0.210)	-10.57% (-0.766)
Number of traded portfolios	30	15	10	7	6	5