

Term Structure of Credit Default Swap Spreads and Cross–Section of Stock Returns*

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Current Version: March 2011

*We thank Leroy A. Yong Duarte and Olumayowa O. Olubori for the excellent data collection and management work. We thank Moody's KMV for providing the EDF data. We thank Aydogan Altı, Michael Brennan, Keith Brown, Zhi Da, John Griffin, Andre Guettler, Umit Gurun, Burton Hollifield, Francis Longstaff, Alessio Saretto, Clemens Sialm, Sheridan Titman, Dragon Tang, Longkai Zhao, Zhongyan Zhu as well as participants of the seminars at Peking University, University of Hong Kong, University of Texas at Austin, University of Toronto, 21st Annual Derivatives Securities and Risk Management Conference, 2011 China International Conference in Finance for helpful discussions and insightful comments. All remaining errors are our own.

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Abstract

The slope of a firm's term structure of credit default swap (CDS) spreads (five-year spread minus one-year spread) negatively predicts future stock returns. Stocks with low CDS slope on average outperform stocks with high CDS slope by over 1% each month for the next six months. Our result can not be explained by standard risk factors, stock characteristics, default risk measures or changes in CDS spreads. We find that CDS slope positively predicts future changes in CDS spreads, but the information content of CDS slope only slowly gets incorporated into stock price. CDS slope predicts return mainly for stocks facing high arbitrage costs.

JEL Classification: G12.

Keywords: cross-section of stock return, credit default swap, term structure, default risk premium, default probability.

1 Introduction

Previous studies have documented that credit spreads - the difference between corporate and treasury yields - forecast economic activity such as output and investment growth (e.g., Stock and Watson (1989), Lettau and Ludvigson (2002)) as well as future stock market returns (e.g., Keim and Stambaugh (1986), and Fama and French (1993)). In this paper, we examine the link between individual firm's term structure of credit default swap (CDS) spreads and the expected stock returns.

The credit default swap market has grown tremendously and become increasingly liquid over the last decade.¹ A CDS is a swap contract in which the protection buyer makes a series of payments to the protection seller and, in exchange, receives a payoff in case of credit events of the reference bond such as downgrading and default. The periodic payment, which is usually expressed as a percentage of the bond's notional value, is called the CDS spread. We observe CDS spreads each day on the same set of maturities (ranging from one to ten years). We use this rich dataset to measure the slope of CDS spreads term structure for individual firms and then study its implication for the cross-section of stock returns.

The CDS data have several important advantages over the corporate bonds data. First, compared to credit spreads, CDS spreads are not subject to the specification of benchmark risk-free yield curve. Second, CDS contracts are much more liquid than corporate bonds. CDS contracts are traded on a daily frequency while corporate bonds are usually held to maturity and may not trade even once in a month. Compared to credit spreads, CDS spreads are less contaminated by non-default risk components (Longstaff, Mithal, and Neis (2005) and Ericsson, Reneby, and Wang (2006)). Third, CDS prices lead credit spreads in the price discovery process (e.g., Blanco, Brennan, and Marsh (2005)). Fourth, the terms of contract are standard and easily comparable across firms, making the CDS data more suitable for cross-sectional study.

¹According to BIS, CDS market grew from \$0.6 trillion in notional amount outstanding in 2001 to \$62 trillion in 2007, but dropped to \$26.5 trillion in July 2009 because of the recent financial crisis.

We find that the slope of the term structure of CDS spreads, defined as the difference between five-year CDS spread and one-year CDS spread, significantly and negatively predicts the cross-sectional stock returns. Stocks ranked in the bottom quintile by CDS slope on average outperform those ranked in the top quintile by more than 1% per month over the next six months. The portfolio that longs low CDS slope stocks and shorts the high CDS slope stocks have a significant positive alpha of over 1% relative to the CAPM model, the Fama-French three-factor model and the Carhart four-factor model. The portfolio alpha remains statistically and economically significant (above 1%) even when we skip up to six months between portfolio formation and evaluation. The negative relation between CDS slope and expected (average future) stock return is robust to weighting schemes. It holds with Fama-MacBeth regressions and is robust to controlling for stock characteristics known to be related to the cross-section of stock return.

We examine several potential explanations for why the slope of CDS term structure negatively predicts stock return. First, we study whether our result can be explained by the relationship between expected stock returns and default risk. There is a large body of research that measures the probability of firm default based on stock market, credit market or accounting information, and then links it to the cross-section of stock return. The predictive power of CDS slope for stock return is robust to controlling for various measures of default risk (e.g., CDS spread, KMV's expected default frequency, and the measure constructed by Campbell, Hilscher and Szilagyi (2008)).

Our study takes advantage of the term structure of CDS spreads, which reflects the shape of the conditional risk-neutral default probability over different future horizons. In contrast, the existing default risk measures only capture the average default probability of a given firm, ignoring the dynamics of default probability, such as the variation or uncertainty in the default intensity.

The term structure of CDS spreads can be steep for a firm because investors require large compensation for the risk of variations in the default intensity. Pan and Singleton (2008)

use the term structure of CDS spreads to estimate the market price of risk associated with the fluctuation in the probability of default. They find a significant default risk premium. Using the Singleton and Pan model, we verify that a higher default risk premium increases the risk-neutral default probabilities relative to the physical default probabilities, leading to higher CDS spreads. The impact is larger for longer-term CDS contracts. An increase in the default risk premium pushes up the long-term CDS spreads more than the short-term CDS spreads, leading to a steeper term structure of CDS spreads. Thus, CDS slope is positively related to default risk premium. However, the positive relation between CDS slope and default risk premium can not explain the negative relation between CDS slope and stock return. If the stock market embeds default risk premium just as the CDS market, then other things being equal, we should see that high CDS slope stocks tend to have higher, not lower, returns.

Alternatively, high CDS slope may indicate that investors expect the firm's credit quality to deteriorate and CDS spreads to increase. Consistent with this "expectation hypothesis", we find that the difference between current long-term CDS spread and short-term CDS spread positively predicts future change in short-term CDS spread. This predictive relation remains significant up to twelve months ahead.

Thus, we find that the current slope of a firm's term structure of CDS spreads not only negatively predicts its future stock return, but it also signals deterioration in firm's credit quality. We argue that slow information diffusion is needed in order to reconcile these two findings. Based on our results, current CDS slope clearly contains useful information about future credit quality of the firm. This information is public. But it is not reflected in the current stock prices. Otherwise, the expected returns for high CDS slope stocks should be higher, not lower. The negative relation between current CDS slope and future stock return is consistent with subsequent changes in stock prices as the information content of the current CDS slope slowly get incorporated into stock prices.

We find that the predictive power of CDS slope for stock return is significant mostly for

stocks facing high arbitrage costs, such as those with small market capitalization, low price, high bid-ask spread, low institutional ownership and high information uncertainty. The CDS slope does not significantly predict return for low arbitrage cost stocks. On the other hand, the current CDS slope significantly predict future change in CDS spreads in all subsamples of stocks sorted by size, book-to-market, leverage, institutional ownership, information uncertainty and various liquidity measures. Our results suggest that the information content of CDS slope is largely reflected in the stock prices when limits to arbitrage are low. Slow diffusion of information occurs only when the limits to arbitrage are high.

Our study contributes to a growing literature documenting evidence of slow information diffusion from derivative markets to the stock market and that various variables constructed from the derivative markets can predict stock returns.² Among them, we are aware of only two papers that link CDS and stock market. Acharya and Johnson (2007) and Ni and Pan (2010) both find that recent change in CDS spread negatively predicts stock return over the next few days. Both find that the predictability is asymmetric, driven mostly by stocks with more positive percentage change in CDS spreads, and therefore more negative information according to the CDS market. Ni and Pan (2010) show that the predictability is caused by short-sale constraints in the stock market.

The predictability of CDS slope lasts for six months, much longer than that for change in CDS spreads.³ We do not find asymmetry in the predictability of CDS slope. Stocks with high CDS slope have negative abnormal returns, and stocks with low CDS slope have positive abnormal returns. Further, the relation between CDS slope and future stock return remains significant after controlling for recent change in CDS spread.

Our study uses the CDS data of North American firms. Berndt and Obrejas (2010)

²See, e.g., Pan and Poteshman (2006), Cremers and Weinbaum (2010), Xing, Zhang, and Zhao (2010) and others. These studies are related to but distinct from research documenting contagions across markets that are not very closely related. For example, Longstaff (2010) finds that returns of subprime CDO indexes forecast stock and Treasury bond returns as much as three weeks ahead during the recent financial crisis.

³Our study uses monthly data rather than daily data in Acharya and Johnson (2007) and Ni and Pan (2010). We find that monthly change in CDS spread has marginally significant predictive power for stock return for one month ahead, but this predictive power becomes insignificant beyond one-month horizon.

study the CDS of European firms. They extract a common factor from CDS returns. While this factor is crucial for explaining variation in CDS returns, it has little contribution to explaining variation in stock returns. They argue that this is due to the limited sensitivity of the value of equity at default to whether the credit event is of systemic or idiosyncratic nature. Our approach is different from Berndt and Obrejas (2010). We focus on the ability of the slope of CDS spreads term structure to forecast the cross-section of stock return. In unreported result, we find that a factor constructed based on the CDS term structure is priced in the equity market.⁴

Our findings are related to but distinct from the literature on the cross-sectional relationship between expected stock returns and default or distress risk. Some studies document that returns are actually lower for firms with high financial distress risk, the so called financial distress risk puzzle (see, e.g., Griffin and Lemmon (2002), Campbell, Hilscher, and Szilagyi (2008)). However, other studies find positive cross-sectional relationship between expected stock returns and default risk (e.g., Vassalou and Xing (2004) and Chava and Purnenandam (2010)). For our sample, there is no significant relation between these proxies of default risk and stock return.

It is well documented that the interest rate term structure is a powerful economic forecasting tool. For example, Harvey (1988) and Harvey (1991) show that real term structure slope (the spread between a long-term yield and a short-term yield) forecasts consumption growth and economic growth. Fama and French (1993) find that excess returns on US stocks and corporate bonds are positively related to the slope of the yield curve. Boudoukh and Richardson (1993) show that ex ante risk premiums on US stocks are negative in periods

⁴Specifically, the factor realization in a given month is the difference of the equal-weighted average returns between the bottom and the top quintile of stocks sorted at the the previous month by CDS slope. We estimate the beta of each stock with respect to this CDS slope factor using rolling regressions and past 60 month returns data. Then we regress the cross-section of stock returns each month from August 2007 to December 2009 on their beta's with respect to the slope factor as well as the Fama-French three factors and the momentum factor. We find that the coefficient of the beta with respect to the slope factor is significantly positive. This result is available upon request.

preceded by inverted yield curves.⁵ The slope of interest rate term structure is believed to track embedded term risk premiums, which are investors' rewards to bearing interest rate risk.⁶

We link the CDS slope to default risk premium, motivated by Pan and Singleton (2008). Driessen (2005) and Berndt, Douglas, Duffie, Ferguson, and Schranz (2008) empirically measure default risk premium as the ratio of risk-neutral to actual default probability. Driessen (2005) finds that risk-neutral default probabilities are significantly higher than actual default probabilities. Berndt, Douglas, Duffie, Ferguson, and Schranz (2008) document large variation of default risk premium over time. Collin-Dufresne, Goldstein, and Helwege (2010) identify three economic sources for the default risk premium. In particular, they emphasize the importance of a credit contagion risk premium, which is due to a market-wide adverse reaction to a given firm's default.

The remainder of this paper is organized as follows. Section 2 discusses the data and summary statistics of key variables. in various ways. Section 3 documents a significant negative relationship between CDS slope and future stock return. Several explanations are examined. Section 4 concludes the paper.

2 Data

We use a comprehensive dataset of single-name credit default swaps. A single-name CDS is a contract that provides protection against the risk of a credit event by a particular company. The protection buyer makes a periodic payment (e.g., every six-month) to the protection seller until the occurrence of a credit event or the maturity date of the contract, whichever is first. This fee, quoted in basis points per \$1 notional amount of the reference obligation, is

⁵For evidence that the term structure of interest rates can forecast aggregate stock returns, see also Campbell (1987), Zhou (1998) etc.

⁶For example, Fama and French (1993) state that "The spread tracks a term or maturity risk premium in expected returns that is similar for all long-term assets."

called the default swap premium, or credit default swap spread. In the event of a default by the reference entity, the protection seller agrees to buy the reference issue at its face value from the protection buyer.

Our CDS data is provided by Markit, a global financial information services company. Markit receives contributed CDS data from market makers from their official books and records. Markit then cleans the data (e.g., discard stale, outliers and inconsistent data) and forms composite price for each CDS contract. We have also obtained CDS spreads data from Bloomberg. Our data covers the August 2002 to December 2009 period. Our sample consists of US dollar denominated CDS written on US entities that are not in the government sectors. We further eliminate the subordinated class of contracts because of its small relevance in the database and its unappealing implications for credit risk pricing. We choose firms that have non-missing month-end values for CDS spreads of all maturities. This leaves us a dataset of CDS spreads that has 49,820 firm-month observations on 695 firms. Mark-it also provides a credit rating for each company, which is the average of the Moodys and S&P ratings adjusted to the seniority of the instrument and rounded to not include the “+” and “-” levels.

The maturities of CDS are uniform across firms. For each firm in the database, we observe CDS spreads for the maturities of 1 year, 2 year, 3 year, 5 year, 7 year and 10 year. Throughout the paper, we measure the slope of CDS term structure by the difference between the 5-year CDS spread and 1-year CDS spread. Alternative definitions of CDS slope, such as 10-year spread minus 1-year spread, do not change our main results materially.

The high quality and rich CDS dataset allows us to measure the shape of credit term structure for individual firms. In contrast, due to data limitation, in previous studies that use corporate bonds, researchers can only examine the average shape of the credit term structure, where the average is taken across firms in a given credit rating. In addition, Helwege and Turner (1999) point out that these studies are subject to potential bias of maturity clustering.⁷

⁷Under a single rating, safer firms are more likely to issue long-term bonds. When credit spreads of

We obtain monthly stock returns, stock price, and shares outstanding from CRSP. Returns of common risk factors and risk-free rate are taken from Kenneth French's website. For control variables, we obtain firm quarterly balance-sheet and annual accounting data Compustat, analyst coverage and earnings forecasts data from I/B/E/S, and quarterly institutional holding (13f filing) from Thomson Financial.

Table 1 reports the summary statistics of credit default swap spreads. The average CDS spread vary widely across ratings and maturities. During our sample period, the mean levels of 5-year CDS spreads are 41.25 basis points (bps) for AAA firms, 59.13 bps for AA firms, 59.92 bps for A firms and 105.43 bps for BBB firms. The mean levels of 5-year CDS spreads are 293.74 (BB), 664.92 (B) and 2,143.01 (CCC) bps for non-investment-grade firms, much higher than those for investment-grade firms. CDS spreads have large standard deviations compared to their mean levels, especially for low rating firms. During the recent financial crisis, the CDS spreads experienced large spikes, especially for B and CCC rated firms. The 5-year CDS spreads of B (CCC) firms jumped from about 400 (1,000) bps pre-crisis to around 2,000 (9,000) bps during the financial crisis.

The average CDS spread increases with maturity for firms rated from AAA to B. For CCC rated firms, however, the average CDS spread decreases with maturity. Table 2 reports the summary statistics of CDS slopes. The average slope is positive, and increases from 14.42 bps (AAA) to 76.83 bps (BB) and 97.20 bps (B). The average slope of CCC rated firms is negative, suggesting that the CCC firms on average have downward sloping credit term structure. Across the whole sample, the mean of CDS slope is around 30 bps and the standard deviation is 410 bps.

Figure 1 displays the monthly time series of the 80 percentile, the median and the 20 percentile for the cross-sectional distribution of CDS slope. All three time series experienced a dramatic drop as the financial crisis worsened between late 2008 and early 2009, with the 20 percentile of CDS slope dipping below zero (leading to inverted CDS term structure). But different maturities are clustered together (because the available bond maturities are different across firms), the safer firms' credit spreads drive the group credit spread for long terms.

by the fall of 2009, they have bounced back to the levels before the crisis. Figure 1 also shows an increasing trend in the cross-sectional dispersion of CDS slope. The spread between the 80 and the 20 percentiles of CDS slope increased from about 20 bps in the first one-third of the sample, to about 60 bps in the second one-third of the sample, and to around 100 bps in the last part of the sample.

3 Empirical Results

3.1 CDS Slope Negatively Predicts Stock Return

To examine the link between the current slope of CDS spreads term structure and future stock returns, we sort stocks into various portfolios based on their CDS slope at the end of each month, and compare their average future returns. Our results are robust to sorting into five or ten portfolios based on CDS slope. They hold for both value and equal weighting schemes.

In Table 3, we sort stocks into deciles based on the previous month-end CDS slope. Decile 10 consists of stocks with the highest CDS slopes while decile 1 consists of stocks with the lowest CDS slopes at the previous month-end. Panel A presents the average raw returns of equal-weighted CDS slope decile portfolios, the difference of average raw returns between the bottom and the top decile portfolios, as well as the alphas of the portfolios with respect to the CAPM, the Fama–French3 factor model and the Carhart 4 factor model. Panel B reports estimated loadings of decile portfolios sorted by CDS slope on the Fama–French factors.

The average return of the decile portfolio sorted by CDS slope declines monotonically, from 2.59% per month for the bottom decile to 0.54% per month for the top decile. The difference is 2.05% per month (24.60% per year), with a t -statistic of 2.81. Figure 2 plots the time-series of the monthly returns to the equal-weighted portfolio strategy that buys the

bottom CDS slope decile and shorts the top decile.

Both the top and the bottom CDS slope decile portfolios have high market beta, but the difference is insignificant. Stocks with high CDS slope have significantly higher exposure to the *SMB* factor than stocks with low CDS slope. On the other hand, stocks with high CDS slope have significantly lower exposure to the *HML* factor. After controlling for the standard common factors in the stock market, the bottom decile portfolio sorted by CDS slope has significant positive alphas (over 1%), while the top decile portfolio has negative alphas. The equal-weighted spread portfolio that is long stocks in the bottom CDS slope decile and short stocks in the top decile has a monthly alpha of 1.95%, 2.00% and 1.96% with respect to the CAPM, the Fama–French 3 factors model and the Carhart 4 factors model respectively. All three alphas are statistically significant at 1% level.

Table 4 reports the average returns of CDS slope decile portfolios over three future horizons. The CDS slopes are measured at time t . $r_{0,1}$ is the return over the month $[t, t + 1]$. $r_{1,2}$ is the return over $[t + 1, t + 2]$ (i.e., we skip a month between the portfolio formation and evaluation periods); and $r_{2,3}$ is the return over the month $[t + 2, t + 3]$. The portfolios are equal weighted in Panel A, and value weighted in Panel B.

For both weighting schemes, we find that low CDS slope stocks significantly outperform high CDS slope stocks in each of the first three months after we sort on CDS slope. The equal-weighted portfolio that is long the bottom decile slope stocks and short the top decile slope stocks has an average return of 2.05%, 1.80% and 1.88% respectively in the first, second and third months after portfolio formation. The alphas of these portfolios are about 1.7% to 2% per month and statistically significant. The returns of the value-weighted portfolios in Panel B are smaller than their equal-weighted counterparts. But the pattern are the same. The value-weighted portfolio that is long the bottom decile slope stocks and short the top decile slope stocks has an average return of 1.68%, 1.66% and 1.52% respectively in the first, second and third months after portfolio formation.

To further document the robustness of the sorting results above, in Table 5 we sort stocks

by CDS slope into quintiles instead of deciles as in the previous two tables. In addition, we skip N months between forming portfolios based on CDS slope and evaluating their returns, for $N = 1, 2, \dots, 9$. For example, in the row labeled by $r_{5,6}$, we report the average returns of quintile portfolios sorted on the CDS slope six months ago. In other words, we examine the returns of portfolios sorted by CDS slope over various future horizons (not just the first month after portfolio formation).

Table 5 shows that a long-short portfolio buying the lowest CDS slope quintile of stocks and shorting the highest CDS slope quintile stocks has an average return of 1.31% over the next month, with a t -statistic of 2.53. This monthly return is significant both economically and statistically, although it is smaller than that in Table 3 where the portfolio consists of stocks with larger dispersion of CDS slope (bottom decile versus top decile). The profitability of the CDS slope portfolio strategy is little changed after controlling for the CAPM, Fama-French three factors or Carhart four factors.

Table 5 further shows that the profitability of our portfolio strategy declines in magnitude when we use the CDS slope information with a longer time lag. But even after skipping several months, the return of the portfolio strategy is still significantly positive. For example, the bottom slope quintile stocks on average outperform the top slope quintile stocks by 0.98% in the sixth month after we sort stocks by CDS slope. The predictive power of CDS slope for the stock returns persists for at least six months.

Table 6 verifies the robustness of our sorting results in various subsamples. In Panel A, just like in Table 3 Panel A, we sort stocks by the slope of their CDS term structure into ten deciles, except that now we exclude the period of the recent financial crisis starting from September 2008, or exclude CCC rated firms, or financial firms. We find that excluding the recent crisis period, low CDS slope decile on average outperforms the top decile by 1.18%. The magnitude of this outperformance is smaller than the full sample case (2.05%), but it is still significant economically and statistically (with a t -stat of 2.24). Excluding the CCC firms or the financial firms only slightly reduces the profitability of the portfolio strategy

that is long the low CDS slope stocks and short the high slope stocks, with the average return being 1.8% and 1.93% respectively. Table 6 Panel B sorts stocks into five quintiles and confirms that our results are not driven just by the recent financial crisis, or financial firms or non-investment grade firms.

In unreported tables, we verify that our results are about equally strong and significant when we measure CDS slope as 10-year CDS spread minus 1-year CDS spread (previous tables measure the CDS slope as 5-year CDS spread minus 1-year CDS spread). This mitigates the concern that the predictive power of CDS slope for stock return is somehow driven by liquidity in the CDS market.⁸ It is known that the 5-year CDS tends to be more liquid than other maturities. But the 1-year and 10-year CDS do not differ in liquidity.

3.2 Controlling for Default Risk

Previous tables document a strong link between the term structure of CDS spreads and stock returns. In this section, we examine whether the relation between CDS slope and stock returns can be explained by default or distress risk. More precisely, we find that high CDS slope stocks on average have abnormally low returns. If stocks with high CDS slope tend to have high default risk, then our result may just reflect the so called financial distress risk puzzle, which refers to the finding that firms with high financial distress risk tend to have lower returns (see, e.g., Griffin and Lemmon (2002), Campbell, Hilscher, and Szilagyi (2008)).⁹

We provide three pieces of evidence suggesting that the relation between CDS slope and stock returns can not be explained by default or distress risk. First, Table 7 shows small

⁸It is not clear to us why CDS liquidity affects the expected stock return, except that CDS liquidity is linked to stock liquidity. However, we show that the predict power of CDS slope is robust to controlling for stock liquidity (see Table 10).

⁹Contrary to this finding, some studies document positive cross-sectional relationship between expected stock returns and default risk (e.g., Vassalou and Xing (2004) and Chava and Purnenandam (2010)). George and Hwang (2009) find that the financial distress risk puzzle disappears after controlling for leverage. Gallappi, Shu, and Yan (2008) show that the relationship between expected stock returns and default risk can be non-monotonic.

negative correlations between CDS slopes and several default risk measures, including one-year CDS spread, the expected default frequency (*EDF*) provided by Moody's KMV, and the Campbell, Hilscher and Szilagyi measure (*CHS*). The correlations of these default risk measures are large and positive, ranging from 0.47 to 0.71. But the correlations of CDS slope with these default risk measures are between -0.03 to -0.17.

Second, Table 8 shows that for our sample, there is no significant relation between proxies of default risk and average stock returns.¹⁰ Each month we sort stocks into quintiles based on CDS level, *EDF* or *CHS*. Then we form an equal-weighted portfolio that is long low default risk stocks and short high default risk stocks. Table 8 report the average returns of these portfolios over various horizons (up to six months following portfolio formation). None of the average returns are significant. These findings are in sharp contrast to the results for CDS slope sorted portfolios in Table 3 to 5. The default measures do not predict future stock returns as CDS slope does.

Third, double sort results in Table 9 show that the predictive power of CDS slope for stock returns is robust to controlling for default risk measures, including book to market ratio of equity, leverage, one-year CDS spread, *EDF* and *CHS*. Each month, we sort stocks based on one of the default risk measures, and then, within each tercile, we sort stocks based on CDS slope. The five CDS slope portfolios are then averaged over each of the three default risk portfolios. Hence, they represent CDS slope quintile portfolios controlling for the default risk.

Table 9 reports the average returns of the CDS slope quintiles (controlled for default risk measures), the difference in returns between the bottom and the top slope quintiles as well as their CAPM alphas, FF-3 alphas and Carhart-4 alphas. We find that after controlling for all the default risk measures, there is still a significant positive return spread between low CDS slope stocks and high CDS slope stocks. The average return to our portfolio strategy based on CDS slope does not change materially after controlling for default risk measures.

¹⁰Consistent with our finding, Anginer and Yildizhan (2010) use corporate credit spreads to proxy for default risk, and do not find default risk to be significantly priced in the cross-section of equity returns.

3.3 Further Robustness Checks

In Table 10, we use Fama-MacBeth regressions to further document the robustness of the negative relation between CDS slope and future stock return. In addition to the default risk measures, we control for log market capitalization (size), book-to-market ratio of equity, past six month stock returns (momentum), stock turnover ratio and institutional share ownership. First, consistent with the double sorting results in Table 9, the negative relation between CDS slope and future stock return remains significant after controlling for the default risk measures including CDS level, *EDF* and *CHS*.¹¹ There is no significant relation between the default risk measures and stock return, confirming the univariate sorting results in Table 8.

Second, the negative relation between CDS slope and future stock return is robust to controlling for size, book-to-market, past stock returns, as well as stock liquidity and institutional ownership. In fact, controlling for these characteristics does not change the estimated coefficient for the CDS slope or its significance. The reason is that there is no systematic relation between these characteristics and the slope of a firm's term structure of CDS spreads. For example, when we regress CDS slope on current month stock return and stock returns over several past horizons (past 6 months and between 12 months and 6 months ago), we find the coefficients are all negative but not significant. The predictive power of CDS slope for stock return is not a mere reflection of momentum or reversal in stock returns.

Table 10 also controls for change in the one-year CDS spread. This is motivated by Archarya and Johnson (2007) and Ni and Pan (2010). Both papers find that recent change in CDS spread negatively predicts stock return. Both papers use daily data. They condition on changes in CDS spreads over the horizon of one day to one week, and examine stock returns over the next few days. In contrast, we study how change in CDS spread over the

¹¹In Table 10 models 2 and 5, we control for the 1-year CDS spread and change in the 1-year CDS spread respectively. In unreported regressions, we also control for the 5-year CDS spread and change in the 5-year CDS spread. The coefficients for the 5-year CDS spread and change in the 5-year CDS spread are both negative but insignificant. CDS slope is still significantly related to the next month's stock return.

past month affects next month's stock return.

Table 10 model 5 and 7 show that change in one-year CDS spread negatively predicts stock return over the next month, but it has no effect on the estimated coefficient of CDS slope. The predictive power of CDS slope is independent of that of change in CDS spread.

3.4 Can Default Risk Premium Explain Our Results?

Why do stocks with high (low) CDS slope on average have low (high) stock returns? To answer this question, we need to understand the information content of the shape of CDS term structure. In this section, we show that one reason a firm can have a steep upward sloping CDS term structure is that there is uncertainty about its default probability and investors require a compensation for the risk associated with the fluctuation in firm's default probability. This default risk premium is similar in spirit to the variance risk premium. Investors generally dislike the randomness of the future default probability and, in equilibrium, demand a premium for accepting this risk. The existence of default risk premium has been established by Driessen (2005) and Berndt et al (2008). Recently, Pan and Singleton (2008) use the term structure of CDS spreads to estimate the market price of risk associated with the fluctuation in the probability of default. We adopt the Pan and Singleton model to show that CDS slope is positively related to default risk premium.

The (annualized) spread of a M -year CDS contract at issuance with semi-annual premium payments is:

$$CDS_t(M) = \frac{2(1 - R^Q) \int_t^{t+M} E_t^Q[\lambda_u^Q e^{-\int_t^u (r_s + \lambda_s^Q) ds}] du}{\sum_{j=1}^{2M} E_t^Q[e^{-\int_t^{t+0.5j} (r_s + \lambda_s^Q) ds}]} \quad (1)$$

where R^Q is a constant risk-neutral recovery of face value (taken to be 0.25 in Pan and Singleton (2008)), and r_t is the riskfree short rate. The risk-neutral mean arrival rate of a

credit event λ^Q follows a mean reverting process under the physical measure P ,

$$d\ln\lambda_t^Q = \kappa^P(\theta^P - \ln\lambda_t^Q)dt + \sigma_{\lambda^Q}dB_t^P,$$

Assume the market price of risk η_t associated with the fluctuation in default intensity is an affine function of $\ln\lambda_t^Q$:

$$\eta_t = \delta_0 + \delta_1\ln\lambda_t^Q. \quad (2)$$

The market price of risk η_t governs the change of measure from the physical measure to risk-neutral measure for λ^Q :

$$d\ln\lambda_t^Q = \kappa^Q(\theta^Q - \ln\lambda_t^Q)dt + \sigma_{\lambda^Q}dB_t^Q, \quad (3)$$

where $\kappa^P = \kappa^Q - \delta_1\sigma_{\lambda^Q}$ and $\kappa^P\theta^P = \kappa^Q\theta^Q + \delta_0\sigma_{\lambda^Q}$. The CDS pricing equation 1 can be evaluated using the risk-neutral dynamics of λ^Q given in 3.

In Pan and Singleton (2008), the estimates for δ_0 and δ_1 are both negative. When $\delta_0 < 0$ and $\delta_1 < 0$, we have $\kappa^Q < \kappa^P$, and $\theta^Q > \theta^P$ (θ^Q is less negative). This means that the long-run mean of default intensity λ^Q under the risk-neutral measure is higher than that under the empirical measure. So even at low arrival rates of credit events, λ^Q will tend to be larger under Q than under P . Moreover, for a given level of λ^Q , there is more persistence under Q than under P (bad times last longer under Q). Thus, negative δ_0 and δ_1 imply that the credit environment is worse under Q than under P . This pessimism about the credit environment reflects investors' aversion towards the risk of variation over time in the default intensity.

To quantify the magnitude of default risk premium embedded in the CDS market, Pan and Singleton (2008) compare $CDS(M)$, the M -year CDS spread given in equation 1 under negative values for δ_0 and δ_1 to its counterpart when there is no default risk premium (i.e.,

$\delta_0 = \delta_1 = 0$; investors are neutral towards the risk of variation over time in λ^Q , and evaluate CDS spreads using its P dynamics). We follow Pan and Singleton (2008) and use the following variable CRP to proxy for the magnitude of default risk premium:

$$CRP^M = \frac{CDS(M) - CDS^P(M)}{CDS^P(M)}. \quad (4)$$

Table 11 shows a strong positive link between the above proxy of default risk premium and CDS slope. The results are based on 1000 simulations under the Pan and Singleton model. Each simulation corresponds to a set of model parameters (κ^P , θ^P , σ_{λ^Q} , r , δ_0 , δ_1 , λ_0^Q). Note that for a given set of model parameters, we can simulate the P and Q dynamics of λ^Q out to five years, compute one-year and five-year CDS spreads, CDS slope as well as our proxy for the size of default risk premium $CRP(1)$ and $CRP(5)$.

All simulations share common parameters governing the P dynamics of λ^Q : $\kappa^P = 0.57$; $\theta^P = -4.61$; $\sigma_{\lambda^Q} = 1.144$. These parameters are based on the maximum likelihood estimates of Pan and Singleton (2008) Table III. In addition, in all simulations, we take riskfree rate to be a constant ($r = 0.05$). However, each simulation corresponds to different parameter values for δ_0 , δ_1 , and initial default intensity λ_0^Q . Thus, the market price of risk associated with the fluctuation in default intensity given in (2) is also different across simulations. This difference in turn leads to differences in both CDS slope and default risk premium across simulations.

Table 11 shows that when the impact of default risk premium on CDS spreads is larger, the slope of the term structure of CDS spreads also tends to be larger. The correlation between CDS slope and $CRP(1)$ is 0.25 and the correlation between CDS slope and $CRP(5)$ is 0.48. The regression coefficient of CDS slope on $CRP(1)$ and $CRP(5)$ are both positive and highly significant.

Intuitively, when investors require compensation for the risk associated with variations in the default intensity, the risk-neutral default probabilities increase relative to the physical

default probabilities, leading to higher CDS spreads. The impact is larger for longer-term CDS contracts as the risk of variation over time in the default intensity increases with horizon. An increase in the default risk premium pushes up the long-term CDS spreads more than the short-term CDS spreads, leading to a steeper term structure of CDS spreads. Thus, CDS slope is positively related to default risk premium.

Although the CDS spreads embed a risk premium for variation in the default intensity, stock market does not seem to price this risk. If investors in the stock market requires compensation for the risk of variation in the default intensity, then high CDS slope stocks would have higher average returns. However, we find a significant negative relation between CDS slope and stock return. Thus, our results can not be explained by the relation between CDS slope and default risk premium.

3.5 Slow Diffusion of Information

In the previous section, we show that a high CDS slope may suggest a large default risk premium. Another reason that a firm can have an upward sloping CDS term structure is that investors expect the credit health of the firm to deteriorate in the future. This is similar to the expectation hypothesis of the (default-free) term structure of interest rates: A higher current long-term rate than the short-term rate may indicate that future short-term rate is expected to be higher.

Table 12 examines the ability of CDS slope (5-year spread minus 1-year spread) to forecast future changes in 1-year CDS spreads. We regress changes in 1-year CDS spreads over various future horizons (from one month to twelve months) on the current CDS slope. We find that the coefficient on CDS slope is positive and significant in all regressions. Thus, consistent with the expectation hypothesis, current CDS slope positively predicts future changes in 1-year CDS spreads. This suggest that the term structure of CDS spreads contains useful information about future credit worthniess of the firm.

The negative relation between CDS slope and future stock returns we document suggests that the public information contained in the CDS term structure is not fully incorporated into the contemporaneous stock prices. Otherwise, stocks with high current CDS slope should command higher expected return, given they are more likely to experience credit deterioration in the future. Yet our results show that high CDS slope stocks tend to have lower returns subsequently. Such low returns are consistent with stock market slowly incorporating the information content of CDS slope.

To further support the slow information diffusion explanation of our results, we examine the predictive power of CDS slope for both future change in CDS spread and future stock return in various subsample sorted by proxies of arbitrage costs. These proxies include firm size, stock price, bid-ask spread, institutional ownership, dispersion in analyst forecasts and idiosyncratic stock volatility.

Table 12 Panel B shows that in all subsamples, CDS slope significantly and positively predicts future changes in 1-year CDS spreads. Table 13 reports the average returns of our portfolio strategy that buys low CDS slope stocks and shorts high CDS slope stocks in various subsamples. Unlike the predictive power for future CDS changes, CDS slope negatively predicts future stock return only among stocks facing high arbitrage costs. This finding holds for different measures of arbitrage costs and is robust to controlling for CAPM, Fama-French or Carhart factors.

Our portfolio strategy based on CDS slope is mainly profitable when applied to stocks with low market capitalization, low price, low institution ownership, high bid-ask spread, high disagreement and high idiosyncratic volatility. These stocks face high arbitrage costs, which prevent the useful information contained in the CDS slope from getting fully incorporated in the current stock prices. The profits of our portfolio strategy can be viewed as rewards to smart investors who understand the information content in CDS slope and bear the costs as well as the risks to arbitrage between the CDS market and the stock market. Our portfolio strategy does not earn significant abnormal profits among the low arbitrage costs stocks,

although for these stocks, CDS slope also contains useful information about future change in credit quality. Thus, slow diffusion of information from CDS market to the stock market occurs mostly for stocks with high arbitrage costs.

4 Conclusion

This paper uses a comprehensive dataset of credit default swaps on North American firms, and documents a strong link between the term structure of credit default swap spreads and the expected stock returns of these firms. The slope of a firm's CDS term structure, defined as the difference between five-year spread and one-year CDS spread, negatively predicts future stock returns. A portfolio strategy that buys low CDS slope stocks and shorts high CDS slope stocks earns an average return of more than 1% each month for the next six months. This result is robust across different weighting schemes and sorting dimensions. The negative relation between CDS slope and expected stock return is also found in Fama-MacBeth regressions. It holds after controlling for various firms' characteristics. It can not be explained by standard risk factors, various measures of default risk, or compensation for the risk of variation in default probability.

The negative relation between current CDS slope and future stock return is consistent with slow information diffusion between the CDS market and the stock market. CDS slope contains useful information about future credit quality of the firm. We find that CDS slope positively predicts future changes in one-year CDS spreads up to one year. Stocks with high current CDS slope tend to experience credit deterioration in the future. But this useful public information appears not fully reflected in the stock prices. As stock market subsequently catches up to the information already reflected in the current slope of CDS term structure, prices of stocks with high current CDS slope drop, leading to lower future returns. As further support for the slow information diffusion explanation of our result, our portfolio strategy based on CDS slope is mainly profitable when applied to stocks facing high arbitrage costs.

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Table 1: Descriptive Statistics – Credit Default Swap Spread Levels

This table presents the summary statistics—mean, standard deviation, min and max values for credit default swap spread levels for 1 and 5 years and for all ratings, AAA, AA, A, BBB, BB, B and CCC ratings respectively. All the spread levels are in basis points. The number is the number of firm–month observations. The CDS dataset is from Mark-it and Bloomberg. The dataset is from August 2002 to December 2009 on a daily frequency. We choose the month–end observations to report the summary statistics.

	Mean	Std	Min	Max	Mean	Std	Min	Max
	All Ratings (Number: 49,820)				AAA Ratings (Number: 569)			
1–Year	198.01	1,052.39	0.89	75,031.17	26.83	80.03	0.89	849.74
5–Year	227.94	732.51	1.00	33,129.54	41.25	84.87	2.67	668.90
	AA Ratings (Number: 2,445)				A Ratings (Number: 11,642)			
1–Year	47.23	264.36	1.08	6,061.41	45.13	182.04	1.06	6,524.64
5–Year	59.13	198.58	3.37	4,845.88	59.92	129.00	2.54	3,606.86
	BBB Ratings (Number: 20,902)				BB Ratings (Number: 8,105)			
1–Year	73.99	193.63	0.95	5,470.82	216.90	534.77	1.00	17,999.49
5–Year	105.43	154.71	3.17	3,275.12	293.74	432.83	3.17	15,228.20
	B Ratings (Number: 4,931)				CCC Ratings (Number: 1,226)			
1–Year	567.73	1,463.50	2.79	42,065.98	2,532.33	5,184.91	7.87	75,031.17
5–Year	664.92	1,047.95	11.20	27,988.91	2,143.01	3,232.43	1.00	33,129.54

Table 2: **Descriptive Statistics – Credit Default Swap Spread Slope**

This table presents the mean, standard deviation, min and max values for the monthly CDS slope measured as the difference between five-year and one-year CDS spreads (in basis points). The CDS dataset is from Mark-it and Bloomberg, covering the period August 2002 to December 2009 on a daily frequency. We choose the month-end observations for the summary statistics. “All” corresponds to the pooled data for all firms with traded CDS over our sample period. “AAA” corresponds to only firms rated AAA (same for other ratings).

Rating	Mean	Std	Min	Max	Number
All	29.93	409.35	-45,787.55	3,925.30	49,820
AAA	14.42	36.48	-180.84	334.55	569
AA	11.91	84.63	-2,231.45	360.51	2,445
A	14.79	67.56	-2,917.78	333.18	11,642
BBB	31.43	68.14	-2,504.42	597.96	20,902
BB	76.83	175.55	-4,029.47	1,480.21	8,105
B	97.20	546.07	-14,950.25	3,925.30	4,931
CCC	-389.32	2,249.80	-45,787.55	3,110.79	1,226

Table 3: **Stock Returns and CDS Term Structure**

Panel A of this table reports the average monthly returns of equal-weighted decile portfolios where we sort stocks by the CDS slope, measured as the difference between the 5-year and 1-year CDS spreads. Besides the average raw returns of portfolios, we also report their CAPM alphas, FF-3 alphas and Carhart-4 alphas. All returns are in percent. Panel B reports the loadings of the 10 portfolios sorted by CDS slope on the Fama French three factors, as well as the differences in factor loadings between the bottom and the top slope decile portfolios. The t statistics (reported in the brackets) are adjusted by Newey–West method. The sample period is from August 2002 to December 2009. * (resp. ** and ***) denotes significance at 10% (resp. 5% and 1%) level.

Panel A: Portfolio Returns and Alphas

	Low-1	2	3	4	5	6	7	8	9	High-10	L-H
Average Return	2.59** (2.06)	1.44* (1.81)	1.23** (2.31)	0.95** (1.96)	0.81 (1.51)	0.90 (1.63)	0.91 (1.52)	0.79 (1.19)	0.75 (1.02)	0.54 (0.54)	2.05*** (2.81)
CAPM Alpha	1.48** (2.06)	0.64* (1.66)	0.59*** (3.37)	0.34 (2.53)	0.16 (0.87)	0.23 (1.41)	0.20 (1.10)	0.03 (0.12)	-0.06 (-0.19)	-0.46 (-0.99)	1.95*** (2.70)
Carhart4 Alpha	1.19*** (2.60)	0.45 (1.56)	0.50*** (2.85)	0.29** (2.24)	0.09 (0.58)	0.15 (0.95)	0.12 (0.68)	-0.12 (-0.62)	-0.27 (-1.11)	-0.77** (-2.05)	1.96*** (3.20)
FF3 Alpha	1.25** (1.97)	0.48 (1.49)	0.51*** (2.88)	0.29** (2.22)	0.09 (0.58)	0.15 (0.96)	0.12 (0.68)	-0.12 (-0.60)	-0.26 (-1.06)	-0.75* (-1.79)	2.00*** (3.02)

Panel B: Loadings on the Fama-French Factors

Factors	Low-1	2	3	4	5	6	7	8	9	High-10	L-H
<i>RM</i>	1.85*** (8.03)	1.22*** (8.21)	0.96*** (15.86)	0.92*** (23.19)	0.98*** (22.86)	1.03*** (19.82)	1.12*** (19.42)	1.16*** (21.91)	1.21*** (16.08)	1.61*** (12.42)	0.24 (0.89)
<i>SMB</i>	0.03 (0.08)	0.28 (1.38)	0.16* (1.67)	0.10* (1.87)	0.06 (0.79)	0.16 (2.62)	0.16*** (2.55)	0.32*** (3.10)	0.42*** (3.53)	0.78*** (4.72)	-0.75*** (-2.38)
<i>HML</i>	1.28*** (3.40)	0.47** (2.10)	0.20** (2.02)	0.08 (1.48)	0.26*** (3.28)	0.18* (1.92)	0.18* (1.88)	0.31*** (3.35)	0.50*** (2.96)	0.38 (1.36)	0.90*** (3.05)

Table 4: Average Returns of CDS Slope Sorted Portfolios

Panel A and B of this table reports respectively the equal and value weighted average monthly returns of decile portfolios sorted by the CDS slopes. $r_{0,1}$ is the return over the month immediately after sorting on CDS slope. $r_{1,2}$ ($r_{2,3}$) corresponds to the return in the second (third) month after portfolio formation. The sample period is from August 2002 to December 2009. All returns are in percent. The t statistics (reported in the brackets) are adjusted by Newey–West method. * (resp. ** and ***) denotes significance at 10% (resp. 5% and 1%) level.

Panel A: Equal Weighted Portfolios Sorted By CDS Slopes.

Monthly Return	Low-1	2	3	4	5	6	7	8	9	High-10	Ave. Ret		Carhart-4 Alpha	FF-3 Alpha
											L-H	Alpha		
$r_{0,1}$	2.59** (2.06)	1.44* (1.81)	1.23** (2.31)	0.95* (1.96)	0.81 (1.51)	0.90 (1.63)	0.91 (1.52)	0.79 (1.19)	0.75 (1.02)	0.54 (0.54)	2.05*** (2.81)	1.95*** (2.70)	1.96*** (3.20)	2.00*** (3.02)
$r_{1,2}$	2.47** (1.99)	1.38* (1.75)	1.27** (2.29)	0.89* (1.76)	0.90* (1.71)	1.01* (1.82)	0.69 (1.18)	0.90 (1.35)	0.72 (0.94)	0.67 (0.66)	1.80** (2.30)	1.72** (2.17)	1.76** (2.47)	1.81** (2.34)
$r_{2,3}$	2.27** (1.96)	1.61** (2.12)	1.13** (2.20)	0.92* (1.75)	1.01* (1.85)	1.10* (1.92)	0.75 (1.35)	0.76 (1.09)	0.97 (1.31)	0.39 (0.37)	1.88*** (2.88)	1.90*** (2.88)	1.98*** (3.33)	2.02*** (3.10)

Panel B: Value Weighted Portfolios Sorted By CDS Slopes.

Monthly Return	Low-1	2	3	4	5	6	7	8	9	High-10	Ave. Ret		Carhart-4 Alpha	FF-3 Alpha
											L-H	Alpha		
$r_{0,1}$	1.79* (1.77)	0.96 (1.52)	0.66 (1.55)	0.57 (1.26)	0.58 (1.22)	0.24 (0.47)	0.61 (1.07)	0.65 (1.02)	0.42 (0.64)	0.11 (0.13)	1.68** (2.11)	1.60* (1.98)	1.76** (2.31)	1.80** (2.38)
$r_{1,2}$	1.69* (1.69)	0.95 (1.48)	0.47 (1.10)	0.46 (0.97)	0.68 (1.55)	0.56 (1.00)	0.36 (0.64)	0.80 (1.28)	0.41 (0.61)	0.02 (0.03)	1.66* (1.97)	1.65* (1.98)	1.71** (2.17)	1.76** (2.19)
$r_{2,3}$	1.17 (1.45)	1.00 (1.78)	0.70 (1.62)	0.45 (0.87)	0.72 (1.53)	0.60 (1.10)	0.45 (0.87)	0.54 (0.85)	0.87 (1.31)	-0.35 (-0.41)	1.52** (2.11)	1.62** (2.12)	1.81** (2.41)	1.84** (2.45)

Table 5: **The Predictive Power of CDS Slope over Different Horizons**

This table reports the average monthly returns of portfolios sorted on CDS slope over various future horizons. Each month, we sort stocks based on CDS slope into five quintiles, and form an equal-weighted portfolio that is long the bottom quintile stocks and short the top quintile stocks. $r_{i,i+1}$ is the portfolio return over the month $[i, i + 1]$ after the portfolio formation. Besides the raw returns of the portfolios, we also report their CAPM alphas, FF-3 alphas and Carhart-4 alphas. The sample period is from August 2002 to December 2009. All returns are in percent. The t statistics (reported in the brackets) are adjusted by Newey–West method. * (resp. ** and ***) denotes significance at 10% (resp. 5% and 1%) level.

Monthly Return	Low-1	2	3	4	High-5	Ave. Ret L-H	CAPM Alpha	Carhart-4 Alpha	FF-3 Alpha
$r_{0,1}$	1.98** (2.02)	1.10** (2.18)	0.85 (1.58)	0.85 (1.36)	0.67 (0.80)	1.31*** (2.53)	1.26*** (2.43)	1.28*** (2.82)	1.31*** (2.72)
$r_{1,2}$	1.90* (1.95)	1.07** (2.08)	0.96* (1.79)	0.80 (1.29)	0.72 (0.83)	1.18** (2.16)	1.15** (2.08)	1.21*** (2.40)	1.24*** (2.36)
$r_{2,3}$	1.92** (2.07)	1.02** (2.00)	1.05* (1.92)	0.76 (1.22)	0.71 (0.82)	1.20*** (2.53)	1.23** (2.57)	1.28*** (2.97)	1.31*** (2.84)
$r_{3,4}$	1.88** (2.13)	1.04** (1.99)	0.95* (1.70)	0.91 (1.45)	0.68 (0.75)	1.20*** (2.61)	1.29*** (2.76)	1.34*** (3.19)	1.37*** (3.01)
$r_{4,5}$	1.83** (2.11)	1.00* (1.94)	0.95* (1.71)	0.91 (1.43)	0.70 (0.77)	1.14*** (2.50)	1.22*** (2.64)	1.33*** (3.16)	1.35*** (3.06)
$r_{5,6}$	1.73** (2.11)	0.98* (1.87)	0.97* (1.72)	1.00 (1.53)	0.74 (0.80)	0.98** (2.04)	1.11*** (2.43)	1.24*** (2.91)	1.25*** (2.88)
$r_{6,7}$	1.40* (1.85)	0.99* (1.93)	0.98* (1.72)	0.96 (1.42)	1.04 (1.09)	0.36 (0.69)	0.53 (1.13)	0.66 (1.54)	0.65 (1.52)
$r_{7,8}$	1.45* (1.96)	0.98* (1.86)	1.03* (1.84)	0.83 (1.24)	1.13 (1.15)	0.31 (0.62)	0.50 (1.17)	0.68* (1.77)	0.66* (1.70)
$r_{8,9}$	1.47** (2.04)	0.89 (1.64)	0.92 (1.64)	1.06 (1.55)	1.05 (1.05)	0.42 (0.75)	0.64 (1.37)	0.84** (2.00)	0.82* (1.95)
$r_{9,10}$	1.40** (2.08)	1.18** (2.15)	0.85 (1.46)	0.92 (1.35)	1.05 (1.04)	0.35 (0.65)	0.60 (1.38)	0.76* (1.93)	0.74* (1.84)

Table 6: Subsample Robustness Checks

This table reports the average monthly returns of portfolios sorted on CDS slope for various subsamples. In Panel A (resp. Panel B), we sort stocks in each month based on CDS slope into deciles (resp. quintiles), and form an equal-weighted portfolio that is long the bottom decile (resp. quintile) stocks and short the top decile (resp. quintile) stocks. We check the robustness of our results (1) excluding the 2008-2009 financial crisis; (2) excluding the CCC rated firms; (3) excluding the financial firms. $r_{0,1}$ is the portfolio return over the first month after the portfolio formation. Besides the raw returns of the portfolios, we also report their CAPM alphas, FF-3 alphas and Carhart-4 alphas. The sample period is from August 2002 to December 2009. All returns are in percent. The t statistics (reported in the brackets) are adjusted by Newey–West method. * (resp. ** and ***) denotes significance at 10% (resp. 5% and 1%) level.

Panel A: Decile Portfolios Sorted by CDS Slope

Monthly Return	Excluding 2008-2009 Crisis Period										Ave. Ret L-H	CAPM Alpha	Carhart-4 Alpha	FF-3 Alpha
	Low-1	2	3	4	5	6	7	8	9	High-10				
$r_{0,1}$	1.82** (2.23)	1.21** (2.44)	1.31*** (3.04)	1.23** (3.03)	0.99*** (2.31)	1.16** (2.84)	1.13* (2.43)	0.88* (1.79)	0.87 (1.75)	0.64 (0.83)	1.18** (2.24)	1.24** (2.31)	1.70*** (3.55)	1.46*** (3.08)

Monthly Return	Excluding CCC Firms										Ave. Ret L-H	CAPM Alpha	Carhart-4 Alpha	FF-3 Alpha
	Low-1	2	3	4	5	6	7	8	9	High-10				
$r_{0,1}$	2.50** (2.08)	1.36* (1.85)	1.17** (2.24)	0.98** (2.01)	0.80 (1.51)	0.98* (1.76)	0.92 (1.50)	0.73 (1.12)	0.85 (1.19)	0.70 (0.73)	1.80*** (2.65)	1.70** (2.54)	1.71*** (3.00)	1.75*** (2.88)

Monthly Return	Excluding Financial Firms										Ave. Ret L-H	CAPM Alpha	Carhart-4 Alpha	FF-3 Alpha
	Low-1	2	3	4	5	6	7	8	9	High-10				
$r_{0,1}$	2.85** (2.50)	1.26** (2.13)	1.22** (2.43)	0.97** (2.02)	0.99* (1.84)	0.87 (1.64)	1.04 (1.69)	0.66 (1.02)	0.80 (1.10)	0.92 (0.96)	1.93** (2.61)	1.91*** (2.72)	1.88*** (2.95)	1.92*** (2.96)

Panel B: Quintile Portfolios Sorted by CDS Slope

Excluding 2008-2009 Crisis Period									
Monthly Return	Low-1	2	3	4	High-5	Ave. Ret		FF-3	
						L-H	Alpha	Carhart-4 Alpha	Alpha
$r_{0,1}$	1.50** (2.44)	1.27*** (3.10)	1.07*** (2.61)	1.00 (2.15)	0.77 (1.27)	0.73* (1.96)	0.75* (1.97)	1.19*** (3.41)	0.99*** (2.91)
Excluding CCC Firms									
Monthly Return	Low-1	2	3	4	High-5	Ave. Ret		FF-3	
						L-H	Alpha	Carhart-4 Alpha	Alpha
$r_{0,1}$	1.90** (2.03)	1.08** (2.16)	0.88 (1.65)	0.82 (1.32)	0.79 (0.98)	1.11** (2.32)	1.07** (2.24)	1.08** (2.57)	1.11** (2.51)
Excluding Financial Firms									
Monthly Return	Low-1	2	3	4	High-5	Ave. Ret		FF-3	
						L-H	Alpha	Carhart-4 Alpha	Alpha
$r_{0,1}$	2.03** (2.46)	1.10** (2.27)	0.92* (1.76)	0.85 (1.36)	0.88 (1.08)	1.15** (2.52)	1.20*** (2.66)	1.23*** (2.92)	1.26*** (2.92)

Table 7: Correlations between CDS Slope and Default-related Variables

This table presents the correlation matrix between CDS slope and default-related variables. *Slope* is the difference between the 5-year and 1-year CDS spread. *Level* is the one-year CDS spread. *EDF* is the expected default frequency provided by Moody’s KMV. *CHS* is the Campbell, Hilscher and Szilagyi distress risk measure (Campbell, Hilscher, and Szilagyi (2008)). *Change* is the change in one-year CDS spread over the most recent month. The sample period is from August 2002 to December 2009.

	Slope	Level	EDF	CHS	Change
Slope	1.00				
Level	-0.17	1.00			
EDF	-0.10	0.71	1.00		
CHS	-0.03	0.47	0.48	1.00	
Change	-0.10	0.05	-0.07	-0.10	1.00

Table 8: **Average Returns of Portfolios Sorted by Default-related Variables**

This table reports the average monthly raw returns of portfolios sorted by various default-related variables. *Level* is the one-year CDS spread. *EDF* is the expected default frequency provided by Moody’s KMV. *CHS* is the Campbell, Hilscher and Szilagyi distress risk measure (Campbell, Hilscher, and Szilagyi (2008)). Each month, we sort stocks into five portfolios based on one of these variables, and form an equal-weighted portfolio that is long the bottom quintile and short the top quintile. $r_{i,i+1}$ is the portfolio return over the month $[i, i + 1]$ after the portfolio formation. The sample period is from August 2002 to December 2009. All returns are in percent. The t statistics (reported in the brackets) are adjusted by Newey–West method. * (resp. ** and ***) denotes significance at 10% (resp. 5% and 1%) level.

Monthly Return	CDS Level	EDF	CHS
	Ave. Ret L-H	Ave. Ret L-H	Ave. Ret L-H
$r_{0,1}$	0.14 (0.19)	-0.34 (-0.44)	0.22 (0.24)
$r_{1,2}$	0.19 (0.26)	-0.48 (-0.64)	-0.28 (-0.30)
$r_{2,3}$	0.16 (0.23)	-0.36 (-0.51)	-0.32 (-0.40)
$r_{3,4}$	-0.00 (-0.00)	-0.00 (-0.00)	1.76* (1.77)
$r_{4,5}$	0.06 (0.09)	-0.15 (-0.24)	0.41 (0.58)
$r_{5,6}$	0.01 (0.01)	-0.13 (-0.21)	0.02 (0.03)

Table 9: **Average Returns of Portfolios Sorted by CDS Slope: Controlling for Default-related Variables**

This table reports the average monthly of equal-weighted quintile portfolio sorted by the CDS slope after controlling for various default-related variables. *B/M* is the book to market ratio of equity. *Leverage* is the ratio of the book value of long-term debt to the sum of the market value of equity and the book value of long-term debt. *Level* is the one-year CDS spread. *EDF* is the expected default frequency provided by Moody's KMV. *CHS* is the Campbell, Hilscher and Szilagyi distress risk measure (Campbell, Hilscher, and Szilagyi (2008)). *LevelChange* is the change in one-year CDS spread over the most recent month. Each month, we sort stocks based on one the default risk measures (book-to-market, leverage, *EDF*, *CHS*, CDS spread level, change in CDS spread) into three portfolios, and then, within each tercile, we sort stocks based on CDS slope. The five CDS slope portfolios are then averaged over each of the three default risk portfolios. We report the average returns of the CDS slope quintiles (controlled for default-related variables), the difference in returns between the bottom and the top slope quintile as well as their CAPM alphas, FF-3 alphas and Carhart-4 alphas. The sample period is from August 2002 to December 2009. All returns are in percent. The *t* statistics (reported in the brackets) are adjusted by Newey–West method. * (resp. ** and ***) denotes significance at 10% (resp. 5% and 1%) level.

	Ranking on Slope								
	Low-1	2	3	4	High-5	L-H	CAPM	Carhart-4	FF-3
<i>B/M</i>	2.06** (2.01)	1.1** (2.16)	0.95 (1.77)	0.8 (1.30)	0.93 (1.14)	1.12** (2.10)	0.74* (1.93)	1.11*** (3.50)	0.94*** (-2.76)
<i>Leverage</i>	2.04** (2.00)	1.11** (2.18)	0.98 (1.85)	0.77 (1.22)	0.94 (1.16)	1.10** (2.07)	0.71* (1.90)	1.08*** (3.49)	0.91*** (2.71)
<i>EDF</i>	1.16 (1.83)	0.77 (1.54)	0.65 (1.23)	0.26 (0.42)	-0.05 (0.06)	1.20** (2.52)	1.25*** (2.89)	1.66*** (4.34)	1.51*** (4.08)
<i>CHS</i>	2.58** (2.87)	1.67** (2.29)	1.12 (1.77)	1.05 (1.74)	0.97 (1.07)	1.61*** (2.70)	1.79*** (2.87)	1.99*** (3.24)	1.94*** (3.22)
<i>Level</i>	1.35 (1.53)	0.75 (1.61)	0.62 (1.26)	0.61 (1.09)	0.43 (0.57)	0.92* (1.97)	0.92* (1.97)	0.99** (2.26)	0.94** (2.09)
<i>Level Change</i>	1.98** (2.00)	1.11** (2.22)	0.83 (1.55)	0.84 (1.35)	0.67 (0.79)	1.31** (2.50)	1.26** (2.40)	1.27*** (2.78)	1.30*** (2.68)

Table 10: **Fama–MacBeth Cross-Sectional Regressions**

This table reports results of monthly Fama–MacBeth regressions. For the cross-sectional regression in month t , the dependent variable is stock return over the month t . All independent variables are measured at the end of previous month. *Slope* is the difference between the 5-year and 1-year CDS spreads (in basis points). *Level* is the one-year CDS spread. *Level Change* is the change of the one-year CDS spread over the last month. *EDF* is the expected default frequency provided by Moody’s KMV. *CHS* is the Campbell, Hilscher and Szilagyi measure of distress risk. *Size* is the log of equity market cap. *B/M* is the book to market ratio of equity. *Past 6 Month Return* is the stock return over the past six months. *Leverage* is the ratio of the book value of long-term debt to the sum of the market value of equity and the book value of long-term debt. *Turnover* is the monthly trading volume divided by total shares outstanding. *Institutional Holdings* is the fraction of common shares owned by institutions based on Thomson 13-F filings. The sample period is from August 2002 to December 2009. The numbers in the brackets are t -statistics. * (resp. ** and ***) denotes significance at 10% (resp. 5% and 1%) level.

	1	2	3	4	5	6	7
<i>Slope</i>	-0.017*** (-2.92)	-0.017*** (-3.00)	-0.018*** (-3.08)	-0.014* (-1.95)	-0.017*** (-2.93)	-0.016*** (-3.46)	-0.017*** (-3.54)
<i>Level</i>		0.000 (0.05)					
<i>EDF</i>			0.103 (0.70)				
<i>CHS</i>				2.824 (0.38)			
<i>Level Change</i>					-0.008* (-1.79)		-0.018* (-1.90)
<i>Size</i>						-0.289*** (-2.68)	-0.276** (-2.50)
<i>B/M</i>						-0.159 (0.44)	-0.129 (0.35)
<i>Past 6 Month Return</i>						0.031 (1.56)	0.020 (1.24)
<i>Leverage</i>						1.719* (1.85)	1.844** (2.05)
<i>Turnover</i>						-0.092* (-1.92)	-0.081* (-1.79)
<i>Institutional Ownership</i>						0.401 (0.60)	0.403 (0.63)
<i>Constant</i>	1.257*** (3.11)	1.263*** (3.45)	1.248*** (3.21)	1.474*** (4.26)	1.241*** (3.09)	5.680** (2.62)	5.437** (2.44)
R-squared	0.01	0.01	0.01	0.00	0.01	0.02	0.03

Table 11: **Default Risk Premium and CDS Slope**

This table is based on 1000 simulations under the Pan and Singleton (2008) model. The risk-neutral mean arrival rate of a credit event λ^Q under the physical measure P satisfies

$$d\ln\lambda_t^Q = \kappa^P(\theta^P - \ln\lambda_t^Q)dt + \sigma_{\lambda^Q}dB_t^P.$$

The market price of risk η_t associated with the fluctuation in default intensity is $\eta_t = \delta_0 + \delta_1\ln\lambda_t^Q$. This gives the following dynamics of λ^Q under the risk-neutral measure:

$$d\ln\lambda_t^Q = \kappa^Q(\theta^Q - \ln\lambda_t^Q)dt + \sigma_{\lambda^Q}dB_t^Q,$$

where $\kappa^P = \kappa^Q - \delta_1\sigma_{\lambda^Q}$ and $\kappa^P\theta^P = \kappa^Q\theta^Q + \delta_0\sigma_{\lambda^Q}$. All simulations share common values for the parameters governing the P dynamics of λ^Q : $\kappa^P = 0.57$; $\theta^P = -4.61$; $\sigma_{\lambda^Q} = 1.144$. These parameters are based on the maximum likelihood estimates of Pan and Singleton (2008) Table III. The parameter values for δ_0 , δ_1 , and initial default intensity λ_0^Q differ across simulations. For each set of model parameters, we simulate the P and Q dynamics of λ^Q out to five years, and then use Equation 1 to compute one-year and five-year CDS spreads and CDS slope. For each set of model parameters, we also compute $CRP(1)$ and $CRP(5)$ (see Equation 4) to measure the impact of default risk premium on CDS spreads.

Panel A: Correlation Matrix.

	<i>Slope</i>	<i>CRP(1)</i>	<i>CRP(5)</i>
<i>Slope</i>	1.00		
<i>CRP(1)</i>	0.25	1.00	
<i>CRP(5)</i>	0.48	0.94	1.00

Panel B: Regression Results.

	<i>Slope</i>	<i>Slope</i>
<i>CRP(1)</i>	11.64*** (6.19)	
<i>CRP(5)</i>		19.09*** (13.22)
<i>Constant</i>	0.12 (0.10)	6.00*** (5.57)
R-squared	0.06	0.22

Table 12: CDS Slope Predicts Changes in CDS Spreads

This table reports the results of monthly Fama–MacBeth regressions of changes in 1-year CDS spread from t to $t+i$ on the CDS slope at time t . $\Delta CDS_{t+i} = CDS_{t+i} - CDS_t$. Panel A is for regressions using the whole sample. Panel B is for regressions on various subsamples sorted by several stock characteristics at time t including size, stock price, bid-ask spread, analyst dispersion and institutional ownership. L (resp. M and H) denotes the subsample of stocks ranked in the bottom (resp. middle and top) tercile. Panel B only reports the regression coefficient on CDS slope. The numbers in the brackets are t -statistics. * (resp. ** and ***) denotes significance at 10% (resp. 5% and 1%) level.

Panel A: Full Sample Results					
	Model 1	Model 2	Model 3	Model 4	Model 5
	ΔCDS_{t+1}	ΔCDS_{t+3}	ΔCDS_{t+6}	ΔCDS_{t+9}	ΔCDS_{t+12}
$Slope_t$	0.255*** (5.54)	0.629*** (3.80)	0.740*** (2.85)	0.743** (2.29)	1.018* (1.91)
$CDS_t - CDS_{t-1}$	0.115* (1.75)	-0.013 (-0.12)	0.013 (0.11)	0.068 (0.31)	0.006 (0.03)
Constant	-9.146*** (-5.61)	-20.619*** (-4.74)	-24.748*** (-3.55)	-29.133*** (-2.67)	-37.157** (-2.38)
R-squared	0.22	0.28	0.27	0.29	0.27

Panel B: Subsample Results

		Model 1	Model 2	Model 3	Model 4	Model 5
		ΔCDS_{t+1}	ΔCDS_{t+3}	ΔCDS_{t+6}	ΔCDS_{t+9}	ΔCDS_{t+12}
All		0.255*** (5.54)	0.629*** (3.80)	0.740*** (2.85)	0.743** (2.29)	1.018* (1.91)
Size	L	0.320*** (6.33)	0.740*** (4.19)	0.824*** (3.31)	0.809** (2.57)	1.112** (2.05)
	M	0.153*** (2.89)	0.321*** (2.71)	0.595** (2.29)	0.724** (2.30)	1.132** (2.38)
	H	0.130** (2.39)	0.399*** (3.16)	0.637** (2.25)	0.524** (2.10)	0.742** (2.15)
Price	L	0.296*** (6.08)	0.694*** (4.07)	0.790*** (3.12)	0.785** (2.58)	1.096** (2.03)
	M	0.167*** (4.78)	0.349*** (3.82)	0.497*** (3.02)	0.772*** (2.68)	1.027** (2.53)
	H	0.156*** (2.95)	0.325*** (3.79)	0.490*** (2.94)	0.609** (2.15)	0.918** (2.10)
Bid – Ask Spread	L	0.207*** (4.41)	0.566*** (3.97)	0.694*** (3.06)	0.783** (2.32)	0.878** (2.19)
	M	0.137** (2.42)	0.444*** (3.96)	0.644*** (2.75)	0.857** (2.41)	1.043** (2.15)
	H	0.280*** (5.25)	0.643*** (3.69)	0.729*** (2.97)	0.724** (2.50)	1.140** (2.04)
Analyst Dispersion	L	0.193*** (3.69)	0.598*** (3.86)	0.668*** (2.94)	0.712** (2.33)	0.793** (2.07)
	M	0.273*** (4.58)	0.546*** (4.20)	0.713*** (2.70)	0.649** (2.30)	0.916** (2.32)
	H	0.272*** (5.39)	0.647*** (3.62)	0.760*** (3.07)	0.869** (2.62)	1.272** (2.14)
Institutional Ownership	L	0.304*** (6.00)	0.703*** (3.63)	0.818*** (3.05)	0.859** (2.56)	1.272** (2.29)
	M	0.289*** (4.47)	0.725*** (3.12)	0.897*** (2.74)	0.691* (1.91)	0.993* (1.98)
	H	0.203*** (3.78)	0.462*** (3.04)	0.629** (2.10)	0.782* (1.99)	0.853* (1.73)

Table 13: **Arbitrage Costs and Average Return of CDS Slope Portfolio Strategy**

This table reports the average monthly return (in percent) of an equal-weighted portfolio that is long stocks with low CDS slope and short stocks with high CDS slope in various subsamples of stocks sorted by proxies of arbitrage costs, including size, stock price level, bid-ask spread, dispersion of analyst forecast, institutional ownership and stock idiosyncratic volatility. At the end of each month, we perform a 3 by 3 independent double sort based on one of these arbitrage measures and CDS slope. We report the average differences in the returns of low CDS slope stocks and high slope stocks in each of the three portfolios sorted by a given arbitrage cost measure. In addition to the raw returns, we also report the portfolio alpha with respect to the CAPM, the Fama-French three factor model, and the Carhart four factor model. The sample period is from August 2002 to December 2009. The numbers in the brackets are t -statistics. * (resp. ** and ***) denotes significance at 10% (resp. 5% and 1%) level.

<i>Size</i>					<i>Price</i>				
	Ave. Ret	CAPM	Carhart-4	FF-3		Ave. Ret	CAPM	Carhart-4	FF-3
Low-1	1.97*** (3.38)	1.55*** (3.25)	1.75*** (3.75)	1.57*** (3.36)	Low-1	1.78*** (3.06)	1.27*** (2.71)	1.18** (2.34)	1.28** (2.53)
2	0.62* (1.85)	0.54* (1.97)	0.76*** (2.81)	0.66** (2.34)	2	0.17 (0.77)	0.18 (0.83)	0.16 (0.73)	0.15 (0.70)
High-3	0.13 (0.52)	0.20 (0.76)	0.44* (1.88)	0.35 (1.37)	High-3	-0.02 (-0.08)	-0.04 (-0.18)	-0.08 (-0.33)	-0.09 (-0.38)
<i>Bid – Ask Spread</i>					<i>Analyst Dispersion</i>				
	Ave. Ret	CAPM	Carhart-4	FF-3		Ave. Ret	CAPM	Carhart-4	FF-3
Low-1	0.05 (0.25)	0.03 (0.15)	0.00 (0.02)	0.03 0.12	Low-1	0.10 (0.39)	0.15 (0.57)	0.16 (0.52)	0.15 (0.47)
2	0.37 (1.29)	0.56** (2.00)	0.54* (1.74)	0.54* (1.81)	2	0.35 (1.21)	0.40 (1.52)	0.44 (1.61)	0.42 (1.55)
High-3	1.56*** (2.71)	1.12*** (2.65)	1.15** (2.53)	1.25*** (2.77)	High-3	1.67*** (2.68)	1.32*** (2.99)	1.30*** (2.82)	1.38*** (3.09)
<i>Institutional Holdings</i>					<i>Idiosyncratic Volatility</i>				
	Ave. Ret	CAPM	Carhart-4	FF-3		Ave. Ret	CAPM	Carhart-4	FF-3
Low-1	1.26** (2.62)	0.81** (2.00)	0.90** (2.18)	0.85** (2.11)	Low-1	0.05 (0.27)	0.07 (0.37)	0.05 (0.25)	0.03 (0.17)
2	0.57 (1.51)	0.38 (1.16)	0.40 (1.13)	0.44 (1.26)	2	0.35 (1.44)	0.41* (1.71)	0.49* (1.86)	0.46* (1.77)
High-3	0.57 (1.51)	0.56 (1.48)	0.54 (1.10)	0.56 (1.17)	High-3	1.51** (2.59)	1.18*** (2.72)	1.08** (2.46)	1.16*** (2.68)

Figure 1: **Time Series Plot of Slopes of Different Percentiles.** This graph plots the time series of the 10th, 50th, and 90th percentiles of the cross-section of individual firm CDS slope. At the end of each month from August 2002 to December 2009, we measure the CDS slope of a firm as the difference between the 5-year CDS and 1-year CDS premiums (in basis points) for that firm.

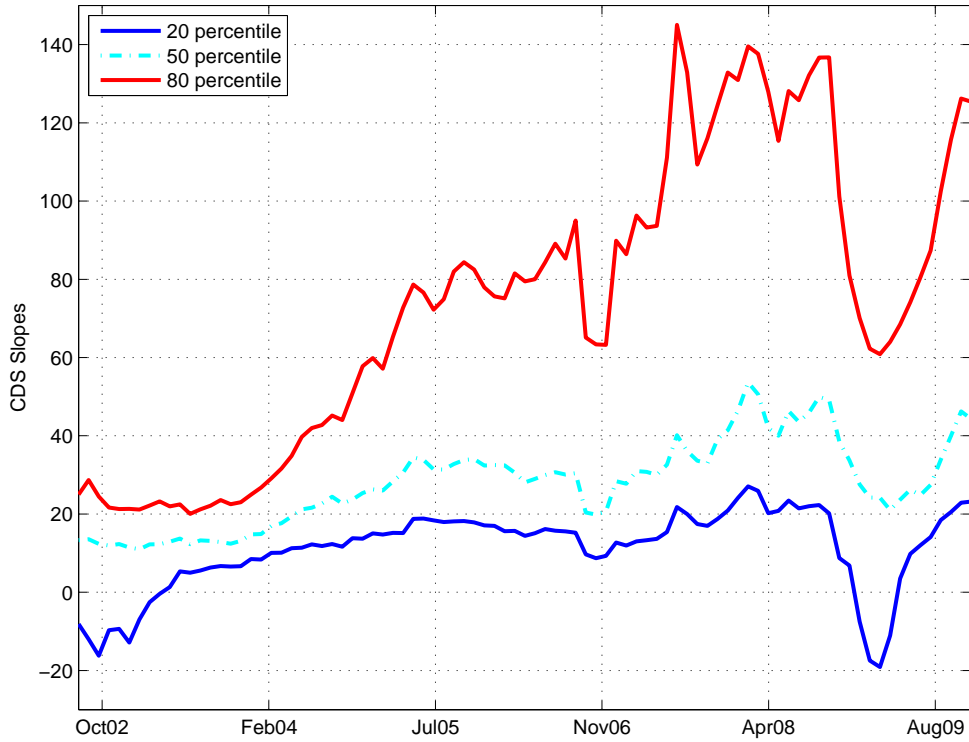


Figure 2: **Time Series Plot of Returns to the Portfolio Strategy Based on CDS Slope.** This graph plots the monthly time series of the return of the equal-weighted long-short portfolio that buys (shorts) stocks ranked in the bottom (top) decile by the CDS Slope. The CDS slope is defined as the difference between the 5-year CDS and 1-year CDS premiums. The sample period is from August 2002 to December 2009.

