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The term structure of credit spreads, firm fundamentals, and expected stock returns☆

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ABSTRACT

We explore the link between credit and equity markets by considering the informational content of the term structure of credit spreads. A shallower credit term structure predicts decreases in default risk and increases in future profitability, as well as favorable earnings surprises. Further, the slope of the credit term structure negatively predicts future stock returns. While systematic slope risk is priced, information diffusion from the credit market to equities, particularly in less visible stocks, plays an additional role in accounting for return predictability from credit slopes. That is, such predictability is less evident in stocks with high institutional ownership, analyst coverage, and liquidity, and vice versa.

1. Introduction

Firms finance their capital needs using a combination of debt and equity. To what extent are markets for these claims linked to each other and to other economic fundamentals? This question has long preoccupied scholars. For example, Fama and French (1993) find that excess returns on US stocks and corporate bonds are positively related to the slope of the Treasury yield curve.[1] Researchers have also shown that aggregate credit spreads forecast economic activities 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; Fama and French, 1993). Previous studies principally

[1] For evidence that the term structure of riskless interest rates can forecast aggregate stock returns, see, for example, Campbell (1987) and Boudoukh and Richardson (1993).

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consider the relation between equity markets, Treasury debt markets, and credit spread levels. The starting point of our paper is the observation that the term structure of credit spreads at the individual firm level (the credit spread slope) can be associated with firms' riskiness and future fundamentals. We provide evidence that the credit spread slope reliably forecasts stock returns in the cross section, even after controlling for various measures of risk such as the levels of credit spreads and the loading on a portfolio constructed by sorting on the slope (i.e., a slope factor). These findings indicate that the slope characteristic contains valuable information for the cross section of equity returns that is complementary to traditional risk measures. Consistent with this notion, the credit spread slope also forecasts firm fundamentals. To the best of our knowledge, these links between the credit spread term structure, firm fundamentals, and expected stock returns have not been shown elsewhere.

To measure the slope of the credit spread term structure, we use data from the market for credit default swaps (CDSs), which has grown tremendously and has become increasingly liquid during recent years.[2] In our data, we observe CDS spreads each day on the same set of maturities (ranging from one to ten years). Barring arbitrage, the CDS spread for a given maturity should be equal to the credit spread; that is, the difference in yield to maturity between a corporate bond and a US Treasury bond with the same maturity.

CDS data have important advantages over corporate bond data. First, unlike credit spread term structures based on bond yields, those based on CDSs are not subject to the specification of a benchmark risk-free yield curve. Second, CDS contracts are much more liquid than corporate bonds in that the former are usually traded on a daily frequency while the latter are usually held to maturity and might not trade even once a month (Edwards, Harris and Piwowar, 2007). Compared with bond-based credit spread term structures, those based on CDSs are less contaminated by non-default risk components (Longstaff, Mithal and Neis, 2005). Third, the contract terms are standard and easily comparable across firms, making the CDS data more suitable for cross-sectional study.[3]

We find that the slope of the term structure of CDS spreads, defined as the difference between a long- and a short-term CDS spread, significantly and negatively predicts cross-sectional stock returns. Thus, for instance, stocks ranked in the bottom decile by the five-year minus one-year CDS slope on average outperform those ranked in the top decile by 1.20% per month (14.40% annualized). The negative relation between the CDS slope and the average future stock return is robust to weighting schemes. It holds with panel regressions and is robust to controlling for stock characteristics known to be related to the cross section of a stock return. The Fama and French factors and the momentum factor explain little of the significant positive average return of the portfolio that buys low CDS slope stocks and shorts high CDS slope stocks. We also attempt to control for systematic risk via including the beta of a stock's return with respect to the long-short portfolio formed by sorting on extreme deciles of the CDS slope. We find that this beta is strongly significant and positive in our regressions, suggesting that systematic risk related to the CDS slope is priced, but the coefficient of the CDS slope remains significant after accounting for the beta. These results suggest that the slope of the CDS term structure contains useful fundamental information about the firm.

Our paper is related to Avramov, Chordia, Jostova and Philipov (2009), who consider the link between credit rating and stock returns. They find that firms with a high credit rating realize higher returns than those with a low credit rating. Their result is primarily due to the poor performance of low credit rating stocks during periods of financial distress. In contrast, our results arise principally from the superior abnormal performance of stocks with low CDS slope. Further, our results remain significant when we exclude low credit rating firms, as well as the period of the recent financial crisis (2008–2009). Another difference between Avramov, Chordia, Jostova and Philipov (2009) and our work is that low credit rating stocks that drive their result are mostly small cap firms, whereas firms with low CDS slope that drive our result are relatively larger firms.

We also examine whether the negative relation between the CDS slope and stock returns can be explained by other default risk measures. This is motivated by Hilscher and Wilson (2015), who find that credit ratings are relatively inaccurate measures of default probability. We find that the correlations of the CDS slope and several default risk measures (such as Moody's KMV default metric and the measure constructed by Campbell, Hilscher and Szilagyi (2008)) are small. More important, the predictive power of the CDS slope for stock returns is robust to controlling for the standard default risk measures in the literature. Conceptually, these measures focus on the level of default risk over a specific horizon, and we go beyond previous literature to consider the term structure of credit risk. To our knowledge, our paper is the first to show that a firm's credit term structure slope contains additional information above and beyond the standard default risk measures.

We further investigate the nature of the information conveyed by the CDS slope. The term structure of CDS spreads is related to the shape of the conditional risk-neutral default probability function across different horizons. A high CDS slope can indicate that investors expect the firm's credit quality to deteriorate and CDS spreads to increase in the future. Consistent with this hypothesis, we find that differences between current long-term and short-term CDS spreads positively predict future changes in firm default risk measures. This predictive relation remains

[2] According to the Bank for International Settlements, CDS markets 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 financial crisis. The total amount of CDS contracts outstanding at end of June 2013 was $24.5 trillion.

[3] Due to these advantages, the CDS data have been used in many insightful studies related to credit risk (see, for example, Jorion and Zhang, 2007; Cao, Yu and Zhong, 2010; Friewald, Wagner and Zechner, 2014; Hilscher, Pollet and Wilson, 2015). However, the CDS data are available only for recent years. We verify the robustness of our findings about the information content of the term structure of the credit spreads using corporate bond data, available for a longer period.

significant up to 12 months ahead. Further, we find the term structure of CDS spreads has significant predictive power for earnings. Firms with a low CDS slope tend to experience more favorable earnings surprises in the next quarter. Similarly, we find that low CDS slope firms tend to have significantly higher profitability in the future than the high slope firms. Thus, different from default risk proxies, the term structure slope of CDS spreads captures valuable information about a firm's fundamentals. This supports Hilscher and Wilson (2015), who argue the need for multiple measures to capture relevant default information given the multidimensional nature of credit quality.

The current term structure of CDS spreads forecasts changes in not only a firm's fundamentals, but also its future stock returns. Why does return predictability of CDS slope arise? One possibility is that the slope characteristic proxies for the loading on a risk factor (Daniel and Titman, 1997). This explanation is supported by our finding that the loading on the long-short slope-based portfolio is positively related to future equity returns. However, the explanatory power of the slope survives after controlling for the loading. Further, the Sharpe ratio of the long-short portfolio based on the slope is substantially higher than that based on the loading on the slope-based portfolio. Thus, while we cannot rule out the notion that the slope characteristic proxies for the loading on an unknown risk factor, based on the evidence, we pursue an alternative explanation. We argue that the CDS slope contains valuable fundamental information, which is more strongly reflected in future (as opposed to current) stock prices for firms with low visibility and high arbitrage costs. Supporting this interpretation, we find that the predictive power of the CDS slope for stock returns is significant mostly for stocks facing high arbitrage costs such as those with high bid-ask spreads, high idiosyncratic risk, and high information uncertainty. We find that low credit slope stocks tend to outperform more strongly for stocks with low market capitalization, institutional ownership, and analyst coverage, i.e., stocks with low visibility. We find that the bulk of the profits arise from the positive future returns of low slope firms. This indicates that a shallow CDS slope portends strong future fundamentals. But, for less visible firms, this information diffuses into stock prices relatively gradually over time.

Our study contributes to a growing literature showing that derivatives market quantities in general are predictive of stock returns. For example, Pan and Poteshman (2006) and Cremers and Weinbaum (2010) provide evidence of slow information diffusion from options to the stock market. Longstaff (2010) finds that returns of subprime collateralized debt obligation indexes forecast stock and Treasury bond returns as much as three weeks ahead during the recent financial crisis.

Concerning information flows between the CDS and stock markets, Acharya and Johnson (2007) provide evidence of informed trading in the CDS market. They find that recent changes in the CDS spread negatively predict stock returns over the next few days. This predictability is stronger for the case of negative information. Ni and Pan (2012) show that CDS spreads' predictive power for stock returns emanates from short-sale constraints in the stock market. However, Norden and Weber (2009) find that stock returns predict changes in CDS spreads, but changes in CDS spreads do not predict stock returns. These papers use data on CDSs with a fixed maturity (five years). In contrast, we study the ability of the CDS term structure slope to predict stock returns. We find that the relation between the CDS slope and future stock returns remains significant after controlling for recent changes in the CDS spreads. Our result is not driven by short-sale constraints, as the bulk of our findings emanate from the abnormally high return of low CDS slope stocks. Thus, our result is more consistent with slow information diffusion creating a lead-lag relation between credit and equity markets.

In a recent paper, Hilscher, Pollet and Wilson (2015) investigate the relative information content of the stock return and the return to buying credit protection via CDSs at the daily frequency (up to four weeks). They focus on where informed investors trade—the CDSs or the stock market. An important consideration is market liquidity. Compared with credit protection return, our key variable, CDS slope, or the difference between two contemporaneous CDS spreads with different maturities, is not directly affected by CDS liquidity. The question we study is different from Hilscher, Pollet and Wilson (2015) in that we examine the information content of the slope of credit term structure in terms of its ability to forecast firm fundamentals as well as future stock return. We do not examine credit protection returns or whether past equity returns predict the CDS slope.[4] Further, all our tests are done at the monthly frequency. Our paper thus complements Hilscher, Pollet and Wilson (2015).[5]

In a related study, Berndt and Obrejas (2010) extract a common factor from CDS returns but do not find that this factor makes a significant contribution to explaining variations in stock returns. Our approach is different from Berndt and Obrejas (2010). Instead of examining systematic factors driving credit events, we study the shape of an individual firm's term structure of credit spreads and its ability to forecast the cross section of stock returns. Thus, our aim is not to identify common risk factors underlying the equity market and the bond and credit market. Instead, we focus on the information flow from the credit market to the stock market.

Extending our main results based on the CDS term structure, we assemble a data set on corporate bond yields from 1973 to 2010 and show that the slope of the term structure of corporate bond yields also significantly and negatively predicts stock returns over the next several months. This result continues to hold after controlling for default risk measures and other stock characteristics related to the cross section of stock returns. We further show that differences between current long-term and short-term

[4] In an unreported test, we find that past stock returns of various horizons are not significantly related to current CDS slope. In contrast, Hilscher, Pollet and Wilson (2015) find that equity returns lead credit protection returns. Thus, the information content of CDS slope and credit protection return are different.

[5] Although not the focus of our paper, we find that monthly change in CDS spreads do not predict stock returns. This is consistent with the finding in Hilscher, Pollet and Wilson (2015) that credit protection returns do not predict equity returns.

bond yields positively predict future changes in short-term bond yields and various default risk measures. This predictive relation remains significant up to 12 months ahead. The term structure of bond yields also has significant predictive power for earnings. Firms with a high bond yield curve slope experience more negative earnings surprises in the next quarter. These findings buttress the idea that the term structure of an individual firm's credit spreads contains useful information about future firm fundamentals and stock prices.

The remainder of this paper is organized as follows. Section 2 discusses the CDS data and provides summary statistics for key variables. Section 3 presents evidence that the CDS term structure contains useful information about the fundamentals of the firm and for the cross section of expected stock returns. We also discuss bond yield slope results in Section 3. Section 4 concludes the paper.

2. CDS data

We use a comprehensive data set of single-name credit default swaps. A single–name CDS is a swap contract that provides protection against adverse credit events of the reference bond. These credit events can be either a downgrade of a bond or a default. The protection buyer makes a periodic payment 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, is called the credit default swap premium, or CDS spread.

Our CDS data are provided by Markit, a global financial information services company.[6] Our data cover the period from August 2002 to December 2012. The sample consists of US dollar–denominated CDSs written on US entities that are not in the government sector. Subordinated CDS contracts are eliminated because of their relatively small presence in the database. We choose firms that have nonmissing month-end values for CDS spreads of all maturities. This leaves a data set of CDS spreads with 60,739 firm-month observations on 776 firms. Markit also provides a credit rating for each company, which is an average of the Moody's and Standard & Poor's (S&P) credit ratings adjusted to the seniority of the instrument and rounded to not include the "+" and " − " levels. This CDS data source has been widely used in recent academic research related to credit derivatives. Compared with other studies in the literature, our data set covers a larger cross section of firms for a longer period.[7]

For each firm in the sample, our data provide CDS spreads across maturities of one, two, three, five, seven, and ten years. Throughout the paper, we measure the slope of the term structure of CDS spreads by the difference between the five-year and the one-year CDS spread. Alternative definitions of the CDS slope, such as the ten-year minus the one-year spread, do not change our main results materially.

We obtain monthly stock returns, stock prices, and shares outstanding from the Center for Research in Security Prices (CRSP). The returns on common risk factors and risk-free rates are from Kenneth French's website.[8] For firm-specific control variables in our cross-sectional regressions, we obtain firm quarterly balance sheet and annual accounting data from Compustat, analyst coverage and earnings forecasts data from Institutional Brokers' Estimate System (I/B/E/S), and quarterly institutional holdings (13F filings) from Thomson Financial.

Panel A of Table 1 reports the summary statistics of CDS spreads and CDS slope. During our sample period, the mean level of CDS spread is 151 basis points (bps) for one-year maturity and 200 bps for five-year maturity. CDS spreads have large standard deviations compared with their mean levels. The CDS slope is positive, on average. During the 2008–2009 financial crisis, CDS spreads experience large spikes, especially for the short maturity, leading to a dramatic drop in the CDS slope, with the 20th percentile of the CDS slope dipping below zero (i.e., an inverted CDS term structure). But, by the fall of 2009, they bounce back to the levels before the crisis. This is illustrated by Fig. 1, which displays the monthly time series of the 80th percentile, the median, and the 20th percentile for the cross-sectional distribution of the CDS slope. The figure also shows an increasing trend in the cross-sectional dispersion of the CDS slope. The spread between the 80th and the 20th percentiles of the CDS slope increases from about 40 bps in the first one-third of the sample, to about 80 bps in the second one-third of the sample, and to around 140 bps in the last part of the sample.

Panel B of Table 1 presents average stock characteristics by deciles of CDS slope. In general, CDS slopes are higher for relatively smaller stocks, value stocks, more levered firms, stocks with a higher turnover ratio, higher institutional ownership, and higher idiosyncratic volatility. Compared with the top slope decile firms, the low CDS slope stocks have lower leverage ratio, higher profitability (return on assets, *ROA*), and lower return volatility (although we verify the differences are not significant except for *ROA*), indicating that the low slope firms are of high quality.

Panel C of Table 1 presents the correlation between the CDS slope and several default risk measures. The slope is negatively correlated with *EDF*, the expected default frequency provided by Moody's KMV, and with *CHS*, the Campbell, Hilscher and Szilagyi (2008) distress risk measure, but it is positively correlated with the level of the five-year CDS spread. The three default risk measures are all positively correlated with each other (with correlations around 0.5). The inconsistent signs across the correlations

[6] Markit receives CDS data from market makers who contribute from their official books and records. Markit cleans the data by discarding stale and inconsistent data points, as well as outliers, and then forms a composite quote for each CDS contract.

[7] For example, Jorion and Zhang (2007) use data for 272 firms from 2001 to 2004; Zhang, Zhou and Zhu (2009), 307 firms from 2001 to 2003; Cao, Yu and Zhong (2010), 377 firms from 2001 to 2006; Jorion and Zhang (2010), 583 firms from 2002 to 2005; Kapadia and Pu (2012), 214 firms from 2001 to 2009; Hilscher, Pollet and Wilson (2015), 650 firms from 2001 to 2007; Friewald, Wagner and Zechner (2014), 675 firms from 2001 to 2010. In contrast, our data cover 776 firms over about 11 years.

[8] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Table 1
Descriptive statistics.
This table presents the summary statistics. Panel A reports mean, standard deviation, 10th and 90th percentile values for one- and five-year credit default swap (CDS) spreads (in basis points) and CDS slope measured as the difference between five-year and one-year CDS spreads. Panel B presents average firm characteristics by slope deciles. *SIZE* equals the natural logarithm of the market value of equity at the end of the month for each stock. *B*/*M* equals the book-to-market ratio. *MOM* is the stock return between six months to one month ago, in percent. *LEV* equals 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. *TO* equals the monthly stock trading volume divided by total common shares outstanding. *IO* equals the fraction of common shares owned by institutions based on Thomson 13F filings. *IVOL* is the idiosyncratic volatility measured relative to the Fama and French three-factor model. *ROA* equals net income scaled by total assets, in percent. Panel C presents the correlation matrix between the CDS slope and default-related variables. *Level* is the five-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 five-year CDS spreads. Our data set obtained from Markit has CDS data on 776 firms from August 2002 to December 2012.

Panel A: Descriptive statistics for CDS spreads and CDS slope

Statistic	Mean	Standard deviation	10th percentile	90th percentile
One-year CDS spread	151.05	742.39	6.99	300.00
Five-year CDS spread	200.32	519.76	24.60	423.74
CDS slope	49.27	308.49	8.07	164.50

Panel B: Stock characteristics by CDS slope decile

Slope decile	*SIZE*	*B*/*M*	*MOM*	*LEV*	*TO*	*IO*	*IVOL*	*ROA*
1 (low)	16.24	0.56	4.32	0.30	0.20	0.69	0.28	1.69
2	16.66	0.44	6.39	0.21	0.16	0.69	0.22	1.80
3	16.53	0.47	7.37	0.22	0.16	0.70	0.22	1.84
4	16.35	0.51	7.34	0.23	0.17	0.71	0.23	1.82
5	16.11	0.55	7.51	0.26	0.17	0.71	0.23	1.72
6	15.90	0.55	7.36	0.28	0.18	0.73	0.24	1.63
7	15.73	0.60	6.71	0.30	0.19	0.74	0.25	1.66
8	15.52	0.64	5.63	0.31	0.21	0.77	0.26	1.45
9	15.23	0.66	6.26	0.34	0.25	0.78	0.30	1.44
10 (high)	14.73	0.66	4.76	0.46	0.29	0.78	0.37	1.08

Panel C: Correlations between CDS slope and default risk variables

Variable	Slope	*Level*	*EDF*	*CHS*	*Change*
Slope	1.00				
Level	0.29	1.00			
EDF	−0.21	0.50	1.00		
CHS	−0.03	0.42	0.54	1.00	
Change	0.28	0.22	−0.07	0.03	1.00

between these default risk measures and the CDS slope as well as the small magnitudes of their correlations (lower than 0.3 in absolute terms) suggest that CDS slope captures different information from default risk measures used in previous studies.

3. Empirical results

This section presents our empirical findings. We first present an analysis of portfolios formed by sorting on the CDS slope (Section 3.1). This is followed by a regression analysis (Section 3.2) and an analysis of the link between firm fundamentals and CDS slope (Section 3.3). We then examine whether return predictability from CDS slope varies by firm characteristics (Section 3.4). Finally, we examine the link between the bond yield curve and stock returns (Section 3.5).

3.1. Equity portfolios formed by sorting on CDS slope

In this subsection, we study the return and risk properties of portfolios formed by sorting on the CDS slope at the end of each month. The returns of these portfolios are computed in the month following portfolio formation.

3.1.1. Basic results

Panel A of Table 2 presents the average raw returns of equal-weighted CDS slope decile portfolios, the differences in average raw returns between the bottom and top decile portfolios, and the alphas of the portfolios with respect to the capital asset pricing model (CAPM), the Fama and French three–factor model, and the Carhart four–factor model. The average returns of the decile portfolios sorted by CDS slope decline monotonically, from 1.90% per month for the bottom decile to 0.70% per month for the top decile. The difference is 1.20% per month (14.40% per year), with a *t*-statistic of 2.25. 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 1.22%, 1.13%, and 1.14% with respect to the CAPM, the Fama and French three-factor model, and the Carhart four-factor model, respectively. All three alphas are statistically significant at the 1% level.[9]

[9] In unreported tables, we verify that our results hold for value-weighted decile portfolios or when we sort stocks into quintiles by the CDS slope. The return spreads between the low and high slope portfolios remain positive and significant.

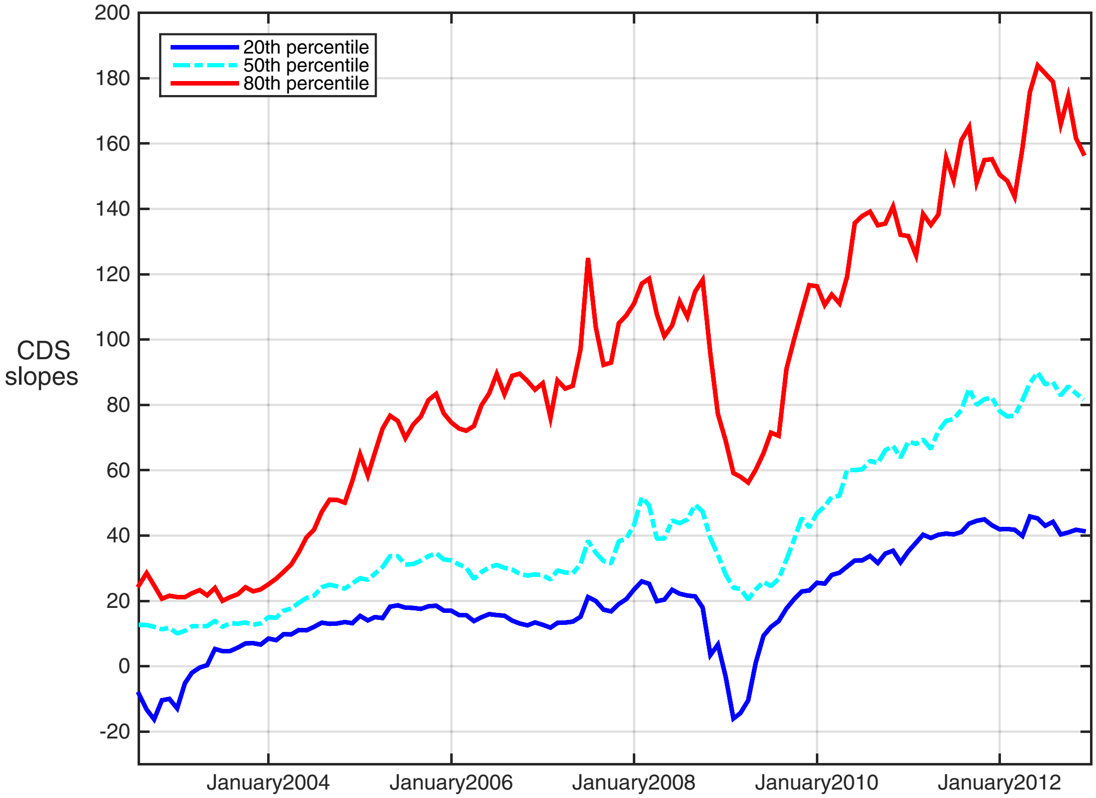

Fig. 1. Time series plot of CDS slopes of different percentiles. This graph plots the time series of the 20th, 50th, and 80th percentiles of the cross section of individual firm credit default swap (CDS) slopes. We measure the CDS slope of a firm, at the end of each month from August 2002 to December 2012, as the difference between the five-year CDS and one-year CDS premiums (in basis points) for that firm.

3.1.2. Properties of the long-short portfolio formed on CDS slope

Panel B of Table 2 shows no statistically significant differences in the market beta, skewness, coskewness (the Harvey and Siddique (2000) measure), or kurtosis between the two extreme groups of firms sorted by CDS slope. Nonetheless, in studying the relation between CDS slope and expected stock return via regression analyses to follow, we systematically control for stock characteristics and risk exposures known to be related to expected stock return.

In untabulated results, we find that the average correlation among stocks belonging to the top decile ranked by the CDS slope is 0.4 and the average correlation among stocks belonging to the bottom decile ranked by the CDS slope is 0.33. Both are significantly higher than the average correlation of all stocks in our sample (i.e., those with CDS traded), which is 0.16. Similarly, when we rank stocks based on their beta (β_{CDS}) with respect to the CDS slope factor (i.e., the low-minus-high CDS slope portfolio), the average correlation among stocks belonging to the top decile ranked by β_{CDS} is 0.58, and the average correlation among stocks belonging to the bottom decile ranked by β_{CDS} is 0.44. While these results indicate relatively high co-movements among stocks having high CDS slope or high exposure to the CDS slope factor, in our regression analyses to follow, we control for a variety of risk measures to ascertain whether the pricing of CDS slope emanates from compensation for covariance risk and other forms of risk such as coskewness or distress measures.

As one piece of evidence on risk-reward arguments, the Sharpe ratio for the low-minus-high CDS slope portfolio is 0.7 annualized and its information ratio is 0.21. MacKinlay (1995) recommends a comparison of Sharpe ratios with an annualized Sharpe ratio of 0.6, a value he suggests is consistent with risk-based pricing. Using the Jobson and Korkie (1981) test, we find that our Sharpe ratio is significantly higher than the MacKinlay (1995) threshold.

We also uncover that while the low-minus-high CDS slope portfolio has insignificant correlations with the Fama and French three factors, it is positively and significantly correlated with some well-known equity strategies: the correlation of low-minus-high CDS slope portfolio with the distress factor of Campbell, Hilscher and Szilagyi (2008) (*CHS*) is 0.235, with the down beta strategy of Ang, Chen and Xing (2006) (ACX) is 0.285, and with the earnings announcer strategy of Savor and Wilson (2016) (SW) is 0.268.[10] These correlations appear modest. Moreover,

[10] The distress factor of Campbell, Hilscher and Szilagyi (2008) is a natural candidate to control for. The other two are prominent equity strategies highlighting dynamic variation in the risk-return trade-off. The distress factor is the difference between the equal-weighted returns of the top decile and the bottom decile portfolios when stocks are sorted by the *CHS* measure. The down beta strategy is the difference between the

Table 2
Stock returns and slope of the credit default swap (CDS) term structure.

Panel A reports the average monthly returns of equal-weighted decile portfolios in which we sort stocks by the CDS slope, measured as the difference between the five-year and one-year CDS spreads. Besides the average raw returns of portfolios, we report their capital asset pricing model (CAPM) alphas, Fama and French three-factor (FF-3) alphas, and Carhart four-factor (Carhart-4) alphas. All returns are in percent. The *t*-statistics (reported in parentheses) are adjusted by the Newey–West method. We include all delisted returns. Panel B presents each of the CDS decile portfolio's market beta β_{Market}, return skewness *SKEW*, coskewness (the Harvey-Siddique measure) *COSKEW*, and kurtosis *KURT*. Panel C reports the summary statistics of four strategies: monthly mean (in percent), annualized volatility, market beta, skewness, kurtosis, and coskewness. The *CDS Slope* strategy is the difference between the equal-weighted returns of the bottom decile and the top decile portfolios when stocks are sorted by CDS slope. The down beta strategy (*ACX*) is the difference between the equal-weighted returns of the top quintile and the bottom quintile portfolios when stocks are sorted by their downside beta estimated over the previous 12 months. The earnings announcer strategy (*SW*) is the difference between the equal-weighted returns of the portfolio, which goes long all stocks that are scheduled to announce their earnings next month and short all the other stocks. The *CHS* strategy is the difference between the equal-weighted returns of the top decile and the bottom decile portfolios when stocks are sorted by the Campbell, Hilscher and Szilagyi distress risk measure (*CHS*) (Campbell, Hilscher and Szilagyi, 2008). The sample period is from August 2002 to December 2012. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Portfolio returns and alphas

	1 (low)	2	3	4	5	6	7	8	9	10 (high)	low - high
Average return	1.90**	1.28**	1.17**	1.14**	0.84*	0.93**	0.94*	0.81	1.07*	0.70	1.20**
	(2.07)	(2.21)	(2.69)	(2.77)	(1.92)	(2.04)	(1.92)	(1.47)	(1.73)	(0.86)	(2.25)
CAPM alpha	1.57*	1.07*	1.05**	1.01**	0.72	0.80	0.79	0.63	0.84	0.34	1.22**
	(1.76)	(1.94)	(2.30)	(2.32)	(1.53)	(1.64)	(1.48)	(1.07)	(1.30)	(0.41)	(2.27)
FF-3 alpha	1.59*	1.17**	1.16**	1.10**	0.80*	0.88*	0.89*	0.71	0.94	0.46	1.13**
	(1.80)	(2.12)	(2.58)	(2.57)	(1.73)	(1.83)	(1.74)	(1.24)	(1.47)	(0.56)	(2.15)
Carhart-4 alpha	1.62*	1.18**	1.16**	1.11**	0.80*	0.88*	0.90*	0.72	0.95	0.48	1.14**
	(1.80)	(2.09)	(2.56)	(2.56)	(1.72)	(1.81)	(1.72)	(1.24)	(1.47)	(0.58)	(2.13)

Panel B: Characteristics of CDS slope-sorted portfolios

	1 (low)	2	3	4	5	6	7	8	9	10 (high)	*p*-value
β_{Market}	1.13	1.08	1.09	1.09	1.12	1.12	1.14	1.13	1.16	1.22	0.92
SKEW	0.08	0.04	0.04	0.04	0.04	0.03	0.02	0.04	0.06	0.10	0.86
COSKEW	1.20	1.00	0.98	0.98	1.00	1.01	1.06	1.15	1.28	1.24	0.68
KURT	3.52	3.37	3.34	3.33	3.31	3.38	3.39	3.39	3.47	3.54	0.62

Panel C: Statistical properties of various strategies

	CDS Slope	*ACX*	*SW*	*CHS*
Mean	1.20	2.91	0.27	−0.21
Volatility	0.21	0.42	0.10	0.25
β_{Market}	0.05	−0.17	0.13	−0.69
SKEW	1.15	0.45	0.37	−1.67
KURT	2.34	2.46	2.23	6.31
COSKEW	1.08	0.11	0.14	−0.21

when we regress the monthly return of the low-minus-high CDS slope portfolio on these risk factors, the intercept term is 1.14% with a *t*-statistic of 2.10. This suggests that the predictive power of CDS slope for stock return is a new finding not explained by the well-known strategies considered above.

In the second column of Panel C of Table 2, we report the mean, volatility, skewness, coskewness, and kurtosis for our CDS slope–based portfolio. The annualized return volatility of the CDS slope–based strategy is 0.21, its market beta is 0.05, its skewness is 1.15, and its kurtosis is 2.34. When we compound the monthly returns to our low-minus-high CDS slope portfolio to annual returns, we find that the largest profit was realized in 2009 followed by 2003, and the largest loss occurred in 2006 with two other minor losses in 2004 and 2010.[11] Panel C also provides a comparison of the various statistics across the CDS slope portfolio and the corresponding portfolios for the ACX, *CHS*, and SW strategies. Panel C shows that the CDS slope–based strategy has a lower mean return and lower volatility compared with ACX, but higher mean and higher volatility when compared with SW. The market beta of the CDS slope–based strategy is close to zero and is the lowest in absolute terms across all strategies. Among other statistics, the most notable one is that the CDS slope–based strategy has higher coskewness than other strategies. We report the results of controlling for coskewness in Section 3.2.

equal-weighted returns of the top quintile and the bottom quintile portfolios when stocks are sorted by their downside beta estimated over the previous 12 months. The earnings announcer strategy goes long all stocks that are scheduled to announce their earnings next month and short all the other stocks.

[11] We also regress the time series of monthly returns of low-minus-high CDS slope portfolio on either the contemporaneous values or the lagged values of the equity market index return, index volatility, credit spread (BAA bond yield minus AAA bond yield), and term spread (five-year Treasury yield minus one-year Treasury yield) but are not able to discern any significant relations.

Table 3
Robustness checks.
Panel A reports the value-weighted average monthly returns of portfolios sorted on the credit default swap (CDS) slope for the subsample excluding the 2008–2009 financial crisis period. We sort stocks in each month into deciles by CDS slope, and we form a portfolio that is long the bottom decile stocks and short the top decile stocks. Besides the average raw returns of portfolios, we report their capital asset pricing model (CAPM) alphas, Fama and French three-factor (FF-3) alphas, and Carhart four-factor (Carhart-4) alphas. Panel B reports the average monthly return of an equal-weighted portfolio that is long the bottom CDS slope decile and short the top decile during various months following the portfolio formation. $r_{i,i+1}$ is the portfolio return over the month $[i, i+1]$ following the portfolio formation. We include all delisted returns. The sample period is from August 2002 to December 2012. All returns are in percent. The t- statistics (reported in parentheses) are adjusted by the Newey-West method. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. CAPM: Capital asset pricing model; FF-3: Fama and French three-factor; Carhart-4: Carhart four-factor.

Panel A: Value-weighted excluding 2008–2009 financial crisis period

	Portfolio 1 (low)	Portfolio 10 (high)	Average return low - high	CAPM alpha	FF-3 alpha	Carhart-4 alpha
Average return or alpha	1.06* (1.80)	0.39 (0.66)	0.67* (1.85)	0.84** (2.09)	0.71** (2.12)	0.80** (2.26)

Panel B: Average returns of spread portfolio sorted by CDS slope

	$r_{0,\,1}$	$r_{1,\,2}$	$r_{2,\,3}$	$r_{3,\,4}$	$r_{4,\,5}$
Average return	1.20** (2.25)	1.13** (1.97)	1.11** (2.28)	1.21** (2.41)	0.99* (1.89)

3.1.3. Other robustness checks

We next verify that our results are not driven by equal-weighting or the 2008–2009 financial crisis. Table 3, Panel A, shows that, excluding the 2008–2009 financial crisis period, the low CDS slope decile on average outperforms the top decile by 0.67% (8.04% annualized) when value-weighted. The difference in the CAPM alphas of the bottom CDS slope decile and the top slope decile is larger in magnitude than the difference in raw returns and is statistically significant at the 5% level. The same is true for alphas under Fama and French three-factor model or the Carhart four-factor model. In results omitted for brevity, excluding the financial crisis months for the case of equally weighted portfolios leads to similar conclusions.

In other unreported tables, we show that our results are robust in other subsamples as well. For example, after excluding financial firms, on an equal-weighted (value-weighted) basis, the average monthly outperformance of the lowest CDS slope decile of stocks over the highest CDS slope decile stocks is 1.62% (1.35%), with a t-statistic of 2.84 (2.43). Further, our results survive when we exclude low–rated (CCC) firms (on average, our sample contains only four CCC–rated firms in each month). We find that even among low credit rating firms, those with low CDS slope have a significant positive average return of 2.35%, which is 1.16% higher than the average returns of high CDS slope stocks with similar credit ratings.[12]

Table 3, Panel B, shows that the return predictability of CDS slope extends well beyond the one-month horizon. We find that low CDS slope stocks significantly outperform high CDS slope stocks in each of the first five months after sorting. The equal-weighted portfolio that is long stocks in the bottom decile slope and short stocks in the top decile slope has an average return of 1.20%, 1.13%, 1.11%, 1.21%, and 0.99%, respectively, in each of the first five months after portfolio formation (i.e., sorting on CDS slope).[13] After skipping six months or longer between portfolio formation and portfolio evaluation, the predictive power of CDS slope for stock return is no longer statistically significant.

In additional unreported analyses, we verify that our results remain strong and significant when we measure the CDS slope as a five-year CDS spread minus a two-year CDS spread, ten-year CDS spread minus a one-year CDS spread, or ten-year CDS spread minus a five-year CDS spread. The fact that our results are robust to using the ten-year spread to measure slope mitigates the concern that our base results are driven by liquidity in the CDS market, because the five-year CDS (used in our base results) tends to be more liquid (as measured by trading activity) than other maturities in the beginning of our sample period. Further, our results remain qualitatively the same when we measure CDS slope as the difference in five-year and one-year CDS spreads scaled by the one-year or five-year CDS spread. For example, when we scale by the five-year CDS spread, the average monthly return spread between the bottom and the top decile of stocks sorted by the scaled CDS slope is 0.64%, with a t-statistic of 2.05. Finally, we find no significant differences between the average returns of the top and the bottom decile portfolios sorted by one of the following default risk proxies over each of the six months after portfolio formations: five-year CDS spreads, the expected default frequency (*EDF*) provided by Moody's KMV, and the Campbell, Hilscher, and Szilagyi distress risk measure (*CHS*).

3.2. Regression results

We use panel regressions to further show the robustness of the negative relation between the CDS slope and future stock returns. Our panel regressions cluster

[12] To obtain this result, we convert the S&P Domestic Short–Term Issuer Credit Rating (obtained from Compustat) to a numerical scale as in Qiu and Yu (2012) and perform a 3-by-3 independent double–sort based the credit rating and CDS slope. Unreported tables are available upon request.

[13] The Sharpe ratio of the portfolio, which goes long low-slope firms and short high-slope firms, grows with the horizon. It increases from 0.7 at the one-month horizon to 1.03, 1.44, 1.90, and 2.01, respectively, for a holding period of two, three, four, and five months.

standard errors at the firm-month level to control for cross-correlations and serial dependence in the residuals (both cross-sectionally and across time).[14] We also include time and year fixed effects to account for shifts in the mean return over time. The key independent variable, the CDS slope, is measured as the five-year CDS spread minus the one-year CDS spread. In addition to default risk measures, we control for log market capitalization, book-to-market ratio of equity, past six-month stock returns (momentum), one-month reversal, leverage, stock turnover ratio, institutional share ownership, and idiosyncratic volatility. We include a measure that interacts the slope with the default risk measure *EDF*, to ascertain if the effect of the CDS slope is greater for firms with higher default risk.[15] We also include a dummy for CCC firms and the dummy's interaction with the CDS slope to determine whether our results are driven by extremely low-grade firms. We consider measures of the volatility of default risk, to account for the likelihood that the CDS slope captures a premium for the risk associated with variations in default intensity; viz. Driessen (2005). We include the standard deviations of the five-year CDS spread and the *EDF* measure over the past 12 months as explanatory variables.

It is reasonable to argue that conditioning on the CDS slope helps us to better measure firm default risk because neither the short-term CDS spread nor the long-term CDS spread fully captures the default risk over various future horizons. But the CDS slope alone does not capture default risk. For example, consider two firms with the same short-term spread. By definition, the firm with the higher CDS slope would have a higher long-term CDS spread, and, thus, higher average default risk. For two firms with the same long-term CDS spread, the firm with the higher CDS slope could have a lower short-term CDS spread and, thus, a lower average default risk. This argument shows that the CDS slope and default risk do not map on to each other precisely.

Confirming the above observation, Panel C of Table 1 shows low correlations between the CDS slopes and several default risk measures, including the five-year CDS spread, the expected default frequency (*EDF*) provided by Moody's KMV, and the Campbell, Hilscher, and Szilagyi measure (*CHS*). The correlations between these default risk measures are large and positive, ranging from 0.42 to 0.54. But the correlations of the CDS slope with these default risk measures are only between −0.21 to 0.29.[16] These numbers are virtually unchanged when we exclude CCC–rated firms from our sample.

The results of panel regressions are reported in Table 4. The level of one-year and five-year CDS spreads are both significantly and positively related to future stock returns. But the coefficients for the other two default risk measures (*CHS* and *EDF*) are opposite in signs: positive yet insignificant for *EDF*, negative but only marginally significant for *CHS*. This is consistent with the mixed results concerning the relation between expected stock returns and default risk reported in the literature. While some studies find a positive cross-sectional relation between expected stock returns and default risk (e.g., Vassalou and Xing, 2004; and Chava and Purnanandam, 2010), other studies show the opposite (e.g., Griffin and Lemmon, 2002; and Campbell, Hilscher and Szilagyi, 2008).

More important, the relation between the CDS slope and stock returns is not accounted for by default or distress risk. Table 4 shows that the negative relation between the CDS slope and future stock returns remains significant after controlling for default risk measures, including the CDS level, *EDF*, and *CHS*.[17] The effect of the CDS slope is marginally greater for firms with higher default risk, but the CCC dummy and its interaction with the slope are not significant.

Table 4 also shows that the negative relation between the CDS slope and future stock returns remains robust to controlling for past returns over various horizons. Thus, the predictive power of the CDS slope for stock returns does not appear to be a reflection of momentum or reversal in stock returns. Further, the predictive power of the CDS slope is independent of that of the lagged one-month change in the CDS spread. The negative relation between the CDS slope and future stock returns is also robust to controlling for additional lags of past monthly changes in CDS spreads. When we include the sum of six lags of past monthly changes in CDS spreads in Table 4, the CDS slope has a coefficient of −0.27 with a *t*-statistic of −3.09.

In the panel regressions of Table 5, we use returns of various portfolios sorted by CDS slope as the dependent variable and the average values of characteristics of stocks in those portfolios for the independent variables. Our results remain robust. We find a significant negative relation between the CDS slope and next month's return in the panel regressions of individual stock returns and in the panel regressions of portfolio returns. The R^2 is generally larger for portfolio regressions that account for noisiness of individual security returns, and this is intuitive.

Within both Tables 4 and 5, we conduct a beta versus characteristic test for the CDS slope by including β_{CDS}, the beta of individual stock return or portfolio return with respect to the CDS slope factor (i.e., the return of an equal-weighted portfolio that goes long the bottom CDS slope decile and short the top slope decile), as a regressor together with CDS slope (as a characteristic). The coefficient for β_{CDS} is positive and significant in both tables, suggesting that covariance with the return on the low-minus-high slope portfolio is priced. However, it does not drive out the predictive power of a firm's own CDS slope as the slope

[14] Standard Fama–MacBeth regressions with Newey–West standard errors yield qualitatively similar results, which are available upon request.

[15] Interaction with *CHS*, the other default measure, yields similar results.

[16] Friewald, Wagner and Zechner (2014) extract new firm-specific measures of credit risk premia from the CDS forward curve and find a strong positive relation between such credit risk premia and equity excess returns. Just like other default risk measures, their credit risk premia are virtually uncorrelated with our CDS slope. We thank the authors for sharing their credit risk premia data with us.

[17] The same robustness holds when we add a categorical variable that transforms the S&P Domestic Short-Term Issuer Credit Rating to numerical values as in Qiu and Yu (2012) with AAA = 1 , AA + = 2, ⋯, CC = 20, C = 21, and D = 22. In the regression, this credit rating categorical variable has a coefficient of 0.001 with a *t*-statistic of 1.77, and the CDS slope has a coefficient of −0.19 with a *t*-statistic of −1.96.

Table 4

Panel regressions of individual stock returns.

This table reports results of panel regressions in which the dependent variable is monthly individual stock returns. All regressions include year fixed effects and cluster the standard errors by firm-month. *Slope* is the difference between the five-year and one-year credit default swap (CDS) spreads. D_{CCC} is a dummy variable that is one for CCC–rated firms and zero otherwise. *CDS*(1) and *CDS*(5) are the one-year and five-year CDS spreads at the end of the previous month, respectively. $\sigma_{CDS(5)}$ is the standard deviation of *CDS*(5) over the past 12 months. β_{CDS} is beta of the stock's return with respect to the CDS slope factor (i.e., the return of an equal-weighted low-minus-high CDS slope decile portfolio). *EDF* is the expected default frequency provided by Moody's KMV. σ_{EDF} is the volatility of *EDF* over the past 12 months. *CHS* is the Campbell, Hilscher and Szilagyi (2008) measure of distress risk. $\Delta CDS(1)$ and $\Delta CDS(5)$ represent changes in the one-year and five-year CDS spreads over the last month, respectively. *SIZE* equals the natural logarithm of the market value of equity at the end of the previous month. *B*/*M* equals the book-to-market ratio. *MOM* equals the stock's market-adjusted return between six months ago and one month ago. Ret_{t-1} is the previous month stock return. *LEV* equals 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. *TO* equals the monthly stock trading volume divided by total common shares outstanding. *IO* equals the fraction of common shares owned by institutions based on Thomson 13F filings. *IVOL* is the idiosyncratic volatility measured relative to the Fama and French three-factor (FF-3) model. We include all delisted returns. The sample period is from August 2002 to December 2012. The numbers in parentheses are *t*-statistics. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Slope	−0.33***	−0.31***	−0.40***	−0.58***	−0.51***	−0.47***	−0.51***	−0.38**	−0.42***	−0.36**	−0.35***	−0.31***	−0.25***	−0.24***	−0.25***
	(−3.79)	(−3.36)	(−4.22)	(−5.01)	(−4.99)	(−3.86)	(−3.59)	(−3.00)	(−4.73)	(−3.00)	(−4.02)	(−3.52)	(−3.59)	(−3.45)	(−3.66)
D_{CCC}		0.02													
		(1.02)													
Slope $\times D_{CCC}$		−0.96													
		(−1.07)													
CDS(1)			0.22***												
			(4.69)												
CDS(5)				0.22***											
				(4.68)											
$\sigma_{CDS(5)}$					0.66***										
					(5.56)										
β_{CDS}						0.01***									
						(3.94)									
EDF							0.00	−0.00							
							(0.25)	(−1.59)							
Slope $\times$ *EDF*								0.00							
								(0.66)							
σ_{EDF}									−0.00*						
									(−1.78)						
CHS										−0.66					
										(−0.28)					
$\Delta CDS(1)$											−0.22			0.05	
											(−1.58)			(0.62)	
$\Delta CDS(5)$												−0.26			0.10
												(−1.61)			(1.00)
SIZE													−0.00***	−0.00***	−0.00***
													(−3.61)	(−3.58)	(−3.63)
B/*M*													0.00***	0.00***	0.00***
													(3.12)	(3.13)	(3.12)

(*continued on next page*)

Table 4 (*continued*)

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
MOM													0.00	0.00	0.00
													(0.14)	(0.18)	(0.19)
Ret_{t-1}													−0.01***	−0.01***	−0.01***
													(−3.08)	(−3.05)	(−3.01)
LEV													0.00	0.00	0.00
													(0.43)	(0.43)	(0.39)
TO													−0.01**	−0.01**	−0.01**
													(−2.30)	(−2.28)	(−2.24)
IO													0.00*	0.00*	0.00*
													(1.75)	(1.73)	(1.73)
IDVOL													0.00	0.00	0.00
													(0.76)	(0.75)	(0.76)
Constant	−0.11***	−0.11***	−0.03***	−0.03***	0.02***	0.00***	−0.11***	−0.11***	0.03***	−0.11***	−0.03***	−0.03***	0.07***	0.07***	0.07***
	(−16.54)	(−16.56)	(−5.94)	(−5.91)	(6.54)	(5.42)	(−10.58)	(−10.26)	(7.62)	(−15.28)	(−4.89)	(−4.89)	(9.84)	(9.85)	(9.90)
Adjusted R^2	4.22%	4.23%	4.49%	4.49%	4.65%	5.30%	6.00%	6.33%	5.32%	4.94%	4.28%	4.29%	6.19%	6.18%	6.20%

Table 5

Panel regressions of portfolio returns.

This table reports results of panel regressions in which the dependent variable is the monthly returns of ten portfolios of stocks sorted by their credit default swap (CDS) slope (measured as the difference between five-year and one-year CDS spreads). These portfolios are rebalanced monthly. The independent variables are the averages of the corresponding values for stocks within a given portfolio. *Slope* is the difference between the five-year and one-year CDS spreads. *CDS*(1) and *CDS*(5) are the one-year and five-year CDS spreads at the end of previous month, respectively. $\sigma_{CDS(5)}$ is the standard deviation of *CDS*(5) over the past 12 months. β_{CDS} is beta of the stock's return with respect to the CDS slope factor (i.e., the return of an equal-weighted low-minus-high CDS slope decile portfolio). *EDF* is the expected default frequency provided by Moody's KMV. σ_{EDF} is the volatility of *EDF* over the past 12 months. *CHS* is the Campbell, Hilscher and Szilagyi (2008) measure of distress risk. $\Delta CDS(1)$ and $\Delta CDS(5)$ represent changes in the one-year and five-year CDS spreads over the last month, respectively. *SIZE* equals the natural logarithm of the market value of equity at the end of the previous month. *B*/*M* is the book-to-market ratio. *MOM* equals the stock's market-adjusted return between six months ago and one month ago. Ret_{t-1} is the lagged one-month return. *LEV* equals 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. *TO* equals the monthly stock trading volume divided by total common shares outstanding. *IO* equals the fraction of common shares owned by institutions based on Thomson 13F filings. *IVOL* is the idiosyncratic volatility measured relative to the Fama and French three-factor (FF-3) model. The sample period is from August 2002 to December 2012. The numbers in parentheses are *t*-statistics. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Slope	−0.65**	−0.85***	−1.30***	−0.50**	−1.68***	−0.60**	−0.65**	−0.48***	−0.61***	−0.72**	−0.75**	−1.18**	−1.12**	−1.15**
	(−2.58)	(−6.42)	(−7.42)	(−2.42)	(−3.26)	(−2.54)	(−2.56)	(−4.24)	(−4.06)	(−2.49)	(−2.55)	(−2.69)	(−2.49)	(−2.54)
CDS(1)		0.73***												
		(6.24)												
CDS(5)			0.70***											
			(10.08)											
$\sigma_{CDS(5)}$				2.32***										
				(4.18)										
β_{CDS}					0.16***									
					(7.93)									
EDF						−0.08	−0.05							
						(−1.36)	(−1.21)							
Slope × *EDF*							0.01							
							(1.09)							
σ_{EDF}								0.02						
								(1.02)						
CHS									9.97					
									(0.71)					
$\Delta CDS(1)$										0.580			−0.81	
										(0.97)			(−1.45)	
$\Delta CDS(5)$											0.810			−1.05
											(0.88)			(−1.60)
SIZE												−0.02***	−0.02***	−0.02***
												(−4.38)	(−4.41)	(−4.23)
B/*M*												0.02	0.03	0.03
												(0.60)	(0.70)	(0.72)
MOM												−0.06***	−0.06***	−0.06***
												(−4.50)	(−4.61)	(−4.27)
Ret_{t-1}												−0.22***	−0.23***	−0.23***
												(−5.25)	(−5.13)	(−5.41)
LEV												0.04	0.04	0.03
												(0.56)	(0.50)	(0.45)
TO												0.02	0.03	0.03
												(0.35)	(0.47)	(0.50)
IO												−0.02	−0.02	−0.02
												(−0.34)	(−0.36)	(−0.41)
IDVOL												−0.25***	−0.25***	−0.25***
												(−3.82)	(−3.74)	(−3.72)
Constant	−0.01	0.00	0.00	0.00	0.07***	0.02***	0.01***	0.02***	0.01	0.01*	0.01*	0.41***	0.40***	0.39***
	(−1.40)	(0.54)	(0.55)	(0.27)	(6.61)	(3.92)	(2.61)	(6.60)	(1.57)	(1.91)	(1.96)	(3.89)	(3.85)	(3.61)
Adjusted R^2	12.27%	13.62%	13.66%	12.99%	19.31%	10.82%	12.15%	13.33%	11.72%	12.44%	12.50%	21.62%	21.68%	21.75%

characteristic remains statistically significant in the presence of β_{CDS}.

In unreported tables, we show that the regression results do not change materially when we winsorize the extreme observations of CDS slope at the 0.5% and the 99.5% level or when we exclude the lowest decile of firms ranked by their CDS slope. We also verify that our results are robust to including an indicator variable for the financial crisis of 2008–2009, and to controlling for stock return skewness and coskewness. Finally, measuring the CDS slope differently, such as a five-year minus a two-year spread or a ten-year minus a one-year spread, yields conclusions similar to those reported above.

Given the significance of β_{CDS}, which is consistent with a covariance risk–based influence of the CDS slope on required returns, it is worth comparing the Sharpe ratio of the long-short portfolio based on β_{CDS} with that from the long–short portfolio based on the slope itself. We sort stocks into deciles based on β_{CDS} every month and then form a long-short portfolio based on the extreme deciles. The average monthly return for this portfolio is 0.71%, and the annualized Sharpe ratio is 0.25. This Sharpe ratio is lower than the MacKinlay (1995) threshold of 0.6, suggesting that returns achievable from the β_{CDS} portfolio are consistent with risk-based pricing. However, the average return and Sharpe ratio for the slope-based portfolio, at 1.20% and 0.7, respectively are substantially (and, we have verified, significantly) higher than the corresponding numbers for the β_{CDS} portfolio, and the Sharpe ratio for the slope-based portfolio is significantly higher than the MacKinlay (1995) threshold (viz. Section 3.1). Further, the average return on the long-short CDS slope–based portfolio amounts to an annualized 14.40%, which is material from an economic standpoint.[18] Overall, while we cannot completely rule out the notion that the slope characteristic proxies for an unknown risk factor, the evidence suggests exploring alternative explanations.

3.3. Information content of the CDS slope

In this subsection, we examine the information content of the CDS slope. One reason a firm can have an upward–sloping CDS term structure is that investors expect the credit health of the firm to deteriorate. This is similar to the expectation hypothesis of the (default-free) term structure of interest rates: A long-term rate that is higher than the short-term rate could indicate that the future short-term rate is expected to be higher.

Table 6 presents the ability of the CDS slope (the five-year spread minus the one-year spread) to forecast changes in one-year CDS spreads. We regress changes in one-year CDS spreads on the current CDS slope, controlling for the one-year as well five-year CDS spreads.[19] We find that the coefficient on the CDS slope is positive and significant in all regressions. Table 6 also considers the predictive ability of the CDS slope for the default measures *EDF* and *CHS*. The slope predicts shifts in these measures as well. However, the R^2 is generally higher for CDS spread levels relative to that for the default measures. Overall, the CDS slope contains useful information about shifts in the future creditworthiness of the firm. An upward–sloping credit term structure indicates that investors in the credit market expect the financial health of the firm to deteriorate.

Table 7 shows that the CDS slope also has significant predictive power for earnings surprises. In Panel A, we sort stocks into quintiles based on the CDS slope (*Slope*). Then, we report the difference in the average future standardized earnings surprises (*SUE*) between the top and the bottom *Slope* quintile for firms that release earnings over the next n-months, $n = 1, 2, 3$. Firms with a high *Slope* on average experience significantly more negative earnings surprises than firms with a low *Slope*, for both value-weighted and equal-weighted averages. In Panel B, we use Fama and MacBeth regressions to confirm that a firm's standardized earnings surprise for the next quarter is significantly negatively related to the current slope of the CDS term structure, controlling for the past month stock return, lagged *SUE*, and consensus analyst forecasts.

In an unreported test, we investigate whether the relation between CDS slope and expected stock return is influenced by the risk-based explanation for the earnings announcement premium recently found by Savor and Wilson (2016). We first calculate each stock's beta (β_{EA}) with respect to the earnings announcer portfolio of Savor and Wilson (2016). Then, in each month and for the low (high) slope portfolio, we take the average values of β_{EA} for all stocks sorted into a portfolio to be the portfolio's beta with respect to the earning announcer factor. We test whether β_{EA}s are significantly different between the low slope portfolio and the high slope portfolio. The p–value for the null hypothesis that the difference is zero is 0.248. This suggests that our results survive the consideration of covariance risk with respect to the earnings announcement portfolio.

The CDS slope also contains useful information about future changes in accounting profitability. We sort firms into quintiles, at the end of each February, May, August, and November, based on their CDS *Slope*. Then, we compare the average *ROA* reported next month (i.e., at the end of each quarter) for firms in the top quintile versus those in the bottom quintile sorted by CDS *Slope*. We find that high CDS slope firms tend to have a significantly lower *ROA* than the low CDS slope firms. The difference is −0.67% (t-statistic = −7.15) when we equal-weight the *ROA* and

[18] We conduct an additional test. We independently sort stocks into terciles by β_{CDS} and the CDS slope, to construct a total of nine portfolios. We find that the differences between the average returns on the low slope and high slope portfolios remain positive and significant at the 5% level within each of the β_{CDS} portfolios, confirming that the slope provides additional explanatory power for returns beyond the loading on the slope-sorted portfolio. Full results are available upon request.

[19] Our results are robust to controlling for the sum of more lags (up to 12) of past monthly changes in CDS spreads and past stock returns. The former allows for longer-term information contained in CDS spreads, and the latter is included to capture information flow from the stock market to the credit market (results are available upon request).

Table 6
Credit default swap (CDS) slope predicts changes in default risk.

This table reports the results of monthly Fama-MacBeth regressions of changes in one-year CDS spread (Panel A), changes in *EDF* (Panel B), and changes in *CHS* (Panel C) from t to $t+i$ on the CDS slope at time t. *EDF* is the expected default frequency provided by Moody's KMV. *CHS* is the Campbell, Hilscher and Szilagyi (2008) measure of distress risk. $\Delta CDS_{t+i} = CDS_{t+i} - CDS_t$. $\Delta EDF_{t+i} = EDF_{t+i} - EDF_t$. $\Delta CHS_{t+i} = CHS_{t+i} - CHS_t$. $CDS(1)$ and $CDS(5)$ are one-year and five-year CDS spreads lagged by one month. $Ret(1, 12)$ is the past one-year stock return in percent. The numbers in parentheses are t-statistics. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: The monthly Fama-MacBeth regressions of changes in one-year CDS spread on the CDS slope

Variable	ΔCDS_{t+1}	ΔCDS_{t+3}	ΔCDS_{t+6}	ΔCDS_{t+9}	ΔCDS_{t+12}
$Slope_t$	0.342***	0.581***	0.680***	0.769***	0.955***
	(8.33)	(13.27)	(10.52)	(12.45)	(10.10)
$CDS(1)$	0.158***	0.259***	0.140**	−0.044	−0.062
	(4.04)	(3.95)	(2.06)	(−0.68)	(−0.74)
$CDS(5)$	−0.202***	−0.333***	−0.312***	−0.250***	−0.305***
	(−5.13)	(−6.20)	(−4.58)	(−3.13)	(−3.48)
$Ret(1, 12)$	−1.040***	−1.566***	−2.589***	−3.029***	−3.263***
	(−2.99)	(−3.31)	(−3.24)	(−3.95)	(−3.38)
Constant	99.761***	152.678***	260.947***	308.048***	334.954***
	(2.87)	(3.22)	(3.24)	(3.98)	(3.42)
R^2	3.22%	8.78%	16.58%	23.10%	27.94%

Panel B: The monthly Fama-MacBeth regressions of changes in EDF on the CDS slope

Variable	ΔEDF_{t+1}	ΔEDF_{t+3}	ΔEDF_{t+6}	ΔEDF_{t+9}	ΔEDF_{t+12}
$Slope_t$	0.078*	0.082*	0.174**	0.272*	0.142*
	(1.65)	(1.78)	(2.03)	(1.93)	(1.87)
$CDS(1)$	−0.098**	−0.169	0.075	0.183	0.092
	(−2.04)	(−1.60)	(0.71)	(1.01)	(0.35)
$CDS(5)$	0.110*	0.209*	0.055	0.035	0.157
	(1.93)	(1.78)	(0.60)	(0.29)	(0.88)
$Ret(1, 12)$	−0.542*	−1.884***	−1.720*	−1.601	−2.185
	(−1.91)	(−3.08)	(−1.71)	(−1.48)	(−1.66)
Constant	51.966*	179.882***	162.447	152.473	212.646
	(1.91)	(3.03)	(1.63)	(1.43)	(1.62)
R^2	3.27%	8.30%	9.19%	7.25%	4.10%

Panel C: The monthly Fama-MacBeth regressions of changes in CHS on the CDS slope

Variable	ΔCHS_{t+1}	ΔCHS_{t+3}	ΔCHS_{t+6}	ΔCHS_{t+9}	ΔCHS_{t+12}
$Slope_t$	0.002**	0.003*	0.001**	0.008**	0.008**
	(1.98)	(1.95)	(2.01)	(2.69)	(2.67)
$CDS(1)$	0.002*	0.004**	0.00	0.00	0.01
	(1.85)	(2.03)	(0.77)	(1.46)	(1.67)
$CDS(5)$	−0.001*	0.00	0.00	0.00	0.00
	(−1.70)	(1.57)	(0.69)	(0.21)	(1.60)
$Ret(1, 12)$	0.022**	0.034	0.022	0.060*	0.032
	(2.28)	(1.47)	(0.52)	(1.69)	(0.67)
Constant	−2.238**	−3.345	−2.16	−5.982*	−3.209
	(−2.28)	(−1.45)	(−0.51)	(−1.68)	(−0.67)
R^2	0.22%	0.05%	0.05%	1.16%	0.61%

−1.01% (t-statistic = −8.77) when we value-weight the *ROA*.

In Table 8, we attempt to discern whether the part of the future change in the CDS spread that can be forecasted by the current CDS slope is a significant determinant of the equity return. This helps test our rationale that the slope contains valuable information about firm fundamentals, which, in turn, affect equity returns. For each firm and in each month, we use a rolling window of 60 months historical data to estimate a predictive regression of change in one-year CDS spreads on lagged CDS slope. The predicted value and the residual of such a regression are denoted by $\Delta\widehat{CDS(1)}$ and $Res_{\Delta CDS(1)}$, respectively. The regressions whose results are reported in Table 8 are identical to those in Table 4, except we replace the key regressor CDS slope by $\Delta\widehat{CDS(1)}$ and $Res_{\Delta CDS(1)}$. The coefficient for $\Delta\widehat{CDS(1)}$ is significantly negative in all specifications, whereas the coefficient for $Res_{\Delta CDS(1)}$ is always insignificant. Thus, the negative relation between CDS slope and future stock return entirely emanates from the part of the slope that predicts future CDS spread changes. This finding provides evidence that accords with the notion that a low CDS slope predicts improved creditworthiness, which in turn, is transmitted to the equity market.

3.4. Firm characteristics and return predictability from CDS slope

The slope of a firm's term structure of CDS spreads significantly predicts changes in the firm's fundamentals such as earnings and creditworthiness. Diffusion of information can explain why stocks with a high (low) CDS slope on

Table 7
Credit default swap (CDS) slope and future earnings surprises.

This table shows that the slope of a firm's term structure of CDS spreads (*Slope*) has significant predictive power for its next earnings surprise. Standardized unexpected earnings (*SUE*) is the difference between announced earnings per share and the latest consensus analyst earnings forecast divided by the standard deviation of analyst forecasts. *Ret* is the lagged one month return. *AF* is the current analyst forecast consensus. Panel A reports the difference in the average future *SUE* between firms whose current *Slope* is ranked in the top quintile and those whose *Slope* is ranked in the bottom quintile, when they release earnings over the next n-months, $n = 1, 2, 3$. *VW* and *EW* correspond to the value-weighted and equal-weighted averages. Panel B reports results of Fama-MacBeth regressions of the *SUE* for firms reporting earnings over the next n-months on their current *Slope* (divided by ten thousand). The sample period is from August 2002 to December 2012. The numbers in parentheses are t-statistics. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Standardized earnings surprises for firms with earnings announcements within the next n months

	VW		EW	
n months	*Slope* (high–low)	t-statistic	*Slope* (high–low)	t-statistic
1	−1.17**	(−2.54)	−0.46*	(−1.68)
2	−0.65***	(−4.64)	−0.41**	(−2.42)
3	−0.42***	(−3.99)	−0.27**	(−2.45)

Panel B: Predicting future earnings surprise within next n months using the last month's CDS Slope

	SUE		
n months	(1)	(2)	(3)
Slope	−6.33*	−40.22**	−41.02***
	(−1.66)	(−2.15)	(−2.34)
SUE(*Lagged*)	−0.02	−0.13	−0.01
	(−0.42)	(−1.24)	(−0.09)
Ret	0.56**	0.99	1.07
	(2.56)	(0.65)	(0.72)
AF	0.06**	0.11	0.06
	(2.90)	(1.05)	(0.55)
Constant	0.06***	0.91***	0.92***
	(2.90)	(3.85)	(3.95)

average have abnormally low (high) stock returns. For example, for firms with negative CDS slope (so that the short-term CDS spread is larger than the long-term CDS spread), credit investors expect future improvement in the credit health of the company over the longer term. Thus, high future returns of low CDS slope stocks accord with a gradual reaction of the stock market to the information content of the CDS slope.

To further support the information diffusion explanation of our results, we examine the predictive power of the CDS slope for future stock returns in various subsamples sorted by proxies of arbitrage costs, including firm size, stock price, bid-ask spread, dispersion in analyst forecasts, and idiosyncratic stock volatility. Table 9 reports the average returns of monthly rebalanced portfolio that is long the bottom CDS slope decile stocks and short the top slope decile stocks over the next six months after portfolio formation in various subsamples. Our portfolio strategy has significant positive abnormal returns when applied to firms facing high arbitrage costs, such as firms with low market capitalization, low price, high bid-ask spread, high analyst disagreement, and high idiosyncratic volatility.

Table 9 also shows that the profitability of buying low CDS slope stocks and shorting high CDS slope stocks exists only among relatively less visible firms, such as those with low institutional ownership, low analyst coverage, and a small number of CDS dealers.[20] These results are consistent with low firm visibility leading to slow information diffusion, which precludes the useful information contained in the CDS slope from being incorporated into current stock prices. The profits of our portfolio strategy can be viewed as rewards to smart investors who pay attention to the information content of the CDS slope and bear the costs as well as the risks of arbitrage between the CDS market and the stock market.[21] Our portfolio strategy does not earn significant profits among low arbitrage cost and high visibility stocks, although we have verified that for these stocks, in the full sample, the CDS slope does contain useful information about future firm fundamentals. Thus, the gradual diffusion of information from the CDS market to the stock market occurs mostly for stocks with less visibility and greater levels of arbitrage costs.

3.5. The bond yield curve and stock returns

Our previous analysis uses CDS data from August 2002 to December 2012 and find strong evidence that the slope of the CDS term structure predicts stock returns. The advantage of CDS data is that CDSs are actively traded and relatively liquid compared with traditional corporate debt. However, the countervailing issue is that CDS data are available only in recent years. The question thus arises as to whether our results are robust to using corporate bond data, available for a longer period. In this subsection, we show conclusions similar to those obtained when we use data on corporate bonds from January 1973 to December 2010. The bond price and trade data are extracted from three sources: (1) the Lehman Brothers Fixed Income Database (LBFI) described by Warga (1998), which covers the period from January 1973 to December 1997, (2) the National Association of Insurance Commissioners (NAIC) transaction database, which covers the period from January 1995 to December 2008, and (3) the Trade Reporting and Compliance Engine (TRACE) database of the Financial Industry Regulatory Authority, which covers the period from January 2002 to December 2010.

The LBFI database contains month-end bid prices for thousands of bonds. The majority of the bids are quotes of an actual trader for round lots of at least five hundred bonds. The NAIC transaction database consists of all buy and sell transactions from 1995 to 2008 by insurance companies. The TRACE system was established by the Financial

[20] The Markit database contains a variable *COMPOSITEDEPTH5Y*, which is the number of distinct dealers providing quotes for five-year CDSs. Firms with fewer CDS dealers are likely to garner relatively less investor interest for trading and, thus, experience low firm visibility.

[21] We have verified that, within each group of stocks sorted by one of the proxies for arbitrage costs or firm visibility, no significant difference exits between the high slope stocks and the low slope stocks in their volatility, skewness, coskewness, kurtosis, or market beta.

Table 8

Decomposing the predictive power of credit default swap (CDS) slope.

This table reports results of panel regressions of which part of credit default swap (CDS) slope predicts stock return: the part that predicts changes in credit spreads versus the residual. The dependent variable is monthly individual stock returns, and all independent variables are measured at the end of the previous month. $\Delta\widehat{CDS(1)}$ and $Res_{\Delta CDS(1)}$ are the predicted value of $\Delta CDS(1)$ and the residual of the regression of the next period $\Delta CDS(1)$ on *Slope*, respectively. We run the regression on the rolling basis for 60 months. D_{CCC} is a dummy variable that is one for CCC–rated firms and zero otherwise. $CDS(1)$ and $CDS(5)$ are the one-month lagged one-year and five-year CDS spreads, respectively. $\sigma_{CDS(5)}$ is the standard deviation of $CDS(5)$ over the past 12 months. *EDF* is the expected default frequency provided by Moody's KMV. σ_{EDF} is the standard deviation of *EDF* over the past 12 months. *CHS* is the Campbell, Hilscher and Szilagyi (2008) measure of distress risk. $\Delta CDS(1)$ and $\Delta CDS(5)$ represent changes in the one-year and five-year CDS spreads over the most recent month, respectively. *SIZE* equals the natural logarithm of the market value of equity at the end of the month for each stock. *B/M* equals the book-to-market ratio. *MOM* equals firms' cumulative market-adjusted return measured over the six months prior to month $t-2$, in percent. Ret_{t-1} is the lagged one-month return. *LEV* equals 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. *TO* equals the monthly stock trading volume divided by total common shares outstanding. *IO* equals the fraction of common shares owned by institutions based on Thomson 13F filings. *IVOL* is the idiosyncratic volatility measured relative to the Fama and French three-factor (FF-3) model. We include all delisted returns. The sample period is from August 2002 to December 2012. The numbers in parentheses are t-statistics. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
$\Delta\widehat{CDS(1)}$	−1.90**	−2.38***	−1.23**	−1.22**	−1.90**	−2.64***	−5.49***	−2.28**	−6.84***	−2.65***	−2.74***	−2.36***	−2.36**	−3.16***
	(−2.09)	(−2.76)	(−2.07)	(−2.06)	(−2.44)	(−3.19)	(−3.02)	(−2.39)	(−3.93)	(−3.13)	(−3.39)	(−3.02)	(−2.59)	(−3.57)
$Res_{\Delta CDS(1)}$	−0.21	−0.16	−0.19	−0.31	−0.15	−0.55	−0.71	−0.07	−1.98	−0.63	−0.58	−0.28	−0.55	−1.10
	(−0.73)	(−0.50)	(−0.61)	(−1.09)	(−0.54)	(−0.24)	(−1.52)	(−0.23)	(−1.63)	(−0.92)	(−1.28)	(−1.08)	(−0.78)	(−1.46)
D_{CCC}		0.04												
		(0.93)												
$\Delta\widehat{CDS(1)}$ $\times D_{CCC}$		−6.79												
		(−1.06)												
$CDS(1)$			−0.01											
			(−0.07)											
$CDS(5)$				0.01										
				(0.04)										
$\sigma_{CDS(5)}$					0.00									
					(0.00)									
β_{CDS}						0.04***								
						(2.98)								
EDF							−0.01							
							(−1.19)							
σ_{EDF}								−0.03						
								(−1.28)						
CHS									−1.98					
									(−1.24)					
$\Delta CDS(1)$										0.37			0.34	
										(0.65)			(0.55)	
$\Delta CDS(5)$											0.61			1.19
											(1.35)			(1.40)

(*continued on next page*)

Table 8 (*continued*)

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
SIZE												−0.00**	−0.00**	−0.00**
												(−2.45)	(−2.31)	(−2.44)
B/M												0.01**	0.00**	0.00**
												(2.62)	(2.59)	(2.44)
MOM												0.00	0.00	0.00
												(0.24)	(0.21)	(0.31)
Ret_{t-1}												−0.01	−0.01	−0.01
												(−0.62)	(−0.69)	(−0.38)
LEV												−0.01**	−0.01**	−0.01**
												(−2.03)	(−2.08)	(−2.00)
TO												−0.02***	−0.02***	−0.02***
												(−2.77)	(−2.86)	(−2.72)
IO												0.00	0.00	0.00
												(0.69)	(0.67)	(0.73)
IDVOL												−0.04***	−0.04***	−0.03***
												(−4.75)	(−4.58)	(−4.37)
Constant	0.01	0.01	0.00	0.00	0.01	0.01	0.03	0.01	0.02	0.00	0.00	0.01	0.00	0.00
	(0.88)	(0.90)	(0.75)	(0.84)	(0.82)	(1.16)	(1.53)	(0.85)	(1.51)	(0.71)	(0.64)	(0.34)	(0.25)	(0.27)
Adjusted R^2	1.01%	0.76%	0.81%	0.71%	0.92%	1.63%	1.53%	1.02%	1.59%	1.42%	1.16%	4.27%	4.27%	4.05%

Table 9
Average return of credit default swap (CDS) slope portfolio strategy by proxies for arbitrage costs.

This table reports the cumulative six–month return (in percent) of an equal-weighted portfolio that is long the bottom decile of stocks and short the top decile ranked by CDS slope in various subsamples of stocks sorted by proxies of limits to arbitrage, including size, stock price level, bid-ask spread, dispersion of analyst forecast, institutional ownership, stock idiosyncratic volatility, analyst coverage, and number of CDS dealers. We perform a 3-by-3 independent double-sort, at the end of each month, based on one of these arbitrage measures and CDS slope. We report the average differences in the returns of the low CDS slope stocks and the high slope stocks in each of the three portfolios sorted by a given arbitrage cost measure. In addition to the raw returns, we report the capital asset pricing model (CAPM) alphas, Fama and French three-factor (FF-3) alphas, and Carhart four-factor (Carhart-4) alphas. We include all delisted returns. The sample period is from August 2002 to December 2012. The numbers in the brackets are Newey-West *t*-statistics adjusted for the overlapping holding period. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Portfolio	Average return	CAPM	FF-3	Carhart-4
Size				
1 (low)	0.97**	1.01***	0.96***	0.96***
	(2.59)	(2.76)	(2.82)	(2.81)
2	0.25	0.26*	0.24	0.24
	(1.64)	(1.67)	(1.64)	(1.64)
3 (high)	0.02	0.02	0.00	0.01
	(0.08)	(0.12)	(0.02)	(0.03)
High-low	−0.95***	−0.99***	−0.96***	−0.96***
	(−3.63)	(−3.85)	(−4.00)	(−3.92)
Price				
1 (low)	0.94***	0.97***	0.92***	0.92***
	(2.71)	(2.78)	(2.93)	(2.92)
2	0.58***	0.61***	0.58***	0.58***
	(3.13)	(3.34)	(3.40)	(3.42)
3 (high)	0.17	0.16	0.16	0.16
	(1.27)	(1.21)	(1.15)	(1.16)
High-low	−0.76**	−0.80***	−0.76***	−0.76***
	(−2.61)	(−2.75)	(−2.94)	(−2.92)
Bid-Ask Spread				
1 (low)	0.34*	0.33*	0.31*	0.31*
	(1.83)	(1.74)	(1.70)	(1.70)
2	0.39	0.41*	0.36	0.37
	(1.64)	(1.66)	(1.58)	(1.58)
3 (high)	1.06***	1.11***	1.05***	1.05***
	(2.85)	(3.03)	(3.23)	(3.21)
High-low	0.72***	0.78***	0.74***	0.74***
	(2.99)	(3.37)	(3.76)	(3.63)
Analyst Dispersion				
1 (low)	0.31	0.32	0.29	0.29
	(1.55)	(1.62)	(1.57)	(1.57)
2	0.31*	0.32*	0.30	0.30
	(1.68)	(1.79)	(1.64)	(1.64)
3 (high)	0.98**	1.02**	0.96**	0.96**
	(2.35)	(2.41)	(2.44)	(2.44)
High-low	0.68**	0.69**	0.67**	0.67**
	(2.14)	(2.18)	(2.21)	(2.17)
Institutional Holdings				
1 (low)	0.50***	0.54***	0.52***	0.51***
	(2.77)	(2.94)	(2.87)	(2.86)
2	0.37*	0.40*	0.34*	0.35*
	(1.80)	(1.91)	(1.80)	(1.80)
3 (high)	0.32*	0.34*	0.30*	0.30*
	(1.88)	(1.93)	(1.70)	(1.71)
High-low	−0.14*	−0.14*	−0.17*	−0.16*
	(−1.71)	(−1.70)	(−1.94)	(−1.84)
Idiosyncratic Volatility				
1 (low)	−0.06	−0.04	−0.05	−0.05
	(−0.44)	(−0.34)	(−0.40)	(−0.40)
2	0.28	0.31*	0.31*	0.31*
	(1.55)	(1.79)	(1.83)	(1.80)
3 (high)	1.15***	1.20***	1.14***	1.14***
	(3.13)	(3.28)	(3.41)	(3.40)
High-low	1.20***	1.24***	1.19***	1.19***
	(3.77)	(3.88)	(4.05)	(3.98)
Analyst Coverage				
1 (low)	0.66**	0.69**	0.65**	0.65**
	(2.42)	(2.59)	(2.54)	(2.55)
2	0.54**	0.53**	0.49**	0.49**
	(2.45)	(2.30)	(2.32)	(2.32)
3 (high)	0.36	0.39	0.36	0.36
	(1.47)	(1.60)	(1.54)	(1.53)
High-low	−0.30**	−0.31**	−0.29**	−0.30**
	(−2.01)	(−2.06)	(−1.97)	(−1.97)
Number of CDS Dealers				
1 (low)	0.65***	0.67***	0.65***	0.65***
	(2.62)	(2.74)	(2.66)	(2.67)
2	0.44*	0.46*	0.42*	0.42*
	(1.79)	(1.80)	(1.77)	(1.76)
3 (high)	0.40	0.43	0.38	0.38
	(1.38)	(1.46)	(1.43)	(1.44)
High-low	−0.25*	−0.22*	−0.27*	−0.27*
	(−1.93)	(−1.90)	(−1.89)	(−1.85)

Industry Regulatory Authority to increase the transparency of the corporate bond market, and it required dealers to report their transactions through the system starting July 1, 2002.

We pool LBFI, NAIC, and TRACE transaction data sets together and delete duplicate records. We merge the pooled data with the Fixed Investment Securities Database to obtain bond characteristic information, such as issue dates, coupon rates, maturity dates, issue amounts, provisions, credit ratings, and so forth. We exclude callable, puttable, convertible, sinking funds, and floater bonds. We also omit non-coupon bonds and bonds with time-to-maturity under one year because they have low liquidity and, thus, could be subject to pricing errors. In the end, we have a total of 354,822 bond-month observations in our sample, covering 7,225 bonds from 1,136 firms.

To construct a measure of the slope of the term structure of corporate bond yields that is comparable across firms, we hold the credit quality of the bonds constant by analyzing multiple bonds within the same priority structure of the same company. In each month and for each firm, we categorize the bonds by maturity into three buckets: (1) short-term bonds between one to four years until maturity, (2) medium-term bonds with four to nine years until maturity, and (3) long-term bonds with over nine years to maturity. The bond yield slope is measured as the difference of the average yields of the medium-term bonds and the short-term bonds, net of the corresponding Treasury bond yields.[22]

[22] In an unreported analysis, we verify the robustness of our results when we first piece-wise linearly interpolate the yield curve for each firm and in each month, based on the yields for traded bonds, and then mea-

Table 10

Panel regressions of individual stock returns on bond yield slope.

This table reports results of panel regressions with individual stock returns as the dependent variable. Panel A is for the full bond sample. Panel B is for the bond sample with credit default swap (CDS) data. All independent variables are measured at the end of the previous month. *Slope* (in basis points) is the difference between the average yields of bonds issued by the firm with time-to-maturity between four to nine years and the average yields of bonds issued by the firm with time-to-maturity between one and three years, with corresponding maturity treasury bond yield subtracted. D_{CCC} is a dummy variable that is one if the Standard & Poor's rating of the bond is equal or worse than CCC+ in Panel A and if the CDS rating is CCC in Panel B. $Yield_S$ and $Yield_M$ are the average short-term bond yield and medium-term bond yield one period lagged respectively. σ_{Yield_M} is the volatility of $Yield_M$ over the past 12 months. β_{BY} is the covariance (beta) of the stock's return with the bond yield low minus high return. *EDF* is the expected default frequency provided by Moody's KMV. σ_{EDF} is the volatility of *EDF* over the past 12 months. *CHS* is the Campbell, Hilscher and Szilagyi (2008) measure of distress risk. $\Delta Yield_S$ and $\Delta Yield_M$ are the change of $Yield_S$ and $Yield_M$ over the last month, respectively. *SIZE* equals the natural logarithm of the market value of equity at the end of the month for each stock. *B/M* equals the book-to-market ratio. *MOM* equals firms' cumulative market-adjusted return measured over the six months prior to month $t-2$, in percent. Ret_{t-1} is the lagged one-month return. *LEV* equals 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. *TO* equals the monthly stock trading volume divided by total common shares outstanding. *IO* equals the fraction of common shares owned by institutions based on Thomson 13F filings. *IVOL* is the idiosyncratic volatility measured relative to the Fama and French three-factor (FF-3) model. We include all delisted returns. The sample period is from January 1973 to December 2010. The numbers in the parentheses are *t*-statistics. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Panel regressions of stock returns on bond yield slope

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Slope	−0.04**	−0.04**	−0.04**	−0.04**	−0.04**	−0.06**	−0.08**	−0.04**	−0.03**	−0.04**	−0.04**	−0.04**	−0.05**	−0.05**	−0.05**
	(−2.20)	(−2.14)	(−2.03)	(−2.10)	(−1.98)	(−2.21)	(−2.03)	(−2.54)	(−2.01)	(−2.15)	(−2.10)	(−2.09)	(−2.06)	(−2.06)	(−2.07)
D_{CCC}		0.03													
		(1.60)													
Slope $\times D_{CCC}$		−0.08													
		(−1.25)													
$Yield_S$			0.00												
			(0.46)												
$Yield_M$				0.00***											
				(4.22)											
σ_{Yield_M}					0.00***										
					(11.34)										
β_{BY}						0.01									
						(1.27)									
EDF							0.01***	0.12***							
							(8.56)	(8.08)							
Slope $\times$ *EDF*								0.35							
								(0.95)							
σ_{EDF}									0.04**						
									(2.47)						

(*continued on next page*)

Table 10 (*continued*)

CHS										0.39					
										(1.39)					
$\Delta Yield_S$											0.00			0.00	
											(0.51)			(0.85)	
$\Delta Yield_M$												0.00			0.01
												(1.04)			(0.77)
SIZE													−0.00***	−0.00***	−0.00***
													(−2.93)	(−2.93)	(−2.93)
B/M													0.02***	0.02***	0.02***
													(5.79)	(5.79)	(5.78)
MOM													−0.01**	−0.01**	−0.01**
													(−2.05)	(−2.04)	(−2.05)
RET(t-1)													−0.03***	−0.03***	−0.03***
													(−3.70)	(−3.70)	(−3.69)
LEV													0.03***	0.03***	0.03***
													(4.22)	(4.22)	(4.23)
TO													0.03**	0.03**	0.03**
													(2.04)	(2.04)	(2.05)
IO													0.02***	0.02***	0.02***
													(2.87)	(2.87)	(2.85)
IDVOL													0.03***	0.03***	0.03***
													(5.86)	(5.86)	(5.87)
Constant	0.02***	0.02***	0.03***	0.02***	0.03*	0.01*	0.02***	-0.01***	0.03	0.02***	0.02***	0.02***	0.05*	0.05*	0.05*
	(6.49)	(6.60)	(7.59)	(6.37)	(1.86)	(1.74)	(3.51)	(2.74)	(1.62)	(6.43)	(6.39)	(6.39)	(1.94)	(1.93)	(1.94)
Adjusted R^2	5.13%	5.15%	4.98%	5.14%	4.89%	4.33%	5.30%	4.95%	4.67%	5.17%	5.11%	5.13%	5.90%	5.91%	5.91%

(*continued on next page*)

Table 10 (*continued*)

Panel B: Panel regressions of stock returns on bond yield slope for the firms with CDS data.

Slope	−0.03***	−0.03***	−0.03**	−0.03**	−0.03***	−0.09***	−0.04**	−0.03***	−0.02**	−0.02**	−0.03**	−0.03**	−0.05***	−0.04***	−0.06***
	(−2.58)	(−2.59)	(−2.15)	(−2.42)	(−3.36)	(−2.58)	(−2.47)	(−2.67)	(−2.51)	(−2.37)	(−2.43)	(−2.51)	(−2.68)	(−2.66)	(−2.62)
D_{CCC}		0.01													
		(0.84)													
Slope × D_{CCC}		0.07													
		(0.29)													
$Yield_S$			0.00												
			(0.69)												
$Yield_M$				−0.00***											
				(−3.73)											
σ_{Yield_M}					0.00***										
					(3.36)										
β_{BY}						0.03									
						(1.17)									
EDF							0.04***	0.00							
							(5.62)	(1.21)							
Slope × *EDF*								−0.03***							
								(−3.91)							
σ_{EDF}									0.01***						
									(3.27)						
CHS										13.94***					
										(10.90)					
$\Delta Yield_S$											−0.00			0.05	
											(−1.37)			(1.59)	
$\Delta Yield_M$												−0.00***			0.07
												(−3.68)			(0.65)
SIZE													−0.00*	−0.00	−0.00*
													(−1.73)	(−1.54)	(−1.66)
B/M													0.06***	0.05***	0.05***
													(5.51)	(5.38)	(5.28)
MOM													−0.04***	−0.03**	−0.03**
													(−2.76)	(−2.01)	(−2.03)
Ret_{t-1}													−0.13***	−0.13***	−0.12***
													(−4.12)	(−4.09)	(−4.05)
LEV													−0.04**	−0.04**	−0.04***
													(−2.36)	(−2.56)	(−2.69)
TO													0.00	0.02	0.02
													(0.17)	(0.92)	(1.01)
IO													−0.04***	−0.03*	−0.03*
													(−2.60)	(−1.83)	(−1.79)
IDVOL													0.06***	0.02	0.02
													(3.09)	(0.70)	(0.69)
Constant	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.00	0.01**	0.02***	0.01	0.02***	0.02***	0.08*	0.12***	0.13***
	(3.83)	(3.83)	(4.86)	(3.91)	(3.83)	(5.25)	(0.33)	(2.03)	(3.59)	(1.49)	(3.92)	(3.92)	(1.80)	(2.61)	(2.74)
Adjusted R^2	1.39%	1.39%	1.34%	1.56%	1.50%	3.73%	2.62%	4.02%	1.60%	2.82%	1.41%	1.55%	9.87%	11.83%	11.67%

Table 11
Bond yield slope predicts changes in default risk.

This table reports the results of monthly Fama-MacBeth regressions of changes in short-term bond yield $Yield_S$ (Panel A), changes in *EDF* (Panel B), and changes in *CHS* (Panel C) from t to $t+i$ on the bond yield slope at time t. *Slope* (in decimal format) is the difference between the average yields of bonds issued by the firm with time-to-maturity between four to nine years and the average yields of bonds issued by the firm with time-to-maturity between one and three years, less the corresponding maturity Treasury bond yield in each case. $\Delta Yield_{S,t+i} = Yield_{S,t+i} - Yield_{S,t}$. *EDF* is the expected default frequency provided by Moody's KMV. *CHS* is the Campbell, Hilscher and Szilagyi (2008)) measure of distress risk. $\Delta EDF_{t+i} = EDF_{t+i} - EDF_t$. $\Delta CHS_{t+i} = CHS_{t+i} - CHS_t$. $Yield_S$ and $Yield_M$ are short-term and medium-term bond yields, in percent. *Ret*(1, 12) is the past one-year stock return in percent. The numbers in the parentheses are t-statistics. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: The monthly Fama-MacBeth regressions of changes in short-term bond yield on Slope

Variable	$\Delta Yield_{S,t+1}$	$\Delta Yield_{S,t+3}$	$\Delta Yield_{S,t+6}$	$\Delta Yield_{S,t+9}$	$\Delta Yield_{S,t+12}$
$Slope_t$	0.341***	0.471***	0.622***	0.691***	0.691***
	(9.35)	(10.56)	(8.55)	(13.09)	(13.92)
$Yield_S$	0.209***	0.196***	0.156**	0.091	0.087
	(6.95)	(4.55)	(2.15)	(1.44)	(1.60)
$Yield_M$	−0.002***	−0.002***	−0.002**	−0.002***	−0.002**
	(−6.33)	(−3.22)	(−2.09)	(−2.78)	(−2.56)
Ret(1, 12)	−0.022***	−0.065***	−0.103***	−0.123***	−0.113***
	(−2.74)	(−4.86)	(−4.30)	(−4.59)	(−4.80)
Constant	0.000	−0.003	−0.003	0.001	−0.001
	(0.31)	(−1.03)	(−0.87)	(0.20)	(0.28)
R^2	14.30%	17.10%	19.60%	18.20%	19.70%

Panel B: The monthly Fama-MacBeth regressions of changes in EDF on Slope

Variable	ΔEDF_{t+1}	ΔEDF_{t+3}	ΔEDF_{t+6}	ΔEDF_{t+9}	ΔEDF_{t+12}
$Slope_t$	0.785*	1.391***	1.883*	2.508**	3.103**
	(1.84)	(2.91)	(1.67)	(2.14)	(2.49)
$Yield_S$	0.001	−0.001	−0.009	−0.006	0.01
	(0.38)	(−0.16)	(−1.06)	(−0.73)	(0.95)
$Yield_M$	−0.009***	−0.001	0.034**	0.062***	0.086***
	(−2.70)	(−0.15)	(2.52)	(3.52)	(4.12)
Ret(1, 12)	−0.073	−0.264	−0.572*	−0.234	−0.111
	(−0.56)	(−0.80)	(−1.74)	(−0.86)	(−0.32)
Constant	0.033**	−0.011	−0.179**	−0.377***	−0.601***
	(2.09)	(−0.28)	(−2.53)	(−3.56)	(−4.76)
R^2	3.18%	4.26%	4.35%	5.10%	5.25%

Panel C: The monthly Fama-MacBeth regressions of changes in CHS on Slope

Variable	ΔCHS_{t+1}	ΔCHS_{t+3}	ΔCHS_{t+6}	ΔCHS_{t+9}	ΔCHS_{t+12}
$Slope_t$	0.001*	0.001*	0.001*	0.001*	0.002***
	(1.89)	(1.75)	(1.80)	(1.89)	(2.66)
$Yield_S$	0.00	−0.002**	−0.001**	0.00	0.000*
	(0.71)	(−2.23)	(−2.07)	(1.49)	(1.79)
$Yield_M$	0.000*	0.001	0.000***	0.000***	0.00
	(1.65)	(1.21)	(2.79)	(3.32)	(0.16)
Ret(1, 12)	0.001***	0.001***	0.002***	0.001***	0.003***
	(4.12)	(3.73)	(7.06)	(4.44)	(7.55)
Constant	−0.000***	0.001	−0.000**	−0.000***	−0.000***
	(−3.14)	(1.19)	(−2.05)	(−4.05)	(−2.85)
R^2	0.20%	0.20%	0.40%	0.30%	0.60%

The panel regression results in Table 10 confirm a significant negative relation between the bond yield slope and future stock returns. This relation is robust to controlling for the level of and change in bond yields, default risk measures, volatility of default risk measures (i.e., the 12-month standard deviations of *EDF* and the longer-term yield), and stock characteristics including size, book-to-market ratio of equity, momentum, one-month reversal, leverage, stock turnover ratio, institutional share ownership, and idiosyncratic volatility. These results corroborate the findings for the CDS data. Thus, the slope of the term structure of credit spreads, inferred from the CDS spreads or corporate bond yields, significantly and negatively predicts future stock returns. Further, Panel B of Table 10 shows that our results are robust for the subsample of bonds limited to firms that have CDS traded on them.

Table 11 examines the ability of the bond yield slope to forecast future changes in bond yield spreads. We regress changes in short-term bond yields over various future horizons (from one month to twelve months) on the current bond yield slope. We find that the coefficient on the bond yield slope is positive and significant in all regressions. Thus, the slope of the term structure of bond yield contains useful information about changes in the future credit-

sure the bond yield slope as the five-year yield minus the one-year yield on the interpolated yield curve. Further, our results do not change materially when we measure bond yield slope as the difference between the average yields of the long- and short-term bonds.

Table 12
Bond yield slope predicts future earnings surprises.

This table shows that the slope of a firm's bond yield slope (*Slope*) has significant predictive power for its next earnings surprise. Standardized unexpected earning (*SUE*) is the difference between announced earnings per share and the latest consensus analyst earnings forecast divided by the standard deviation of analyst forecasts. *Ret* is the lagged one-month return. *AF* is the current consensus analyst forecast. In Panel A, we sort stocks into quintiles based on *Slope*. We report the difference in the average future *SUE* between firms whose current *Slope* ranked in the top quintile and those that ranked in the bottom quintile when they release earnings over the next n-months, $n = 1, 2, 3$. *VW* and *EW* correspond to the value-weighted and equal-weighted averages. Panel B reports results of Fama-MacBeth regressions of the *SUE* for firms reporting earnings over the next n-months on their current *Slope* (divided by ten thousand). We include all delisted returns. The sample period is from January 1973 to December 2010. The numbers in the parentheses are t-statistics. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: SUE for firms with earnings announcements within the next n months.

	VW		EW	
n months	*Slope* (high–low)	t-statistic	*Slope* (high–low)	t-statistic
1	−0.91*	(−1.94)	−0.88*	(−1.72)
2	−0.60	(−1.38)	−0.33*	(−1.85)
3	−0.13	(−0.68)	−0.35*	(−1.77)

Panel B: Predicting SUE within next n months using the last month's Slope.

	SUE		
Variable	One month	Two months	Three months
Slope	−3.15**	−14.95*	−11.58*
	(−2.10)	(−1.86)	(−1.79)
SUE(Lagged)	0.01	0.22**	0.20***
	(0.89)	(2.24)	(3.28)
Ret	0.34	−3.02	−2.44
	(1.34)	(−0.98)	(−0.87)
AF	0.10	0.43**	0.27*
	(1.29)	(2.13)	(1.71)
Constant	0.08**	0.67**	0.88***
	(2.03)	(2.26)	(4.91)

worthiness of the firm. An upward sloping bond yield term structure indicates that investors in the credit market expect the financial health of the firm to deteriorate. We obtain the same conclusion using KMV's *EDF* or the Campbell, Hilscher and Szilagyi (2008) measure of default risk.

Table 12 shows that the slope of the bond yield term structure also has significant predictive power for future earnings. In Panel A, we sort stocks into quintiles based on the bond yield slope (*Slope*). We report the difference in the average future standardized earnings surprises (*SUE*) between the top and the bottom *Slope* quintile firms that release earnings over the next n-months, $n = 1, 2, 3$. Firms with a high *Slope* on average experience significantly more negative earnings surprises than firms with a low *Slope*, for both value-weighted and equal-weighted averages. In Panel B, we use Fama-MacBeth regressions to confirm that a firm's standardized earnings surprise for the next quarter is significantly negatively related to the current slope of the bond yield term structure, controlling for the past month stock return, lagged *SUE*, and consensus analyst forecast.

We also examine the predictive power of the bond yield slope for future stock returns in various subsamples sorted by proxies of arbitrage costs, including firm size, stock price, bid-ask spread, institutional ownership, dispersion in analyst forecasts, and idiosyncratic stock volatility. Table 13 reports the average returns of our portfolio strategy that buys low bond yield slope stocks and shorts high bond yield slope stocks in various subsamples, as well as their alphas with respect to the CAPM, the Fama and French three-factor model, or the Carhart four-factor model. The table shows that, just as for Table 9, our portfolio strategy has significantly higher abnormal returns when applied to firms with low market capitalization, low price, low institutional ownership, high bid-ask spread, high disagreement, and high idiosyncratic volatility.

4. Conclusion

Using a comprehensive cross section of credit default swap spreads and corporate bond yields, we find an economically meaningful link between equity and credit markets via the term structure of credit spreads. We show that a firm's CDS term structure slope, defined as the difference between a long- and a short-term CDS spread, reliably forecasts stock returns. For example, a portfolio strategy that buys stocks in the lowest decile of the five-year minus one-year CDS slope and shorts those in the highest decile of the slope earns an average return of 1.20% each month (14.40% annualized). While we cannot completely rule out the possibility of a missing risk factor or a risk-based explanation, our result is not able to be captured by standard risk factors in the stock market, covariance risk with a slope-sorted portfolio's return, various measures of default risk, or compensation for the risk of variation in default probability. Our findings support Hilscher and Wilson (2015), who argue that one default proxy cannot capture all the relevant information given the multidimensional nature of credit quality.

By focusing on the relative default probabilities across different horizons, the term structure slope of CDS spreads embeds valuable forward-looking information about a firm's fundamentals that is not available from existing default risk measures. Further, we show that the slope of the term structure of corporate bond yields significantly and negatively forecasts stock returns. The stock return predictability of the credit spread slope is stronger for stocks with relatively small market capitalization, low analyst coverage, and low institutional ownership, which are likely to be less visible stocks with greater arbitrage costs. This indicates that the credit spread term structure contains information about the future financial health of firms, which diffuses to the equity market over time. Supporting this notion, we find that stocks with low credit slope tend to experience future improvements in financial health, higher profitability, and more favorable earnings surprises. As a variable not previously considered in the literature, the slope of the credit term structure, as an indicator of future firm health, deserves more attention. For example, whether managers condition on the slope of the credit term structure to make corporate decisions (such as allocations of

Table 13
Arbitrage costs and return of bond yield slope portfolio strategy.

This table reports the average monthly return (in percent) of an equal-weighted portfolio that is long stocks with a low bond yield slope and short stocks with a high bond yield 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. We perform a 3-by-3 independent double-sort, at the end of each month, based on one of these arbitrage measures and bond yield slope. We report the average differences in the returns of the low bond yield slope stocks and the high slope stocks in each of the three portfolios sorted by a given arbitrage cost measure. In addition to the raw returns, we report the portfolio alpha with respect to the capital asset pricing model (CAPM), the Fama and French three-factor (FF-3) model, and the Carhart four-factor (Carhart-4) model. We include all delisted returns. The sample period is from January 1973 to December 2010. The numbers in the parentheses are *t*-statistics. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Portfolio	Average return	CAPM	FF-3	Carhart-4
Size				
1 (low)	0.61**	0.61**	0.67**	0.75**
	(2.03)	(2.02)	(2.07)	(2.22)
2	−0.30*	−0.30*	−0.22	−0.28
	(−1.78)	(−1.72)	(−1.24)	(−1.62)
3 (high)	0.08	0.08	0.07	0.10
	(0.48)	(0.48)	(0.38)	(0.60)
High-low	−0.53*	−0.53*	−0.60*	−0.65*
	(−1.78)	(−1.76)	(−1.68)	(−1.65)
Price				
1 (low)	0.56**	0.53**	0.56**	0.57**
	(2.14)	(2.00)	(2.01)	(2.04)
2	0.27	0.30*	0.34*	0.25
	(1.55)	(1.68)	(1.86)	(1.37)
3 (high)	0.12	0.15	0.10	0.08
	(0.77)	(0.91)	(0.61)	(0.50)
High-low	−0.44*	−0.38*	−0.46*	−0.49*
	(−1.72)	(−1.70)	(−1.71)	(−1.70)
Bid-Ask Spread				
1 (low)	0.17	0.19	0.41	0.44
	(0.47)	(0.49)	(1.19)	(1.25)
2	0.32	0.42	0.41	0.46
	(1.01)	(1.18)	(1.16)	(1.24)
3 (high)	0.49**	0.55**	0.53**	0.52**
	(2.12)	(2.35)	(2.20)	(2.15)
High-low	0.32*	0.36*	0.12*	0.08*
	(1.71)	(1.76)	(1.76)	(1.71)
Analyst Dispersion				
1 (low)	−0.04	−0.08	−0.16	−0.24
	(−0.17)	(−0.37)	(−0.74)	(−1.12)
2	0.43**	0.50**	0.51**	0.60***
	(2.14)	(2.44)	(2.40)	(2.91)
3 (high)	0.68**	0.67**	0.78**	0.82**
	(2.31)	(2.21)	(2.47)	(2.57)
High-low	0.72*	0.75**	0.94**	1.06***
	(1.96)	(2.03)	(2.48)	(2.81)
Institutional Holdings				
1 (low)	0.75***	0.70***	0.77***	0.65**
	(2.98)	(2.78)	(3.03)	(2.52)
2	−0.17	−0.16	−0.11	−0.04
	(−0.74)	(−0.67)	(−0.44)	(−0.17)
3 (high)	−0.05	0.01	−0.02	−0.00
	(−0.24)	(0.05)	(−0.07)	(−0.01)
High-low	−0.80**	−0.69**	−0.79**	−0.65*
	(−2.45)	(−2.06)	(−2.34)	(−1.94)
Idiosyncratic Volatility				
1 (low)	−0.00	−0.03	−0.03	−0.02
	(−0.03)	(−0.18)	(−0.19)	(−0.13)
2	0.19	0.20	0.17	0.17
	(0.98)	(1.01)	(0.86)	(0.81)
3 (high)	0.75**	0.80**	0.89***	0.87***
	(2.47)	(2.54)	(2.81)	(2.64)
High-low	0.75**	0.83**	0.92**	0.89**
	(2.47)	(2.18)	(2.41)	(2.26)

real investment) would seem to be a fruitful area for future research.

References

Acharya, V.V., Johnson, T.C., 2007. Insider trading in credit derivatives. Journal of Financial Economics 84, 110–141.
Ang, A., Chen, J., Xing, Y., 2006. Downside risk. Review of Financial Studies 19, 1191–1239.
Avramov, D., Chordia, T., Jostova, G., Philipov, A., 2009. Credit ratings and the cross section of stock returns. Journal of Financial Markets 12, 469–499.
Berndt, A., Obrejas, I., 2010. Decomposing European CDS returns. Review of Finance 14, 189–233.
Boudoukh, J., Richardson, M., 1993. Stock returns and inflation: a long-horizon perspective. American Economic Review 83, 1346–1355.
Campbell, J.Y., 1987. Stock returns and the term structure. Journal of Financial Economics 18, 373–399.
Campbell, J.Y., Hilscher, J., Szilagyi, J., 2008. In search of distress risk. Journal of Finance 63, 2899–2939.
Cao, C., Yu, F., Zhong, Z., 2010. The information content of option-implied volatility for credit default swap valuation. Journal of Financial Markets 13, 321–343.
Chava, S., Purnanandam, A., 2010. Is default risk negatively related to stock returns? Review of Financial Studies 23, 2523–2559.
Cremers, M., Weinbaum, D., 2010. Deviations from put–call parity and stock return predicability. Journal of Financial Quantitative Analysis 45, 335–367.
Daniel, K., Titman, S., 1997. Evidence on the characteristics of cross-sectional variation in stock returns. Journal of Finance 52, 1–33.
Driessen, J., 2005. Is default event risk priced in corporate bonds? Review of Financial Studies 18, 165–195.
Edwards, A., Harris, L., Piwowar, M., 2007. Corporate bond market transaction costs and transparency. Journal of Finance 62, 1421–1451.
Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3–56.
Friewald, N., Wagner, C., Zechner, J., 2014. The cross section of credit risk premia and equity returns. Journal of Finance 69, 2419–2469.
Griffin, J.M., Lemmon, M.L., 2002. Book-to-market equity, distress risk, and stock returns. Journal of Finance 57, 2317–2336.
Harvey, C.R., Siddique, A., 2000. Conditional skewness in asset pricing tests. Journal of Finance 55, 1263–1295.
Hilscher, J., Pollet, J.M., Wilson, M., 2015. Are credit default swaps a sideshow? Evidence that information flows from equity to CDS markets. Journal of Financial and Quantitative Analysis 50, 543–567.
Hilscher, J., Wilson, M., 2015. Credit ratings and credit risk: is one measure enough? American Finance Association meetings paper, 2013, San Diego, CA.
Jobson, J.D., Korkie, B.M., 1981. Performance hypothesis testing with the Sharpe and Treynor measures. Journal of Finance 36, 889–908.
Jorion, P., Zhang, G., 2007. Good and bad credit contagion: evidence from credit default swaps. Journal of Financial Economics 84, 860–883.
Jorion, P., Zhang, G., 2010. Credit contagion from counterparty risk. Journal of Finance 64, 2053–2087.
Kapadia, N., Pu, X., 2012. Limited arbitrage between equity and credit markets. Journal of Financial Economics 105, 542–564.
Keim, D.B., Stambaugh, R.F., 1986. Predicting returns in the stock and bond markets. Journal of Financial Economics 17, 357–390.
Lettau, M., Ludvigson, S., 2002. Time-varying risk premia and the cost of capital: an alternative implication of the q-theory of investment. Journal of Monetary Economics 49, 31–66.
Longstaff, F.A., 2010. The subprime credit crisis and contagion in financial markets. Journal of Financial Economics 97, 436–450.
Longstaff, F.A., Mithal, S., Neis, E., 2005. Corporate yield spreads: default risk or liquidity? New evidence from the credit default swap market. Journal of Finance 60, 2213–2253.
MacKinlay, A.C., 1995. Multifactor models do not explain deviations from the CAPM. Journal of Financial Economics 38, 3–28.
Ni, X., Pan, J., 2012. Trading puts and CDS on stocks with short-sale ban. Unpublished working paper, Massachusetts Institute of Technology and Hong Kong University of Science and Technology, Cambridge, MA, and Hong Kong.
Norden, L., Weber, M., 2009. The co-movement of credit default swap, bond, and stock markets: an empirical analysis. European Financial Management 15, 529–562.
Pan, J., Poteshman, A.M., 2006. The information in option volume for future stock prices. Review of Financial Studies 19, 871–908.
Qiu, J., Yu, F., 2012. Endogenous liquidity in credit derivatives. Journal of Financial Economics 103, 611–631.

Savor, P., Wilson, M., 2016. Earnings announcements and systematic risk. Journal of Finance 71, 83–138.
Stock, J.H., Watson, M.W., 1989. New indexes of coincident and leading economic indicators. In: NBER Macroeconomics Annual, 4, pp. 351–409.
Vassalou, M., Xing, Y., 2004. Default risk in equity returns. Journal of Finance 59, 831–868.
Warga, A., 1998. A Fixed Income Database Manuscript. University of Houston.
Zhang, B., Zhou, H., Zhu, H., 2009. Explaining credit default swap spreads with the equity volatility and jump risks of individual firms. Review of Financial Studies 22, 5109–5131.