“Inclusion of debt claims in asset pricing models: Evidence from the CDS Index”

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INCLUSION OF DEBT CLAIMS IN ASSET PRICING MODELS: EVIDENCE FROM THE CDS INDEX

Abstract

Asset pricing theory suggests that the correct proxy for the market portfolio should contain both the debt and equity claims of the economy, whereas prevailing empirical studies fail to include the debt claim. Motived by the discrepancy between the theoretical and empirical models and the difficulty in constructing proxies, the study uses the Credit Default Swaps (CDS) market index as a proxy for the debt market and empirically tests its explanatory power in explaining stock return variations. Employing panel regression and Fama-MacBeth regression of all publicly traded U.S. companies from 2005 to 2020, the study finds a negative relationship between CDS index returns and stock returns. On average, a one standard deviation increase in CDS index return is associated with a 0.02% decrease in daily stock returns. Results of two-stage regressions show that the estimated systematic credit risk is positively priced in stock returns with similar economic magnitude as the well-documented beta risk. These results support asset pricing theories in the inclusion of debt claim and the risk-return tradeoff, while contradicting the credit risk puzzle documented in prior studies.

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INTRODUCTION

One of the key assumptions in asset pricing models is homogeneity of investor expectations. Investors are assumed to have access to all risky assets in the market and subsequently agree on the risks and expected payoffs of these risky assets (Markovitz, 1959; Sharper, 1964; Lintner; 1965). That is, asset pricing theory implies that both a economy's debt and equity claims should be included when proxying for the market portfolio to capture both aspects of market risk. However, prevailing empirical analyses focus on factors constructed with stock portfolio returns and overlook the debt claims of the economy. Basu (1977), Banz (1981), Shanken (1985), and Fama and French (1992, 1993), among others, use equity-only proxies for the market portfolio and find that the unconditional CAPM performs poorly in explaining the cross section of average stock returns.

Consistent with implications of classic models, a few studies develop proxies to include debt claims in the market portfolio. Ferguson and Shockley's (2003) model proposes that the correct proxy for the market portfolio should include both the economy's debt and equity claims. They form additional factors by a firm's relative distress risk and show that such factors complement the equity market index in explaining stock returns. Aretz and Shackleton (2010) estimate a proxy for the total debt portfolio based on the Merton (1974) model and find no evidence that it improves pricing performance. Both studies use proxies that require further calibration.

Given the discrepancy between the theoretical and empirical models and the difficulty in constructing proxies used in existing studies, the optimal solution is to use a market derived measure for the credit market. This study evaluates the Credit Default Swaps (CDS) market index as a proxy for the debt market and empirically tests its explanatory power in explaining stock return variations. Further, the paper examines whether a firm's exposure to systematic risk is priced in the credit market.

1. LITERATURE REVIEW

The credit market plays an important role in the financial system, as well as in the broader economy. Despite the importance of the credit market, only stock market factors are included in prevailing asset pricing models. For instance, most empirical studies use stock market returns as the proxy for market returns when considering the capital asset pricing model (CAPM) and find that CAPM has weak explanatory power on cross section of average stock returns, especially for portfolios formed by size and book-to-market ratios (Basu, 1977; Banz, 1981; Shanken, 1985; Fama & French, 1992, 1993). In response to the poor performance of CAPM, Fama and French (1993) develop a three-factor model. The Small-minus-Big (*SMB*) and High-minus-Low (*HML*) factors in the Fama-French three-factor model are differences in stock returns on portfolios formed by size and book-to-market ratios. These factors do improve the performance of the model.

Extending the work of Merton (1974) and Roll (1977), Ferguson and Shockley (2003) build a theoretical model to show that the correct proxy for the market portfolio should include both the economy's debt and equity claims. This work provides two implications. First, empirical "anomalies" based on the capital asset pricing model (CAPM) are due to the omission of debt claims from the market portfolio proxy. Second, beta estimation errors from an equity-only proxy increase with a firm's distress risk. In addition, the authors construct portfolios based on debt-related firm characteristics and find that loadings on these portfolios outperform *SMB* and *HML* factors in explaining cross-sectional returns. Based on the Merton (1974) model, Aretz and Shackleton (2010) estimate the value of debt as a function of equity value, implied asset value and asset volatility. However, their empirical results provide no evidence that the estimated proxy enhances CAPM pricing performance.

This study uses the CDS market index as a proxy for the debt market for the following reasons. First, CDS pricing data is easily attainable and does not require further calibrations as other proxies used in prior studies (Ferguson & Shockley, 2003; Aretz & Shackleton, 2010). Düllmann and Sosinska (2007) find that reduced-form models of CDS spreads are more informative than structural models for banks engaging in major investment banking activities. Second, unlike bond prices, CDS spreads are directly associated with a firm's credit risk and less affected by other factors such as systematic risk, tax differences, and contractual features. Tang and Yan (2010) document that a major portion of individual CDS spreads can be explained by a firm's default risk, while only a small portion is contributed by macroeconomic variables. Finally, the CDS market is more liquid than the bond market and thus more efficient in processing information (Norden & Weber, 2004; Forte & Pena, 2009; Fang & Lee, 2011).

Related research on default risk suggests that the relation between the CDS index return and stock returns may vary across firms. Nickell et al. (2000) conclude that the credit risk puzzle (i.e., stocks with high distress risk tend to have low future returns) is due to the poor performance of low-rated stocks at times of credit rating downgrades. Ferguson and Shockley (2003) suggest that estimation errors using an equity-only proxy increase with a firm's leverage. Avramov et al. (2009, 2012) investigate a set of anomaly-based trading strategies and find that such strategies are only profitable in stocks with the lowest credit ratings. Thus, the explanatory power of CDS Index returns is expected to be stronger for distressed firms.

Earlier studies find that stock behavior and their respective betas vary in bull and bear markets, which implies that the explanatory power of CDS index returns could differ across time. Kim and Zumwalt (1979) and Chen (1982), among others, show that investors expect to receive a risk pre-

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mium for downside risk and pay a premium for upside variation of returns. In addition, research in the credit risk literature finds that corporate default varies with macroeconomic covariates (Duffie et al., 2007). This evidence suggests that the relation between CDS index returns and stock returns is stronger when the market is down and overall distress risk is more intense.

Several studies show that, on average, firms with higher distress risk have lower subsequent stock returns, hence the "credit risk puzzle" (Dichev, 1998; Dichev & Piotroski. 2001; Campbell et al., 2008). Griffin and Lemmon (2002) suggest that such negative relation is driven by the poor performance of low book value of equity (BE) to market value of equity (ME) firms. On the contrary, Vassalou and Xing (2004) estimate default risk based on Merton's (1974) model and find positive relation between distress risk and stock returns for small or high BE/ME firms. The center of the debate is whether distress risk, as measured by different proxies, is systematic and therefore should be priced. This study contributes to this area by first estimating a stock's sensitivity to changes in the credit market and then investigating whether such systematic risk is priced.

To sum up, only a limited number of empirical studies have included debt claims in the market portfolio, partially due to the difficulty in constructing a proper proxy for the credit market. Motivated by prior findings that the CDS market is more efficient in measuring a firm's credit risk, this study contributes to the literature by employing the CDS index as a proxy for the credit market. The study tests the following hypotheses:

H_0 *Returns of CDS index do not explain variation of stock returns (H_0: $\gamma = 0$).*

H_1: *The relation between CDS index returns and stock returns is stronger for firms with higher leverage and more distress risk.*

H_2: *The relation between CDS index returns and stock returns is stronger when the market is down.*

H_3: *A firm's exposure to changes in CDS index returns is priced in subsequent stock returns.*

2. DATA AND METHODOLOGY

2.1. Data

Credit default swaps (CDS) are defined by the International Swaps and Derivatives Association (ISDA) as bilateral agreements designed explicitly to shift credit risk between two parties. Therefore, CDS spreads are closely correlated with corporate default risk. Specifically, an increase in credit risk leads to an increase in the CDS spread. Given that there is no index covering all CDS contracts in the market, this study uses the Markit CDX North America Investment Grade Index as a proxy for the credit market portfolio. The Markit CDX North America Investment Grade Index is an equal weighted index of 125 credit default swaps on investment grade North American entities and rolls every six months in March and September. The last trading price is collected from Bloomberg to calculate index returns as log returns. The Markit CDX North American High Yield Index is also used and yields similar results.

The sample includes all publicly traded U.S. companies covering the period from January 2005 to December 2020. Daily returns for all New York Stock Exchange, the American Stock Exchange, and NASDAQ common stocks come from CRSP. Market factors, benchmark portfolio returns, and industry portfolio returns are from Kenneth R. French's website. Firm accounting and credit rating data come from COMPUSTAT.

2.2. Methodology

First, this study tests whether returns in the CDS index explain variations in stock returns (H_0), and whether such explanatory power varies across firms and time (H_1 and H_2). The empirical analyses start with the Capital Asset Pricing Model (CAPM) and the Fama-French three-factor model, and then include the returns on the CDS Investment Grade Index:

$$r_{i,t} = \alpha + \beta\left(r_{mkt,t} - r_{f,t}\right) + \varepsilon_{i,t}, \quad (1)$$

$$r_{i,t} = \alpha + \beta\left(r_{mkt,t} - r_{f,t}\right) + \gamma r_{CDX,t} + \varepsilon_{i,t}, \quad (2)$$

$$\begin{gathered} r_{i,t} = \alpha + \beta\left(r_{mkt,t} - r_{f,t}\right) + \\ + sSMB_t + hHML_t + \varepsilon_{i,t}, \end{gathered} \quad (3)$$

$$r_{i,t} = \alpha + \beta\left(r_{mkt,t} - r_{f,t}\right) + \\ +sSMB_t + hHML_t + \gamma r_{CDX,t} + \varepsilon_{i,t}, \quad (4)$$

where $r_{i,t}$ = the return of stock i on day t; $r_{mkt,t} - r_{f,t}$ = the excess stock market return on day t; $r_{CDX,t}$ = the return of CDS index on day t; SMB_t = the "Small-Minus-Big" firm size factor for day t; HML_t = the "High-Minus-Low" Market-to-Book ratio factor for day t.

For each model, pooled regressions as well as Fama-MacBeth regressions are employed to further control for time fixed effects. Specifically, this paper first estimates the monthly cross-sectional regression models in equations (1) to (4) and then computes the mean of these cross-sectional regression coefficients. The corresponding t-statistics are based on the standard errors of the time-series mean regression coefficient (Bernard, 1987; Fama & MacBeth, 1973; and Goyal, 2012).

Next, model (4) is re-estimated with subsamples to investigate whether the explanatory power of CDS index returns varies across firms, industries, and time. Leverage subsamples are constructed by sorting the cross section of stocks every year into two groups by their leverage. The high leverage subsample contains firms with the highest 50% of leverage every year, and low leverage subsample includes those with the lowest 50% leverage. Subsamples are also formed by S & P Long-term Credit Ratings: investment grade subsample includes firms with BBB+ rating or higher, the remaining firms are included in the Junk grade subsample. Industry subsamples are formed as the twelve Fama-French 12 industries.[1]

Finally, building on Ferguson and Shockley's (2003) proposition to include both the economy's debt and equity claims in the market portfolio, this study argues that the estimate of *gamma* – a stock return's sensitivity to changes in the credit market, is analogous to the *equity beta* in the asset pricing literature, which captures stock return's sensitivity to changes in equity market returns. Therefore, whereas the *equity beta* measures a stock's systematic risk associated with the equity market, the estimate of *gamma* is the *debt beta* that measures a stock's systematic risk associated with the debt market. That is, *gamma* is a proxy of systematic distress risk. This paper then further examines whether such systematic credit risk is priced. The pricing of "gamma risk" is examined in two stages. First, monthly gamma for each firm $\gamma_{i,t}$ is obtained by daily regressions from Equation (4) for each firm (i) and for every month (t). Then the pricing of $\gamma_{i,t}$ is estimated with monthly Fama-MacBeth regressions of the following form:

$$r_{i,t} = a_0 + b_1\,\beta_{i,t-1} + b_2\,s_{i,t-1} + \\ +b_3\,h_{i,t-1} + b_4\left(-\gamma_{i,t-1}\right) + \varepsilon_{i,t}, \quad (5)$$

where $\gamma_{i,t-1}$, $\beta_{i,t-1}$, $s_{i,t-1}$, $h_{i,t-1}$ are risk factor loadings for stock i and month $t - 1$ from Equation (4).

3. EMPIRICAL RESULTS AND DISCUSSION

Table 1 presents summary statistics on variables used in this study. The table shows that returns on the Markit CDX index are much more volatile compared to returns on other market factors: the CDX index return has a standard deviation of 5.10%, while the standard deviations of S&P 500 Index return, Small-minus-Big (*SMB*) and High-minus-Low (*HML*) factors are 1.31%, 0.56%, and 0.70%, respectively.

Table 1. Summary statistics

Variable	Number of observations	Mean	Std. Dev.	Min	Max
Price per share	11,071,270	38.1522	91.7028	23.04	5
Markit CDX Index	11,071,270	80.62	42.35	68.18	19.52
Stock return	11,071,270	0.087%	3.15%	0.00%	–86%
CDX Index return	11,071,270	0.00%	5.10%	–0.09%	–42.21%
S&P 500 Index return	11,071,270	0.58%	1.31%	0.52%	–11.40%
Small – Big	11,071,270	0.01%	0.56%	0.00%	–3.60%
High – Low	11,071,270	–0.01%	0.70%	–0.02%	–5.02%
Total assets ($M)	11,071,270	12369	87166	1164	0.118
Total liabilities ($M)	11,071,270	9710	77691	680	0.000
Leverage	11,071,270	0.576	0.303	0.572	0.000

1 Definitions of 12 industries are obtained from Kenneth R. French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_12_ind_port.html

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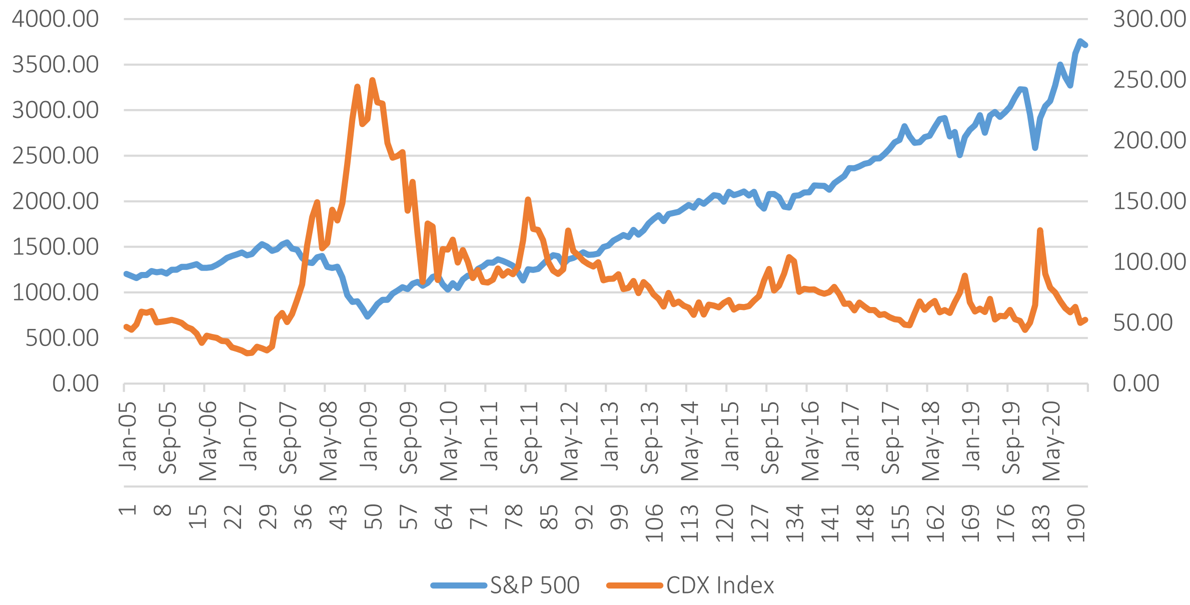

Figure 1. CDS Index and S&P 500 Index between 2005 to 2020

Table 2 reports correlation coefficients between variables in regression analyses. Pearson correlations are presented above the diagonal, and Spearman rank correlations are presented below the diagonal.

Table 2. Correlation coefficients

Variable	(1)	(2)	(3)	(4)	(5)	(6)
(1) CDS Index	1	–0.049	0.003	–0.001	–0.009	0.000
	–	<.0001	<.0001	<.0001	<.0001	0.329
(2) Stock return	–0.100	1	0.006	0.059	–0.249	0.034
	<.0001	–	<.0001	<.0001	<.0001	<.0001
(3) CDX Index return	0.026	–0.003	1	–0.102	0.330	0.201
	<.0001	<.0001	–	<.0001	<.0001	<.0001
(4) S&P500 return	–0.005	0.039	–0.204	1	–0.215	–0.067
	<.0001	<.0001	<.0001	–	<.0001	<.0001
(5) Small – Big	–0.008	–0.404	0.356	–0.356	1	0.184
	<.0001	<.0001	<.0001	<.0001	–	<.0001
(6) High – Low	–0.001	0.022	0.265	–0.130	0.221	1
	<.0001	<.0001	<.0001	<.0001	<.0001	–

To illustrate the relationship between stock returns and CDS index returns, Figure 1 plots the values of the S&P 500 and Markit CDX North American Investment Grade Index. The figure suggests an overall negative relation between stock returns and CDS index returns.

Table 3 presents regression results for models (1) to (4) with our full sample. OLS regression coefficients are reported in Panel A, and Fama-MacBeth regression coefficients are presented in Panel B. The t-statistics corrected for heteroskedasticity and firm-level clustering of standard errors are reported in *italics*. As indicated in Panel A, the coefficient for CDS index returns, γ, is statistically significant across all specifications. While the absolute value of γ is small compared with other market factors, the economic impact remains significant given the high volatility in the CDS market. For example, γ equals –0.003 with t-value of –15.05 in model (2). That is, when market credit risk increases and daily CDS index return increases by one standard deviation, 5.10%, average daily stock returns will decrease by 0.015%. Panel B shows that γ remains economically and statistically significant after controlling for time fixed effects. Thus, the null hypothesis that CDS index returns (r_{CDX}) do not explain variation of stock returns (H_0: $\gamma = 0$) is rejected. In addition, the adjusted R^2 increases slightly after the inclusion of r_{CDX}, providing evidence that inclusion of CDS index returns improves the Fama-French three-factor model. These results are consistent with the theoretical models that the debt claims should be included in the market portfolio (e.g., Markovitz, 1959; Sharper, 1964;).

Regression results for model (4) using leverage and credit rating subsamples are presented in Table 4. Overall, there is weak evidence supporting H_1. First, the coefficient of CDS index returns (r_{CDX}) is negative and statistically significant at the 1% level

Table 3. Regression analyses with full sample

Model	Intercept	$r_{mkt,t} - r_{f,t}$	SMB_t	HML_t	$r_{CDX,t}$	Adj. R^2
Panel A: OLS regression with full sample						
CAPM	0.000	1.060	–	–	–	14.84%
	45.13	915.45	–	–	–	–
CAPM + CDS	0.000	1.060	–	–	–0.003	14.87%
	45.31	900.26	–	–	–15.05	–
Fama-French three factor	0.000	0.940	0.688	0.24	–	16.46%
	48.85	780.27	303.44	119.23	–	–
FF + CDS	0.000	0.940	0.688	0.238	–0.002	16.49%
	48.98	766.92	303.42	119.23	–10.71	–
Panel B: Fama-MacBeth regression with full sample						
CAPM	0.000	1.088	–	–	–	12.11%
	4.23	83.61	–	–	–	–
CAPM + CDS	0.000	1.088	–	–	–0.004	12.21%
	4.45	64.91	–	–	–1.99	–
Fama-French three factor	0.000	0.917	0.673	0.168	–	13.31%
	13.17	199.97	130.54	27.55	–	–
FF + CDS	0.000	0.913	0.673	0.166	–0.004	13.32%
	13.93	170.17	128.41	27.64	–3.20	–

Table 4. Regression analyses – with leverage and credit rating subsamples

Subsample	Intercept	$r_{mkt,t} - r_{f,t}$	SMB_t	HML_t	$r_{CDX,t}$	Adj. R^2
Panel A: Subsamples by leverage						
Bottom 50%	0.001	0.970	0.769	0.055	–0.0017	14.91%
	38.84	556.85	235.95	18.86	–6.30	
Top 50%	0.000	0.910	0.607	0.421	–0.0022	18.89%
	30.08	528.99	193.13	155.86	–9.62	
Panel B: Subsamples by credit ratings						
Investment	0.000	1.064	0.401	0.236	–0.0001	29.36%
	17.55	549.34	113.85	62.54	–0.66	
Junk	0.001	1.150	1.392	1.066	–0.0043	15.61%
	1.65	31.51	18.90	10.90	–1.64	

for highly leveraged firms and less significant for firms with low leverage. Next, regression results from credit rating subsamples provide supporting evidence that the relationship between CDS index returns and stock returns is stronger for firms with lower ratings. Stock returns of Junk grade rated firms are negatively associated with r_{CDX}, whereas the relation between stock returns and r_{CDX} is negative but insignificant for firms with Investment grade rating.[2]

Table 5 reports regression results using observations in each year of the sample period. The relation between stock returns and CDS index returns is strongest in 2015, followed by the years of 2005, and 2017. In addition, model (4) is estimated by month and the monthly coefficients on CDS index return are plotted in Figure 2. Overall, both Table 5 and Figure 2 suggest that the explanatory power of CDS index returns varies across time and becomes stronger post 2011. However, there is no supporting evidence for H_2 that such relation is associated with overall market performance.

Table 6 presents regression results for Fama-French 12 industries. The coefficient on CDS index returns differs across industries. It is most negative and significant for firms in Healthcare, Medical Equipment, and Drugs (–0.006 with t-value= –9.78), followed by Consumer Durables, Business Equipment, and Energy (Oil, Gas, and Coal Extraction and Products). This may be a function of industry structure where these industries require considerable infrastructure and oper-

2 The data on credit rating ends in February 2017, when the Compustat S&P Ratings database discontinued.

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ations facilities. Because this structure is inherently more expensive, credit is of larger importance.

Table 5. Regression analyses by year

Year	Intercept	$r_{mkt,t} - r_{f,t}$	SMB_t	HML_t	$r_{CDX,t}$	Adj. R^2
2005	0.0005	0.841	0.616	0.134	−0.0089	8.0%
	16.79	168.40	83.15	10.61	−7.56	–
2006	0.0005	0.811	0.639	0.0947	−0.0032	9.7%
	17.97	148.29	91.08	7.27	−3.35	–
2007	0.0003	0.885	0.6	0.1542	0.00008	12.0%
	11.02	253.49	83.77	15.58	0.26	–
2008	0.0005	0.947	0.633	0.1846	−0.00256	22.3%
	10.66	267.36	104.98	40.42	−3.29	–
2009	0.0008	0.996	0.623	0.1907	−0.00112	23.1%
	16.97	192.76	90.87	32.50	−2.35	–
2010	0.0004	0.911	0.672	0.1514	−0.00037	23.4%
	12.54	224.17	113.39	20.86	−1.43	–
2011	0.0003	0.936	0.697	0.1666	−0.00629	32.8%
	9.41	204.89	112.93	26.39	−3.10	–
2012	0.0003	0.97	0.687	0.1665	−0.00012	14.6%
	10.71	163.37	95.21	21.43	−0.06	–
2013	0.0004	0.933	0.672	0.1466	−0.00012	11.1%
	14.37	136.70	90.50	15.97	−0.07	–
2014	0.0003	0.927	0.702	0.1217	−0.00282	12.2%
	10.55	162.60	120.01	14.81	−1.95	–
2015	0.0002	0.912	0.718	0.1285	−0.0097	11.2%
	7.77	163.31	107.82	20.34	−4.10	–
2016	0.0003	0.994	0.73	0.1455	−0.00082	13.3%
	8.99	148.83	106.36	24.68	−0.41	–
2017	0.0004	0.894	0.706	0.1525	−0.0043	6.0%
	12.30	83.01	89.28	23.59	−1.74	–
2018	0.0003	0.907	0.69	0.1829	−0.00413	9.7%
	8.27	169.12	94.65	25.00	−2.13	–
2019	0.0005	0.968	0.705	0.2052	0.00352	8.3%
	13.64	116.35	81.91	31.16	1.53	–
2020	0.0009	0.992	0.769	0.3141	0.00578	21.7%
	15.87	195.29	113.06	80.92	3.44	–

Table 6. Regression analyses by industry

Industry	Intercept	$r_{mkt,t} - r_{f,t}$	SMB_t	HML_t	$r_{CDX,t}$	Adj. R^2
NoDur	0.0004	0.801	0.547	0.23	−0.00006	15.0%
	9.86	162.35	55.86	29.13	−0.09	–
Durbl	0.0003	1.069	0.863	0.433	−0.00371	24.8%
	5.45	147.07	62.76	35.11	−2.92	–
Manuf	0.0004	1.073	0.78	0.376	−0.00087	26.3%
	15.93	301.63	124.57	69.98	−1.61	–
Enrgy	0.0003	1.228	0.63	0.507	−0.00209	21.3%
	5.58	154.57	45.42	37.47	−1.89	–
Chems	0.0004	1.043	0.631	0.249	−0.00063	23.8%
	7.40	149.07	49.05	24.16	−0.57	–
BusEq	0.0005	1.037	0.708	−0.089	−0.0037	17.9%
	22.05	368.40	130.64	−19.32	−8.11	–
Telcm	0.0004	0.955	0.571	0.18	−0.00036	19.3%
	7.26	132.17	41.41	16.48	−0.34	–
Utils	0.0002	0.726	0.086	0.082	0.00088	24.6%
	8.15	155.60	10.64	12.68	1.49	–
Shops	0.0004	0.926	0.744	0.299	0.00011	18.9%
	16.90	238.04	100.36	49.10	0.21	–
Hlth	0.0007	0.883	0.691	−0.203	−0.00645	10.4%
	20.83	193.24	74.12	−24.41	−9.78	–
Money	0.0002	0.781	0.572	0.686	−0.00175	21.4%
	12.27	297.94	123.66	158.54	−4.40	–
Other	0.0006	0.992	0.864	0.074	−0.00036	12.3%
	24.11	314.60	150.83	15.47	−0.72	–

Lastly, this study investigates whether the estimate of stock return's sensitivity to changes in the credit market, γ, is priced and reports results of equation (5) in Table 7. Given that, on average, stock returns decrease when CDS index return increases ($\gamma < 0$ from first stage regression), a firm i's exposure to systematic risk in the credit market is defined as $-\gamma_i$. That is, similar to beta risk with the equity market, this "gamma risk" captures a stock's co-movement

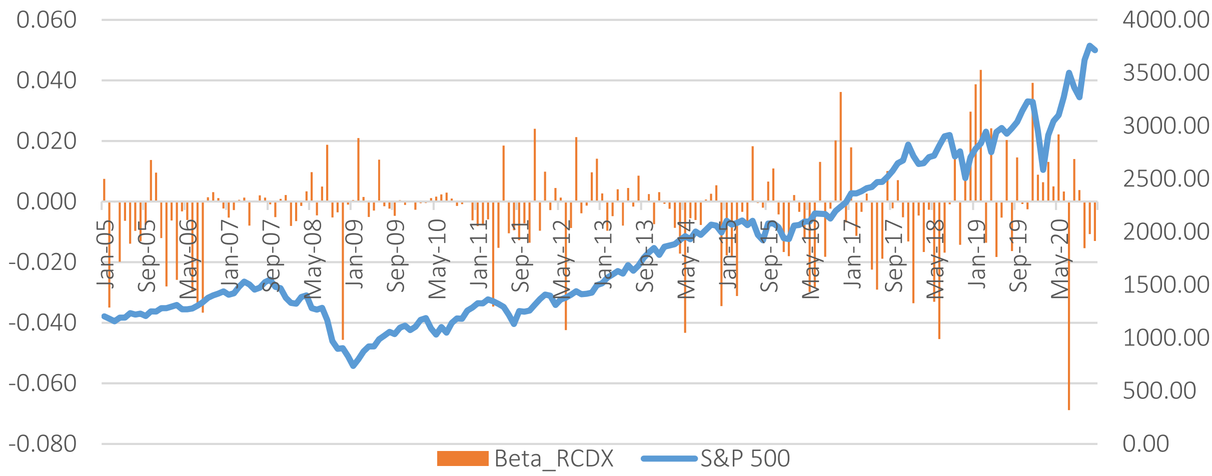

Figure 2. Coefficients on CDS Index Returns

Table 7. Credit market beta as additional risk factor

Model	Intercept	$\beta_{i,t-1}$	$s_{i,t-1}$	$h_{i,t-1}$	$-\gamma_{i,t-1}$	Adj. R^2
FF three factors	0.015	0.00005	0.00001	0.00002	–	0.002%
	89.99	3.65	0.38	2.33	–	–
With CDX	0.015	0.00011	0.00003	0.00003	0.00016	0.005%
	88.82	5.27	2.08	2.55	3.88	–

to changes in the credit market. The results are supportive of H_3 that a stock's sensitivity to changes in the credit market is positively associated with subsequent stock returns. The coefficient on $-\gamma_{i,t-1}$ has similar economic magnitude as $\beta_{i,t-1}$, and it is statistically significant at 1% level. That is, the proxy of systematic credit risk is positively associated with subsequent stock returns. This finding is consistent with the classic risk-return trade-off theory and provides evidence against the "credit risk puzzle" (Dichev, 1998; Campbell et al., 2008).

To conclude, Table 3 reports negative and statistically significant coefficients for CDS index returns across all specifications and hence rejects the null hypothesis H_0 that CDS index returns do not explain variation of stock returns. Meanwhile, Table 7 indicates that a firm's exposure to changes in CDS index returns is positively priced in subsequent stock returns. Thus, H_3 is accepted. On the other hand, subsample regression estimates presented in Tables 4 to 6 provide weak evidence for H_1 that the relation between CDS index return and stock returns is stronger for firms with more distress risk, while there is no supporting evidence for H_2 that such relation is stronger when the market is down.

This paper also relates to the stream of studies on CDS. There is a decent amount of research on various aspects of the CDS market, such as CDS pricing, CDS contracts and market structure, and the relative efficiency of the CDS market. The global financial crisis has sparked many studies on the impact of CDSs on firm risk and performance. Related studies on the relation between the CDS, stock, and bond markets indicate that the CDS market leads the bond market in price discovery, while providing mixed results on the lead-lag relation between the CDS and stock market (Norden & Weber, 2004; Forte & Pena, 2009). Fang and Lee (2011) examine the variance decomposition and contagion effects from the ABX index to the CDX indices and from the CDX indices to stock indices. Their results provide supporting evidence that the CDS markets lead stock markets. This study differs from this stream of literature in that this study does not analyze the lead-lag relation between the CDS and stock markets. Instead, this study uses the CDS index as an additional market factor and investigates its explanatory power in cross-sectional stock returns.

CONCLUSION

This study attempts to empirically test the theoretical implication that the correct proxy for the market portfolio should include both the economy's debt and equity claims. Using the CDS index as a proxy for the credit market, the paper investigates two research questions: Does the CDS index return explain stock returns? Is a firm's exposure to systematic credit risk priced? First, the coefficients of CDS index returns are negative and statistically significant, suggesting that the CDS index has additional explanatory powers on stock return variations after controlling for the Fama-French three factors. Second, regression results show that a firm's exposure to systematic risk in the credit market, measured as $-\gamma_{i,t-1}$ from the first stage regression, is positively associated with subsequent stock returns. This finding implies that the systematic component of a firm's distress risk is priced.

This paper contributes to three streams of existing studies. First, it contributes to the asset pricing literature by providing empirical evidence that including a proxy for debt claims improves current asset pricing models. The findings also shed light on the credit risk puzzle. Empirical results show that, on

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average, a firm's exposure to systematic risk in the credit market is priced in its stock returns. Lastly, the study adds to the literature on Credit Default Swaps by documenting that CDS market returns can explain variations in stock returns.

AUTHOR CONTRIBUTIONS

Conceptualization: Lijing Du, Susan M. V. Flaherty.
Data curation: Lijing Du.
Formal analysis: Lijing Du.
Methodology: Lijing Du, Susan M. V. Flaherty.
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