Distress Risk Premiums and the Performance of CDS Spread Change Regressions*

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Abstract

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JEL Classification: G12; G13

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* We thank discussants and conference participants at European Financial Management Association (EFMA) 2015 annual meeting and Financial Management Association (FMA) 2015 for their discussion. We also thank Young Ho Eom, Woon Wook Jang, Tong Suk Kim, Suk Joon Byun, Jinyong Kim, Kun Soo Park, and Sojung Park for helpful comments and suggestions. We are responsible for any remaining errors. This work was supported by the National Research Foundation of Korea Grant funded by the Korean Government. [NRF-2014S1A5B5A02014654]

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Abstract

We investigate the effect of distress risk premiums on the performance of structural models of CDS spreads. The results show that structural variables inspired by theory are more likely to fail in accounting for the CDS spreads of firms with higher distress risk. We argue that the distress risk premium embedded in CDS spreads is culpable in hampering empirical studies using the structural approach because the distress risk premiums are unrelated to firm-specific default rates. Rather, the main driving forces of distress risk premiums are market-wide factors. Our findings point a new direction to empirical tests of structural models.

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1. Introduction

The option pricing model by Black and Scholes (1973) and Merton (1974) is one of the most successful works in finance literature in recent decades. However, the model application to the pricing of corporate debt, typically referred to as a structural approach, is less satisfactory. Even though previous studies using linear regressions show that structural variables such as the leverage ratio, asset volatility, and riskless short rate are statistically significant in explaining corporate bond spreads or CDS spreads, low explanatory power of the structural approach is questionable[1]; the change in corporate bond/CDS spreads is significantly unexplained by the change in the structural factors inspired by Merton's (1974) theory (e.g., Collin-Dufresne *et al.*, 2001; Ericsson *et al.*, 2009). Specifically, most of the studies show that in the change regressions, the explanatory power of the model is, at most, approximately 20% in terms of average R^2, and the residuals of the model for each firm have (economically unknown but statistically pronounced) systematic co-movements.

We show that a distress risk premium implicit in a CDS spread makes the Merton model fail to explain CDS spreads. Although a number of empirical studies have attempted to increase a strikingly weak explanatory power of structural variables by adding possibly omitted variables, none of the studies has paid much attention to cross-sectional variation in the explanatory power. The *average* explanatory power of structural variables on CDS spread changes in our sample is similarly low (about 26.8%,

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[1] Another strand of the literature provides calibration evidence to test structural models. Similarly with regression studies, calibration studies report that structural models perform poorly in accounting for the empirical prices of corporate bonds. For example, Jones *et al*. (1984), Eom *et al*. (2004), and Huang and Huang (2012) calibrate many Merton-type structural models to historical bond price data and find that any structural model, even with the incorporation of realistic and complicated features, barely match the prices observed in the market. Most structural models that the authors investigate underestimate market prices. The failure of the structural approach has been surprising to academics.

on average) to previous studies. However, we find that the power differs from firm to firm. For instance, taking a closer look into the results, we find that while the explanatory power in terms of R^2 is 0.8% for Franklin Resources Incorporated, it is as high as 78.7% for Lehman Brothers Holdings Incorporated. This finding motivates us to examine whether such variation is non-trivial and if it is attributable to certain firm-specific characteristics, to other factors, or to nothing. Thus, the research questions of this study are to explain why the variation exists and to what factors it may be attributable.

Interestingly, the variation in the Merton model performance (in terms of R^2s of linear regressions) has a relation with the proportion of a distress risk premium in a CDS spread, even after controlling for other factors investigated in the literature such as liquidity and quality (e.g., Collin-Dufresne *et al*. (2001), Berndt (2015), and Junge and Trolle (2015)). We argue that a *distress risk premium* (DRP hereafter) implicit in CDS spreads is culpable in the weakening of the explanatory power of structural variables on CDS spreads because the individual DRPs are *not* explained by the structural variables but they are closely related to market-wide risk premiums.

We assume that CDS spreads include DRPs. Consider two CDS contracts for firms A and B, which have the same expected default probabilities regardless of the way in which they are measured (e.g., structural variables or credit ratings). The only difference between the two firms is the extent to which their conditional default risk varies over time in an unexpected way. For example, the asset value of firm A could be highly sensitive to unpredictable changes in market covariates and, subsequently, the firm is more likely to suffer from severe and unexpected ups-and-downs of its conditional default rate compared to firm B. All else being equal, CDS sellers would command a higher CDS spread for firm A than firm B because, when offering insurance for the event of firm A's default, the sellers experience more exposure to unexpected changes in conditional default risk, which is typically referred to as *distress risk* or *spread risk* (Driessen, 2005; Jarrow, Lando, and Yu, 2005; Pan and Singleton, 2008; Díaz, Groba, and Serrano, 2013). As a result, CDS sellers require compensation for bearing distress risk and, hence, CDS sellers command DRP in addition to a spread for the conditionally expected default risk. This implies that the same expected default rate does not necessarily lead to the same level of CDS spreads.

To measure the DRPs implicit in CDS spreads, we estimate a reduced-form model under a doubly stochastic one factor assumption, borrowing the idea of Pan and Singleton (2008) (PS hereafter). We explicitly specify the market price of risk associated with unexpected changes in instantaneous default probability and estimate CDS term structures under both risk-neutral and physical measures, which allows the identification of the related risk premium by taking the difference between the risk-neutral and physical expectations on future default risk. The result shows that 19.17% of a given CDS spread is because of a DRP on average for U.S. firms.

From the estimated DRPs, next, we examine whether the future change in default probability is systematically priced. If this is so, the individual DRP should only respond to the fluctuation of aggregate risk premiums when we regress the individual DRPs on both firm-specific structural variables and aggregate risk premium proxies. As expected, we find that individual DRPs co-move with several market-wide risk premium proxies. However, they are not explained by the measures of firm-specific default rates (or structural variables inspired by the Merton model).

To show that the DRP weakens the structural model's power, finally, we investigate a cross-sectional relation between DRPs and the performance of the Merton model, as measured by adjusted R^2 of the linear regression. To do so, we sort the firms into five groups based on their DRPs and we examine patterns of the R^2s. The result shows that the explanatory power of the Merton model monotonically decreases with the DRP proportion in a CDS spread. The performance difference between two extreme groups is statistically significant. In the bivariate sort analysis, we also find a monotonically decreasing pattern and statistically significant differences in all groups controlled for firm-specific characteristics including the leverage ratio, historical and implied volatility, rating, stock liquidity, and CDS liquidity. Two robustness tests confirm that our main findings are intact; i) we estimate DRPs using a model-free approach, ii) we test the sub-sample period excluding the recent financial crisis.

Our study relates and contributes to the literature in three ways. First, the results of our study imply that time-varying market-wide risk premiums should be considered in the tests of structural models. A number of papers have shown that market-wide variables have an impact on CDS and/or bond spreads although this effect cannot be reconciled within the Merton framework. For example, Hackbarth *et al*. (2006), Chen (2010), and Tang and Yan (2010) argue that macroeconomic risk is an important factor in structural models. Collin-Dufresne *et al*. (2001) and Ericsson *et al*. (2009) test market variables such as the VIX, the S&P 500, and the yield curve slope in their regression analyses. Galil *et al*. (2014) also show that Fama and French's (1993) three factors and Chen *et al*.'s (1986) five factors have statistical significance for CDS spread changes. Wang *et al*. (2013) consider the market-wide variance risk premium when explaining CDS spreads. The implications of these studies can be interpreted from our framework's perspective as attempts to capture DRPs that are unrelated to firm-specific default factors. We add empirical evidence that market-wide factors beyond the structural variables play an important role in explaining CDS spreads in an alternative way.

Second, we contribute to the literature by providing comprehensive speculation on a variety of attributes related to the systematic differences in explanatory powers or pricing errors of a structural model. To our knowledge, few empirical studies explain the systematic variation in pricing errors or explanatory powers. Two exceptions are Jones *et al*. (1984) and Eom *et al*. (2004). In their calibration experiments, the authors find that pricing errors are systemically related to several firm characteristics including leverage ratio, asset volatility, bond maturity, and bond rating. Among the tested characteristics, the authors argue that leverage ratio has the most significant effect on pricing errors. Although we address the same question in a different framework, that is, a linear regression rather than non-linear calibration, our findings are consistent with those of the authors. Moreover, we find another significant dimension, or a DRP that previous studies have overlooked. We provide strong evidence that the amount of DRPs in CDS spreads are a significant dimension related to explanatory power, even after controlling for firm characteristics shown to be important factors related to pricing errors in the previous studies.

Finally, to the best of our knowledge, this study is the first to investigate cross-sectional variation in the explanatory power of linear regressions in the literature on CDS/bond spread models. Most previous studies have attempted to increase low average explanatory power (e.g., Collin-Dufresne *et al*., 2001; Alexander and Kaeck, 2008; Das *et al*., 2009; Ericsson *et al*., 2009; Zhang *et al*., 2009; Cao *et al*., 2010; Tang and Yan, 2010; Wang *et al*., 2013; and Galil *et al*., 2014). A better understanding of the cross-sectional variation in the explanatory powers of a structural model will help to devise the structural model and improve its performance for pricing contingent claims on credit risk.

The remainder of this article proceeds as follows. Section 2 implements a preliminary analysis to show the motivation of this study, the cross-sectional variation in explanatory power. We provide empirical evidence to support our hypotheses in Section 3. Section 4 examines robustness for the results in several ways. Finally, we present conclusions in Section 5. The Appendix describes the econometric details concerning the estimation of DRP measures and the calculation of explanatory variables.

2. A preliminary analysis and motivation

Before testing our arguments related to DRPs in the next section, we confirm the empirical findings of previous studies with our sample. This step confirms that our sample is qualitatively the same as the samples in the literature although this study covers a different period and includes different firms. By doing so, we also introduce new empirical findings that have motivated this study; that is, cross-sectional variation in the explanatory powers of the structural models.

We present here a general description of the data used. A detailed description is presented in the Appendix. Monthly observations of CDS spreads are obtained from Markit. Compared with the stock prices and firms' accounting data, CDS data are available only for a relatively short period; therefore, our sample period based on the availability of CDS data is from January 2001 to November 2012. We limit our attention to US corporate CDS spreads with modified restructuring (MR) for dollar-denominated senior unsecured debt.[2] Throughout the paper, we analyze CDS spreads maturing in five years. However, term structure data having different maturities are also necessary for estimating DRPs using the PS model. For estimation purposes, we require that firms have CDS spread observations for one-, five-, and ten-year maturity contracts. Additionally, based on Markit's sector classification, we exclude firms in the utility sector,[3] which are typically protected by the government, and hence the nature of default risk may be rather different from other private firms.

In addition to the CDS data, we require daily equity prices and quarterly accounting data for the sample firms to calculate Merton variables such as leverage ratio and asset volatility. We first link the Center for Research on Security Prices (CRSP) database to the COMPUSTAT database. Next, using entity CUSIPs in Markit's Reference Entity Database (RED), we match the CRSP/COMPUSTAT merged database to the CDS sample. After merging all databases, we select only the firms with over 20 monthly observations to avoid spurious results from regressions. Finally, we have 388 firms and 40,397 firm-month observations.

In the preliminary analysis, we choose a benchmark model to compare the results of previous studies such as Collin-Dufresne *et al*. (2001) and Ericsson *et al*. (2009) with the model used in this study. The benchmark structural model we test throughout this paper is the Merton model in a linearized framework. The Merton model suggests that

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[2] Since the introduction of the CDS Big Bang in April 8, 2009, the market standard has changed from modified restructuring (MR) to no restructuring (XR) in the North American convention. Despite of the change, we use MR for the entire period to avoid inconsistency which may be involved due to the existence of restructuring premiums as shown in Berndt *et al*. (2007). We have enough MR contract data to investigate, and the number of the quotes with MR is merely the same with XR even after the Big Bang.

[3] Financial firms are also excluded in previous studies on structural models largely due to the complexity of capital structure of them. In addition, academics have paid little attention to financial firms' credit risk because it is believed that their credit risk is relatively low and economically less important. After the recent financial crisis that our sample period covers, however, financial sector's credit risk became significant. For the reason, we do not exclude financial firms in the main analysis. Our conclusion barely changes when firms in the financial sector are excluded (not reported but available upon request).

the likelihood of firm default is determined by three variables or structural variables:[4] i) leverage ratio, ii) asset volatility, and iii) the risk-free rate. We test the explanatory power of the Merton model with linear regressions. Hence, the specification of *level regressions* is:[5]

$$CDS_{i,t} = \beta_0 + \beta_1 LEV_{i,t} + \beta_2 HV_{i,t} + \beta_3 IV_{i,t} + \beta_4 RF_t + \varepsilon_{i,t}. \tag{1}$$

Similarly, the specification of *change regressions* is:

$$\Delta CDS_{i,t} = \beta_0 + \beta_1 \Delta LEV_{i,t} + \beta_2 \Delta HV_{i,t} + \beta_3 \Delta IV_{i,t} + \beta_4 \Delta RF_t + \varepsilon_{i,t}, \tag{2}$$

where LEV, HV, IV, and RF denote the leverage ratio, historical volatility, implied volatility, and risk-free rate, respectively, and $\Delta X_t = X_t - X_{t-1}$ represents their differences. Refer to the Appendix for the details on the source of the data and the method for calculating the variables.

[Insert Table 1 about here]

We test the level and change regressions in Table 1. Firstly, to examine the suggested three variables, the leverage ratio, historical volatility, and risk-free rate are used as explain variables in the regression model M1. In M2, historical volatility is replaced with implied volatility as an alternative asset volatility measure. The final regression model M3 represents the above regressions (1) and (2). The results

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[4] Throughout this paper, we use the terminology of Merton variables and structural variables interchangeably. Both terms indicate the leverage ratio, asset volatility, and risk-free rate. Firm-specific structural variables particularly indicate the leverage ratio and asset volatility.

[5] Merton's (1974) model implies a non-linear relationship between structural variables and default risk. Nonetheless, the simulation experiment in Collin-Dufresne *et al*. (2001) shows that linearization does not affect the performance. They argue that the poor performance of the empirical study may be attributable to other systematic factors. To examine an effect of DRPs on explanatory power of the linear regression, we choose the linear Merton model tested by Collin-Dufresne *et al*. (2001) as the base model.

represented in Table 1 are similar to those of previous studies. That is, the structural variables are statistically and economically significant in explaining both the level and change of CDS spreads. Additionally, consistent with literature, the average R^2 notably drops in the change regressions, as shown in Panel B. Specifically, while the R^2 of the level regression of M3 is approximately 72% on average, it drops to 27% for the corresponding change regression. This significant drop in explanatory power is observed in all specifications from M1 to M3, although the coefficients of the structural variables retain similar values in the level and change regressions. This implies that the ability of the structural model to explain the change in CDS spreads is much lower than the ability to explain the level. Despite previous efforts by academics to increase the average explanatory power of structural models, the poor performance of the change regression persists and continues to flummox academics.

This paper shifts the attention from increasing the low average explanatory power to explaining the cross-sectional variation in the performance of the Merton model, which will help to explain the reason for the poor performance. The lower panels in Table 1 show that a significant variation exists in the R^2 across firms. In the M3 change regression, for example, the ability of the Merton model is only 5% for the fifth percentile firm. In contrast, it is as much as 54%, as measured by R^2, for the 95th percentile firm. That is, although the Merton model does a poor job explaining CDS spread changes on average, there is significant variation; therefore, the model is effective for some firms but completely fails for others. Thus, we examine whether a reason exists for such variation. If we can attribute the variation to a firm characteristic, we contribute to the literature that questions the poor performance of the structural approach. Moreover, we expect that one of the reasons could be a DRP contained in a CDS spread because it is not related to firm-specific structural variables.

3. Empirical analysis

This section consists of three parts presenting empirical evidence to support our three hypotheses. The first part describes our model for estimating DRPs, illustrates the implications of DRPs with a numerical example and provides empirical evidence with real data. We argue that a CDS spread contains a DRP both theoretically and empirically. The second part provides evidence that the DRPs contained in CDS spreads are driven by market-wide risk factors, yet they are unrelated to firm-specific structural variables. Therefore, we expect that the amount of a DRP will weaken the power of structural models on CDS spreads. In the final part, we test the hypothesis by using the methods of DRP-based sorts and cross-sectional regressions. We show that the explanatory power of a structural model decreases with the proportion of the DRP.

3.1 CDS spreads contain DRPs

3.1.1 The model

Insight suggests that CDS spreads generally include premiums for distress risk, as defined by DRPs, and expected default risk. Our econometrical challenge is to disentangle a DRP from a CDS spread. We allow a conditional probability of default to stochastically evolve over time to obtain a model-implied risk premium for future change in the probability. Our approach to modeling and estimating DRP implicit in CDS spreads closely follows the work of PS, who consider that a risk premium for future change in default risk is priced as the difference between expectations under the risk-neutral and physical measures.[6]

The model is constructed as follows. First, we assume that conditional instantaneous default risk is driven by a single factor. Particularly, we assume that (risk-neutral) intensity λ^Q follows a log-normal process with a Brownian motion W^P under the physical (or P) measure:

$$d\ln\lambda^Q = \kappa^P(\theta^P - \ln\lambda^Q)dt + \sigma dW^P. \tag{3}$$

Next, we specify the market price of risk by $\Lambda_t = \delta_0 + \delta_1 \ln\lambda_t^Q$ so that the stochastic movement of intensity follows $dW^Q = dW^P + \Lambda dt$ under the risk-neutral (or Q) measure, and the log-normal property of the intensity process remains even after the change of the measure. The market price of risk allows us to price a fair spread of a CDS under Q (Harrison and Kreps, 1979). With this setting, we can obtain the model price of a CDS and estimate the model parameters related to the intensity process and the market price of risk process.

The unpredictable future change in default risk, which is instantaneously captured by σdW^P, is priced in a CDS spread by changing the dynamics of intensity under Q with $\kappa^Q = \kappa^P + \delta_1\sigma$ and $\kappa^Q\theta^Q = \kappa^P\theta^P - \delta_0\sigma$. Alternatively, such disparity of parameters between the two measures arises because of the risk-averse attitude of market participants toward the future change in the default probability or distress risk. Thus, the risk premium associated with the volatility risk of the conditional default risk[7]

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[6] This idea is further used by, for example, Longstaff *et al*. (2011), Díaz *et al*. (2013), Zinna (2013), and Friewald *et al*. (2014) to study CDS-implied risk premiums.

[7] We use the term of *risk* twice to emphasize the fact that our model is doubly stochastic.

is implicit in the difference between Q-expected default probability and P-expected default probability.

To extract the implicit risk premium for the distress risk (or DRP), we compute a "pseudo-CDS" spread with the physical default probability (P-measure) as in PS. Specifically, the pseudo-CDS spread, denoted by CDS^P, is computed using the estimated parameters under the P-measure (i.e., using κ^P and θ^P instead of κ^Q and θ^Q), whereas the model spread of a CDS is computed using the estimated parameters under the Q-measure (the rule of risk-neutral pricing of contingent claims implies that a model CDS spread should be calculated under the Q-measure). Thus, the additional spread because of the risk premium, denoted by DRP, is obtained from the difference between the model spread and the pseudo-spread; that is, the DRP for firm *i* at time *t* is defined by

$$DRP_{i,t} \equiv CDS_{i,t} - CDS^P_{i,t}. \tag{4}$$

Additionally, we define DRP proportion as the ratio of the DRP to the CDS spread

$$p^{DRP}_{i,t} \equiv \frac{DRP_{i,t}}{CDS_{i,t}}, \tag{5}$$

which measures the amount that is a result of the distress risk in a given CDS spread.

Our approach using the PS model might over/underestimate DRPs for several reasons. First, a doubly stochastic model might not be appropriate to describe historical default rates. For example, Das *et al*. (2007) and Duffie *et al*. (2009) argue that historical data on default are hardly reconciled with doubly stochastic model. However, Doshi *et al*. (2013) show that the doubly stochastic model with observable variables well explain CDS spreads. Our focus is on pricing of CDS spreads, not on historical default itself. The second possibility of overestimation is due to the assumption of a constant recovery rate. Chen *et al*. (2009) argue that time variation in LGD is essential to explain credit spreads. Ignoring this effect can lead to upward bias on the DRP estimation.

Despite these possibility of biases, we believe that our conclusions are not affected by such biases. We will examine the cross-sectional relation between the DRP proportions and the performance of structural models. Even though such biases affect DRP, the direction of the biases is consistent for all firms in our sample. Therefore, in sorting analysis the relative rakings based on this measure will not be influenced. In addition, we will use a model-free measure for DRPs in the section of robustness checks.

3.1.2 A numerical example

We illustrate the implications of DRPs with a numerical example. To demonstrate the effect of the premium for distress risk on a CDS spread, we change the volatility parameter σ from zero to one, keeping P-expected probability of default until the CDS maturity, and we calculate corresponding model spreads of a CDS with a maturity of five years for the different values of the model parameters.

[Insert Figure 1 about here]

Figure 1 displays the model spread of a five-year CDS (left panel) and the DRP proportion (right panel) for different σ values while the expected default probability under the P-measure (denoted by DP) remains at 0.05, 0.10, or 0.15 (and hence CDS^P is constant at approximately 61, 124, or 189 bps, respectively). Consistent with intuition, the left panel of Figure 1 shows that higher distress risk causes higher CDS spreads because of DRPs, although the P-expected default probability (and, in turn, CDS^P) is constant. For example, controlling for the P-expected default probability at 0.10, we see that CDS is the same with CDS^P at 124 bps for no distress risk; that is, $\sigma = 0$, while CDS at 350 bps is approximately twice as high as CDS^P for the highest distress risk; that is, $\sigma = 1$. The right panel of Figure 1 shows that, in the case with the highest distress risk, DRP is 226 bps and $p^{DRP} = 64\%$. This numerical experiment suggests that the presence of a DRP causes a higher CDS spread, explicitly demonstrating our intuition on DRPs. The implication from the cross-sectional perspective is that investors would command a higher CDS spread for a firm with highly unpredictable change in the future default risk because, even if conditionally expected default risks are the same for two firms, investors require additional compensation for the higher distress risk as well as a premium for the conditionally expected default risk.

3.1.3 The estimation result

We provide the empirical result for DRPs estimated with real data. We employ the maximum likelihood (ML) method to estimate our model. The details on the procedure of the estimation and the descriptive statistics for the resulting ML estimates of the model parameters are provided in Appendix A. In this section, we describe the empirical implications on the cross-sectional and time series properties of the estimated DRPs.

To describe the cross-sectional properties, we report the descriptive statistics for the CDS observations, estimated DRPs, and resulting DRP proportions in Table 2, along with the statistics for other regression variables, which will be used in the next analyses. With the exception of market variables, we calculate the cross-sectional statistics from the individual firm averages of the time series data because the data we analyze are panel data, and we intend to focus on cross-sectional properties.

[Insert Table 2 about here]

Two points regarding cross-sectional properties of the DRPs are notable in Table 2. First, as expected, CDS spreads contain significant amounts of DRPs. While the CDS spread of an average firm is approximately 162 bps, the DRP is 27 bps. On average, 19% of a CDS spread is a result of the DRP.[8] The fraction is more pronounced when we consider the median; DRPs account for 37% of a CDS spread, amounting to as much as one-third of the spread. Second, the estimated DRPs and DRP proportions, in common with the CDS spreads, exhibit substantial variation across firms. The individual DRPs range from the 5th percentile of -130 bps to the 95th percentile of 181 bps with a standard deviation of 119 bps. Similarly, the individual DRP proportions range from the 5th percentile of -76% to the 95th percentile of 69% with a standard deviation of 67%.[9] Table 12 in Appendix A shows that the volatility parameter σ, which captures the degree of uncertainty of future intensity, is widely dispersed firm-by-firm. Additionally, we include firms with various credit qualities. The CDS spreads, which can be a proxy for the credit quality, are widely dispersed, ranging from 34 bps (5th percentile) to 490 bps (95th percentile) with a standard deviation of 173 bps. This implies that our sample is not biased.

Next with respect to the time series properties of the DRP and DRP proportion, we confirm that both vary significantly over time and, particularly, both have co-movement

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[8] The mean DRP proportion is not exactly the same as the mean DRP divided by the mean spread because of a convexity in its calculation.

[9] Negative risk premiums are also found in previous studies using the PS model. For example, Longstaff *et al*. (2011) studying sovereign risk premium included a country with a negative median for risk premium in their sample. Friewald *et al*. (2014) reported negative risk premiums in some cases in a study of corporate CDS-implied risk premiums. As shown in Table 7 of the paper, the lowest two groups sorted by risk premiums in percentage terms have a negative mean value. The problem of negative DRPs occurs because we use a model-dependent measure. The positive ML estimates of the price of risk, δ_0 and δ_1, generate negative DRPs; this problem is not serious because the parameters are estimated as negative values for most of the sample firms. To be robust, we use an alternative, model-free measure in the robustness test in Section 4.

with several market variables. We plot the time series of the aggregate DRP and aggregate DRP proportion[10] in Figure 2 and Figure 3, respectively, along with macro variables such as the risk-free rate, variance risk premium, term premium, and corporate default premium. We summarize the empirical features in three points. First, the aggregate DRP and DRP proportion exhibit positive values most of the time, which reveals that investors require premiums on expected future changes in credit worthiness on average, which is already confirmed by the cross-sectional property. Second, the time series behavior of the aggregate DRP and DRP proportion varies considerably depending on market conditions. The aggregate DRP and DRP proportion rapidly soar during the recent financial crisis, also known as the credit crisis. This implies that the high levels of CDS spreads observed in the market during the crisis are attributable to the significant increase in DRPs as well as to the increase in default risk. Interestingly, the DRP proportion shows high persistence. Whereas the level of the aggregate DRP falls as the market recovers after the crisis, the DRP proportion maintains a persistent high level. In other words, investors' risk appetite does not easily change. Once the appetite changes because of a great shock, however, the investors continue to require a large portion of risk premium.[11] The final implication we note is that the DRP and DRP proportion have a strong correlation with variables measuring market conditions. Particularly, the aggregate DRP fluctuates together with the corporate default premium with a correlation of 0.79. The aggregate DRP proportion is negatively related to the risk-free rate (the level risk factor of government bond yields) with a correlation of -

[10] The terminology "aggregate" denotes a cross-sectional average; the time series of the aggregate DRP is obtained by averaging individual DRPs over firms every month. Similarly, aggregate DRP proportion is defined.

0.82, but has a positive co-movement with the term premium (the slope risk factor of government bond yields) and the default premium with similar correlations of 0.58.

[Insert Figure 2 about here]

[Insert Figure 3 about here]

To summarize, we confirm three aspects in the estimation result. First, a CDS spread contains a significant amount of DRP. Second, the amount of DRP, or its fraction, is different among firms. Third, a DRP or DRP proportion significantly changes over time, particularly depending on market conditions.

3.2 DRPs are unrelated to firm-specific default factors

This section explores the factors that determine the time variations of the individual corporate DRPs. Given that our DRP estimates compensate for unpredictable changes in conditional default risk, the DRP is likely to respond to the movements of market-wide risk premiums because firm value risk (and subsequently future changes in conditional default probability) co-varying with the state of the economy should be priced and not entirely captured by the movement of equity price. This is contradictory to the basic concept of the complete market that option pricing models following Merton (1984) typically assume. Our assumption can be reconciled with *unspanned volatility risk* models. See, for example, Collin–Dufresne and Goldstein (2002), Andersen and Benzoni (2010), and Joslin *et al.* (2014) for deeper discussion. We have graphically shown that the aggregate DRP and DRP proportion vary markedly over time and,

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[11] The reason that we are able to capture the different behaviors of DRP and DRP proportion in a given CDS spread is that we use the term structure data when estimating the model. The change in investors' appetite is reflected in the shape of the CDS term

particularly, co-move with market-wide factors suggesting that the individual DRP could potentially be related to several market risk premiums. Thus, we examine whether the individual DRP and DRP proportion are driven by a variety of market-wide risk premiums, firm-specific structural variables, or both. We expect that aggregate risk premiums drive the individual DRPs but the firm-specific variables that measure the conditionally expected default rates are not linked with individual DRPs.

3.2.1 The effect of aggregate risk premiums

We start by running firm-by-firm regressions of either a DRP or a DRP proportion as a dependent variable $y_{i,t}$ on a set of aggregate risk premiums as explanatory variables. Guided by literature, we employ aggregate risk premiums stemming from three important financial markets – equity, bond, and options markets. First, from the bond market, we obtain the risk-free rate measured by the ten-year Treasury bond yield (Collin-Dufresne *et al*., 2001; Ericsson *et al*., 2009), the term premium measured by the difference between 20-year and one-year US Treasury yields, and the default premium measured by the difference between yields on Baa and Aaa corporate bonds (Chen *et al*., 1986). The Treasury yield and term premium can also be interpreted as the level and slope factors of interest rate risk from the term structure model's perspective (Duffie and Kan, 1996). Second, we obtain three equity risk premiums from the stock market, the MKT, SMB, and HML (Fama and French, 1993) and market liquidity risk premium (Pástor and Stambaugh, 2003). Third, we consider the variance risk premium from the option market measured by the VIX minus the realized volatility of the S&P 500,

structure.

consistent with Bollerslev *et al*. (2009), Carr and Wu (2009), Todorov (2010), and Wang *et al*. (2013).

The time series regression for firm *i* is nested within the following specification:

$$\Delta y_{i,t} = \beta_0 + \beta_1 \Delta RF_t + \beta_2 \Delta VRP_t + \beta_3 MKT_t + \beta_4 SMB_t + \beta_5 HML_t + \beta_6 PSLIQ_t + \beta_7 \Delta UTS_t + \beta_8 \Delta UPR_t + \varepsilon_{i,t}, \tag{6}$$

where the independent variables are the risk-free rate (RF), variance risk premium (VRP), three equity risk premiums (MKT, SMB, and HML), liquidity risk premium (MLIQ), term premium (UTS), and corporate default premium (UPR). Note that MKT, SMB, HML, and MLIQ are not differenced because they represent the returns on factor mimicking portfolios; however, all other variables are differenced. Table 3 presents the result; the dependent variable is DRP in Panel A, whereas it is DRP proportion in Panel B. Each kind of aggregate risk premium variables is first tested through the regression models M1 to M5, and then the specification of (6) is performed in M6. Following Collin-Dufresne *et al*. (2001) and Ericsson *et al*. (2009), parameter estimates and adjusted R^2 are averaged across firm-by-firm regressions, and the associated *t*-statistics are calculated for the average estimates.

[Insert Table 3 about here]

As expected, both of the individual DRPs and DRP proportions are driven by the aggregate risk premiums that we test.[12] Several results are noteworthy. First, the

[12] Note that we run firm-by-firm regressions in line with Collin-Dufresne *et al*. (2001) and Ericsson *et al*. (2009) and test the loadings on market premiums. Thus, one should interpret the results with care. Significance of the loadings implies individual DRPs

coefficients are statistically and economically significant in the simple and multiple regressions. With the exception of some cases showing marginal significance, the aggregate risk premiums from the three important markets are all significant at the most conservative level or 1%. The aggregate risk premiums explain the movements of DRPs as well as DRPs per unit spread (or DRP proportion), which suggests that DRPs and DRP proportions are strongly related to aggregate risk premiums. This also provides evidence that the credit derivative market is closely linked to the other financial markets. It is particularly interesting that the (equity) market liquidity risk premium (MLIQ) is linked with the individual DRPs measured in the CDS market.

Additionally, adding all the market-wide risk premiums into a multiple regression shows that all the variables hold their significance when explaining the individual DRPs per unit spread (see M6 in Panel B of Table 3). The evidence is slightly weak for the regression of individual DRPs, but the MKT factor and equity market liquidity risk premium are statistically and economically significant.

Finally, the signs of the coefficients of premiums are the same for both the DRP regressions and the DRP proportions regressions. For example, the risk-free rate, MKT and SMB factors, and equity market liquidity risk premium are negatively related to the individual DRPs and DRP proportions, whereas the variance risk premium, HML factor, term premium, and default premium are positively related to the individual DRPs and DRP proportions (see M1 to M5 in Table 3).

respond to market premiums with similar sensitivities. Most previous studies employ this methodology to find determinants of CDS spreads.

In summary, whether we measure CDS-implied risk premiums by an amount or its proportion, we verify that individual CDS-implied risk premiums are closely related to the aggregate risk premiums of other financial markets.

3.2.2 The effect of firm-specific default risk factors

Next, we examine whether the individual DRPs are affected by firm-specific determinants of default rates. As before, the dependent variable $y_{i,t}$ is either the DRP or the DRP proportion for firm *i* at month *t*, and the firm-by-firm time series regressions are nested in the specification below:

$$\Delta y_{i,t} = \beta_0 + \beta_1 \Delta LEV_{i,t} + \beta_2 \Delta HV_{i,t} + \beta_3 \Delta IV_{i,t} + \gamma' X_t + \varepsilon_{i,t}. \quad (7)$$

LEV, HV, and IV denote leverage ratio, historical volatility, and implied volatility, respectively, and the vector X includes all the market-wide risk premiums used in (6). We control for the effect of market-wide risk factors using X_t.

[Insert Table 4 about here]

Firstly, changes of firm-specific variables are put into independent variables in the regression model M1 of Table 4. From M2 to M6, each kind of variables for market-wide risk premiums is added to explain the DRP or the DRP proportion. Finally, the firm-specific and all the market-wide risk factors are tested together as the specification of equation (7).

When the DRPs or DRP proportions are regressed only on firm-specific structural variables (or not controlled for market-wide risk factors), we find a conflicting result with our prediction (refer to M1 in Table 4). That is, the firm-specific variables seem tao be statistically significant. However, after controlling for the effect of aggregate risk premiums, the significance of the firm-specific variables disappears, whereas the significance of the market-wide factors remains (refer to M7 in Table 4). The reason for this could be that the seemingly significant effects of the firm-specific variables are attributable to the correlation with the market-wide factors, which is justified by the results of M2 to M6 in Table 4. For example, the effect of leverage disappears when we control for Fama-French three factors, which can be justified by the notion that the variation in leverage of a firm is mostly driven by the variation in equity price, and the equity price is strongly affected by Fama-French pricing factors (see M4). Similarly, it is not surprising that the market-wide volatility premium subsumes the effects of individual historical and implied volatilities (see M3). Therefore, the movements of DRPs and DRP proportions are mostly captured by the movements of market-wide factors rather than firm-specific variables. Compared to the result of regression (6) in Table 3, it is particularly interesting that the estimated coefficients and their significance remain unchanged when we add firm-specific variables in Table 4. That is, the risk-free rate, MKT and SMB factors, and the equity market liquidity risk premium are negatively related to the individual DRPs and DRP proportions, whereas the variance risk premium, HML factor, term premium, and default premium are positively related to the individual DRPs and DRP proportions, as before.

We conclude that the DRPs and DRPs per unit spread are determined by the aggregate risk premiums. More importantly, we verify that DRPs are unrelated to firm-specific determinants of conditionally expected default rates. Conversely, we conclude that the model-implied DRP is a reliable proxy for the DRP that we define for our purpose.

3.3 A higher DRP proportion leads to weaker explanatory power

As shown earlier in Section 2, the performance of the Merton model is very different among firms regardless of whether the test is a linear regression of CDS spread levels or changes. We argue that such variation in the explanatory power is attributable to the amount of DRP because we proved that the DRP and DRP proportion are unrelated to firm-specific structural variables in Section 3.2. To support the argument, this section tests the hypothesis that a higher DRP leads to weaker explanatory power of structural models in four ways. Throughout this section, the explanatory power of the level regression is calculated using OLS residuals of regression (1) and (2) for level regressions and change regressions, respectively, as described in the preliminary test in Section 2.

3.3.1 R^2 analysis

We examine whether the unconditional mean of DRP proportion has any effect on the explanatory power of structural models in terms of adjusted R^2 obtained from the level and change regressions.[13] We test whether the cross-sectional variation in adjusted R^2s, if present, is attributable to the cross-sectional variation in the unconditional means of DRP proportions.

We first sort all firms by their average DRP proportions. The average DRP proportion of firm i, $\bar{p}_i^{DRP}$, is calculated by

$$\bar{p}_i^{DRP} = \frac{1}{T}\sum_{t=1}^{T}\frac{DRP_{i,t}}{CDS_{i,t}}, \quad \text{for } i = 1, \ldots, N. \tag{8}$$

[13] To be conservative, we use adjusted R^2 rather than ordinary R^2. All results remain intact even if we measure the explanatory power in terms of ordinary R^2.

Next, we assign each firm to five groups – that is, from the lowest average DRP proportion group denoted by G1 to the highest group denoted by G5. For each firm, we obtain the adjusted R^2 from regressions (1) and (2). Then, we compare the average adjusted R^2 for each group. The result is plotted in Figure 4 to show any tendency, and the regression details are reported in Table 5. The regression model M1 tests only the explanatory power of the leverage ratio. From M2 to M4, historical volatility or implied volatility are added to the leverage ratio. In the model M5, all four variables including risk-free rate are used as independent variables; that is, the regression specifications equal to equations (1) and (2).

[Insert Figure 4 about here]

The left and right panels of Figure 4 show the patterns of average adjusted R^2 of level and change regressions, respectively. At a glance, we can see a tendency of the adjusted R^2 to decrease with $\bar{p}_i^{DRP}$ for all structural models that we test. For example, when we add all structural variables inspired by the Merton model in the level regression (refer to M5 in the left panel of Figure 4), the average adjusted R^2 is 74.8% for the lowest group G1, whereas it is 59.7% for the highest group G5. Similarly, in the change regression, we can see that the average explanatory power of a group decreases from 28.9% to 18.5% as the average DRP proportion of the group increases. This tendency is consistent for all models regardless of whether the regressions are implemented in a form of level or change as shown. Our finding indicates that structural models are more likely to have weak explanatory power for firms with a higher average DRP proportion; or, on average, the more DRP in CDS spreads, the more likely the model is to fail for structural variables in accounting for CDS spreads in both level and change regressions.

We implement *t*-tests on the explanatory power difference between G1 and G5 to formally test the argument. In the level regressions, the *t*-statistics of the explanatory power for G1 minus G5 are 5.98, 5.16, 5.42, 5.34, and 5.04 for M1 to M5, respectively.[14] In the change regressions, these statistics are 2.58, 3.30, 4.34, 4.57, and 3.94 for M1 to M5, respectively. Therefore, we strongly reject the null hypothesis (at the 1% level) that the average explanatory power of a structural model is the same for different groups. We instead find evidence that it is statistically significant that, on average, the explanatory power for the lowest DRP proportion group G1 is stronger than that of the highest group G5. Therefore, we again confirm the same result in this formal test.

[Insert Table 5 about here]

Whether such differential explanatory power stems from the insignificance of structural variables or inconsistencies with respect to the theory for some groups, particularly G5, is explained by the regression details in Table 5; the regression details show that this is not the case. Each panel in Table 5 presents the regression result for each group from G1 to G5. Following Collin-Dufresne *et al*. (2001) and Ericsson *et al*. (2009), we report average estimates and *t*-statistics for the cross-sectional average in Table 5. We note that all structural variables are statistically and economically significant. Additionally, the signs of the estimates are consistent with the theory for all

[14] The *t*-tests are conducted under an equal-variance assumption. However, the results are almost the same with those under an unequal-variance assumption.

DRP groups. Previous studies have already analyzed the meaning of the estimates, which is beyond the scope of this paper; therefore, we do not address the regression results further. Instead, we emphasize that structural models are significant for all groups. However, the difference in explanatory power is noticeable. The decreasing tendency of R^2 is not a result of insignificance or inconsistency with theory for some groups. Therefore, we argue again that the unconditional mean of DRP proportion, $\bar{p}^{DRP}$, has a significant impact on the explanatory power of structural models in both level and change regressions.

3.3.2 RMSE approach

Next, we consider the effect of the time varying property of DRP proportions. The previous section analyzed the effect of the unconditional mean of DRP proportion, but DRP proportions vary significantly over time. This implies that, for example, a firm with a high average DRP proportion does not necessarily remain in the high group at every point in time. The constituents may differ time point to time point. Therefore, a firm in G1 in one month could be assigned to G5 the following month. Figure 3 shows that DRP proportion changes significantly over time.

We test the time-varying effect of DRP proportion by tracking the pricing errors of the DRP groups evaluated at each point in time. The specific procedure for the test is as follows. First, we estimate the linear structural models (1) and (2) and obtain a time series of residuals for each firm,[15] denoted by $\varepsilon_{i,t}$. Then, at month *t*, we rank all firms

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[15] We use *studentized* residuals rather than ordinary residuals. The studentized residuals represent a standardized version. We choose studentized residuals in our analysis because a comparison of the size of residuals should control for the trivial difference in residuals from total variation of a dependent variable. For example, when CDS spreads are high, the residuals (or pricing errors) of models are proportionally increasing, and this effect will lead to the wrong conclusion. This consideration is similar to R^2, which is calculated from the variation in regressors and the total variation in a dependent variable.

by their month-*t* DRP proportion, $p_{i,t}^{DRP}$, and allocate the firms to five bins. We calculate the root-mean-squared errors for group *G* at month *t* by

$$RMSE_t^G = \sqrt{\frac{1}{N}\sum_{i=1} \varepsilon_{i,t}^G}\,,\ \ \text{for G} = 1(\text{Low}), \ldots, 5(\text{High}), \tag{9}$$

where $\varepsilon_{i,t}^G$ denotes the residual for firm i, which is ranked in group *G* at month *t*. That is, we track over time the RMSEs for each group ranked based on each month's DRP proportion. Finally, we have five time series of RMSEs: $RMSE_t^1$ for low to $RMSE_t^5$ for high. As with the R^2 analysis, we focus on the difference between group 1 and group 5. If our conjecture that higher DRP proportion leads to weaker explanatory power of structural models is true, the average pricing error for G5, $RMSE_t^5$, will be consistently higher over time than the average pricing error for G1, $RMSE_t^1$. To statistically test this hypothesis, we perform a *t*-test on the time series difference between G1 and G5. If the mean of the difference of $RMSE_t^1 - RMSE_t^5$ is significantly negative, we infer that pricing errors for G1 (lowest DRP) are small, implying strong explanatory power. This is not a novel idea. In option literature, for example, Trolle and Schwartz (2009) employ the idea to test pricing performance for commodity options. We conduct the *t*-test for pricing errors of the five structural models analyzed in the previous section.

For all of the models tested, we find strong evidence that structural models have greater explanatory power for G1 (lowest DRP proportion) than G5 (highest DRP proportion). Specifically, for M1 to M5, the associated *t*-statistics are -2.55, -3.01, -3.05, -3.03, and -3.07 for the level regressions, respectively, and -3.18, -3.19, -3.14, -3.19, and -3.10 for the change regressions, respectively. At the 1% significance level, all of these tests reject the null hypothesis that the pricing errors are not significantly different between the two groups. Thus, we obtain the result that, for firms with higher DRP proportion, structural variables are more likely to lose some degree of their explanatory power on CDS spread levels and changes consistently at each point in time.

3.3.3 Controlling for firm characteristics

The results of Collin-Dufresne *et al*. (2001) show that the explanatory power of structural models decreases with the leverage ratios, although the authors do not note this explicitly. Therefore, it is doubtful that the observed pattern of explanatory power in our study is attributable to firm-specific characteristics such as the leverage ratio, historical volatility, option-implied volatility, equity liquidity, CDS liquidity, and credit rating. To verify that the decreasing pattern is not a result of other firm characteristics, we control for these effects. Our empirical methodology to address this issue is straightforward. We repeat the R^2 and RMSE analyses presented in subsections 3.3.1 and 3.3.2, respectively. The only difference is that, instead of univariate-sorting, we double-sort all of the firms independently based on their DRP proportions and either of the firm characteristics such as the leverage ratio, historical volatility, implied volatility, and equity liquidity to control for the effects. To guarantee a sufficient number of firms in each sort, this analysis assigns firms into 3 by 3 sorts. The specific ways of ranking firms and evaluating the measures of the explanatory power are the same as previously mentioned. We only run the change regression for Model 5 in the previous section because of space limitations; that is,

$$\Delta CDS_{i,t} = \beta_0 + \beta_1 \Delta LEV_{i,t} + \beta_2 \Delta HV_{i,t} + \beta_3 \Delta IV_{i,t} + \beta_5 \Delta RF_t + \varepsilon_{i,t}. \qquad (10)$$

[Insert Table 6 about here]

Table 6 shows the average adjusted R^2s of each sort. We find a monotonically decreasing pattern of the average explanatory power along the DRP dimension in every controlled group, except for the medium historical volatility groups that show a slightly inverted-V shape. Interestingly, average explanatory power does not show any noticeable pattern along the dimension of controlling characteristics. Exceptionally, along the dimension of leverage ratio, every DRP group shows a monotonically increasing pattern, which will be discussed in Section 3.3.4 with cross-sectional regressions.

As with the previous univariate sort, we note the difference in average explanatory power between two extreme groups in each controlled group. Except for the lowest implied volatility group, we see that the difference, denoted by L-H, is statistically significant. Economically, the low DRP groups for various controlled groups have stronger explanatory power by approximately 5% to 13% compared to the high DRP groups. The magnitude of the explanatory power difference is similar regardless of controlled firm characteristics.

[Insert Table 7 about here]

Next, we consider the time-varying property of DRP proportion. We perform the RMSE analysis again, controlling for firm characteristics. Table 7 simply reports the *t*-statistics for the difference of the pricing errors between two extreme groups along the DRP dimension.[16] For each level of firm characteristics, the difference between the two groups with the lowest and the highest DRP proportions is tested. All *t*-statistics are

[16] We sort firms into three groups along the DRP dimension. We find, but do not report, that the result is robust according to how many groups we construct from two to five.

negative and significant, except for the group with the highest equity illiquidity and the highest rating. These results indicate that firms with high DRP proportions tend to have poor explanatory power with respect to Merton variables on CDS spread changes, and this tendency is not attributable to individual firm characteristics.

3.3.4 Cross-sectional regressions

To provide more robust evidence for the negative relation between the DRP proportion and the explanatory power of structural models, we perform cross-sectional regressions with a specification nested in the following:

$$R_i^2 = \alpha + \beta \times \bar{p}_i^{DRP} + \gamma' X_i + \varepsilon_i, \tag{11}$$

where the dependent variable R_i^2 represents firm *i*'s adjusted R^2 value obtained from the level regression in (1) and the change regression in (2)[17], $\bar{p}_i^{DRP}$ denotes the time series average of the DRP proportion of firm i, and X_i is the vector of control variables including the leverage ratio (LEV), historical volatility (HV), implied volatility (IV), equity illiquidity (ILLIQ), CDS liquidity (DEPTH), and ratings. All control variables are averaged over the sample period and standardized to gauge their relative importance in the regressions. The intercepts are zero by construction in every regression. Appendix B.2 provides details on the calculations for the average ratings of each firm.

[Insert Table 8 about here]

Table 8 shows several models of the regression in (11). Only the average of the DRP proportion is used in M1. From regression model M2 to M7, each control variable mentioned above is added to the cross-sectional regressions. In M8, lastly, all the control variables as well as the average of the DRP proportion are put into regressions in both panels of Table 8. Panel A of Table 8 shows the result of using the level regression explanatory power as the dependent variable. Most importantly, the average DRP proportion is economically and statistically significant in explaining the cross-sectional variation in explanatory power of the level regression model. The coefficient particularly is estimated as negative values (ranging from -0.17 to -0.21) for every regression we investigate. That is, no matter which variables we control for, the effect of DRP proportion on the explanatory power of a structural model is negative (and quite stable), consistent with our hypothesis. This provides an economic implication that an increase in DRP proportion by one standard deviation leads to a decrease in R^2 by approximately 0.2 standard deviations in a cross-sectional sense. A similar conclusion can be reached for Panel B of Table 8. We use the change regression explanatory power as the dependent variable of the second-pass, cross-sectional regression. The coefficient of DRP proportion ranges from -0.16 to -0.27 at the 1% significance for every model, which suggests that a structural model in a change regression performs better when explaining CDS spread changes for firms with lower average DRP proportions.

The results also provide other interesting insights. The coefficient of the DRP proportion remains significant, and the sign does not alter whether the first-pass regression is level or changes (as shown in Panels A and B of Table 8, respectively); however, other firm characteristics have different effects. For example, historical volatility (HV) and credit rating (RATING) significantly account for the variation in

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[17] Thus, we obtain (adjusted) R^2 values from the first-pass regressions, and we run the second-pass regressions in (11) using

level regression R^2s, but not for the variation in change regression R^2s. Rather, the leverage ratio and CDS liquidity are important characteristics accounting for the variation in change regression explanatory power. Also, the economic implication of the coefficient of RATING is interesting. We report that the coefficient of RATING is positive at 0.23 in the level regression case, which suggests that CDS spread levels are explained by a structural model more satisfactorily for firms with higher credit quality.[18] This is interesting because our result seems inconsistent with previous studies using a calibration method. Eom *et al*. (2004) and Huang and Huang (2012), for example, report that structural models have greater difficulty matching empirical credit spreads of investment grade bonds than the spreads of non-investment grade bonds. However, our regression study provides indirect evidence that the difficulty may be partly due to a large amount of risk premiums of investment grade bonds. After controlling for the effect of DRPs, the structural model performs 5.6% better (in terms of adjusted R^2) for investment grade firms than for non-investment grade firms (not reported). This result is invariant in a variety of robust tests, as will be shown later in Section 4.

With respect to liquidity in Table 8, the equity and CDS liquidities have different aspects. M8 of Panel A reveals a coefficient of ILLIQ of -0.13 with a *t*-statistic of -2.40, while DEPTH is insignificant. In contrast, M8 of Panel B shows that the coefficient of DEPTH is 0.40 with a *t*-statistic of 8.59, whereas ILLIQ is -0.08 and marginally significant. This suggests that equity liquidity is a superior characteristic for explaining CDS spread levels, but CDS liquidity is superior in explaining changes. Additionally,

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the first-pass R^2s as the dependent variable.

[18] In our study, a higher value of RATING corresponds to higher credit quality. In unreported results, we find that the implication does not alter when we use a dummy variable instead of RATING to distinguish investment grades and non-investment grades.

the coefficient's sign implies that firms with illiquid equity have weak explanatory power in level regressions, whereas firms with an illiquid CDS have weak explanatory power in change regressions. Particularly noticeable is the important role of CDS liquidity in explaining CDS spread changes. Panel B shows that the relative importance of the coefficient of DEPTH is largest among the firm characteristics, and it is the most significant; the coefficient and the associated *t*-statistic are 0.4 and 8.59, respectively.[19] This implies that CDS liquidity is relatively the most important factor for explaining CDS spread changes, and much of the pricing errors in the CDS spread changes are attributable to the illiquidity of CDS contracts.

In summary, the cross-sectional regressions offer strong evidence that the fraction of CDS spreads that is a result of distress risk is significant in determining the structural model performance, whether the model is implemented by a CDS level regression or a CDS change regression. Consistent with our expectations, a higher DRP proportion hampers the model performance. Aside from the DRP proportion, the finding that credit rating is a significant factor in determining the performance is consistent with the literature. Moreover, we find that CDS liquidity plays an important role in model performance when explaining CDS spread changes.

4. Robustness checks

To strengthen our main argument that the DRP diminishes the explanatory power of the structural model in explaining credit spreads, we examine the robustness of our results provided in Sections 3.3.3 and 3.3.4. We repeat the analyses of double sorts and cross-sectional regressions by i) using an alternative measure of DRPs and ii) using a

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[19] Higher DEPTH implies greater liquidity.

sub-sample excluding the period of the recent financial crisis (defined as the period from August 2007 to June 2009).

The measure of DRPs used so far has been model-dependent. An inherent risk in employing a model-dependent approach is misspecification. As stated earlier, the DRPs we estimate have negative values in some cases, which is difficult to reconcile with theory. To address this issue, we use an alternative measure of DRPs using a model-free approach following Friewald *et al*. (2014). In addition, overall CDS spreads were high and the level of risk aversion was elevated during the crisis. Therefore, we test whether our results are caused by the effect of the rare event, which will further reinforce the current paper's argument if the results remain the same.

To elaborate on the estimation of the alternative measure of DRPs, we provide details of the new measure in the next subsection and briefly summarize the results of the two robustness checks because the analyses are a simple repetition of the previous analyses.

4.1 A model-free measure of DRPs

The idea of Friewald *et al*. (2014) is closely related to that of PS in that both use information incorporated in the term structure of CDSs and estimate risk premium according to the difference between the Q- and P-expectations. Borrowing this idea, we summarize the procedure of estimating an alternative (model-free) measure of DRPs.

The τ-period expected risk premium in a T-year CDS spread at time t, denoted by $E_t[RP_{t+\tau}^T]$, is the difference between expected CDS spreads starting at time $t+\tau$ under the Q- and P-measures; that is, $E_t[RP_{t+\tau}^T] \equiv E_t^Q[CDS_{t+\tau}^T] - E_t^P[CDS_{t+\tau}^T]$. We consider a future CDS spread at time $t+\tau$ because a risk premium related to a CDS contract is spread risk (future change in spreads), consistent with the model-dependent approach that models intensity risk by future change in intensity, σdW_t^P, in (3).

Motivated by Cochrane and Piazzesi (2005) who extract interest rate risk premium from the term structure of bond yields, Friewald *et al*. (2014) use the approach to estimate current risk premium related to CDS spread risk that can be estimated from the information available at time *t* incorporated in the term structure of CDS spreads. Following the authors, we consider

$$E_t[RP_{t+\tau}^T] \equiv E_t^Q[CDS_{t+\tau}^T] - E_t^P[CDS_{t+\tau}^T] = \beta' X_t, \tag{12}$$

where X_t is the information of CDS term structure available at time *t* and, specifically, consists of $(1, CDS_t^1, F_t^{1\times 1}, F_t^{3\times 1}, F_t^{5\times 1}, F_t^{7\times 1})$. $F_{\mathrm{t}}^{\tau\times T}$ denotes the forward CDS spread starting at time $t+\tau$ and maturing in T years. Under the assumption of non-stochastic interest rates, the Q-expected CDS spread $E_t^Q[CDS_{t+\tau}^T]$ can be replaced by the forward CDS spread $F_{\mathrm{t}}^{\tau\times T}$. Finally, by allowing for a forecasting error, we suggest the following forecasting regression to estimate (12):

$$F_{\mathrm{t}}^{\tau\times T} - CDS_{t+\tau}^T = \beta' X_t + \varepsilon_{t+\tau}. \tag{13}$$

Then, we compute the expected risk premium with the predicted part of (13), $E_t[\widehat{RP_{t+\tau}^T}] = \hat{\beta}' X_t$.[20] In the left hand side of (13), the choice of the maturity T is somewhat arbitrary. Thus, we average the spreads of one-, three-, five-, and seven-year maturities. We use $E_t[\widehat{RP_{t+\tau}^T}]$ as a new measure of DRP.

[20] The forward CDS spreads are bootstrapped from CDS term structure by the market standard approach. The detail is described in O'Kane (2011).

To compare this DRP with that of PS' method, for each firm, we compute pairwise correlation of the DRP values from the two methods, and it shows that the median (mean) of the correlations is 0.47 (0.31). This high positive value indicates that the risk premiums from the two methods have similar variations, and the model-free DRP can be a good alternative of the PS model-implied one.

4.2 The results of robustness tests

Tables 9 through 11 show the results of the robustness tests. A number of combination of robustness checks may be possible; however, we only report the major analyses to conserve space. Including unreported results, we confirm that the main results remain unchanged qualitatively. The conclusion is identical even if we use a new proxy of DRPs, or we exclude the crisis period.

Specifically, we re-examine the cross-sectional variation in the adjusted R^2s by sorting based on the new proxy of DRPs when firm characteristics are controlled. In Panel A of Table 9, we see the monotonically decreasing pattern of the average adjusted R^2 in almost all cases regardless of the specific firm characteristics, similar to the results of using the PS model-implied DRPs. We also confirm the statistically significant difference between the two extreme DRP groups in all controlled groups. The RMSE analysis is also performed using the new DRP, and the result is shown in Panel A of Table 10. All the negative *t*-statistics prove that firms belonging to the group with higher DRP proportions have substantially larger pricing errors regardless of the level of the other firm characteristics.

Next, we exclude the time series data of the financial crisis period (from August 2007 to June 2009) from our sample (we use PS DRPs here). The results of the R^2 and

RMSE approach are shown in Panel B of Tables 9 and 10, respectively. Again, we find that the average value of adjusted R^2s decreases as the DRP proportion increases, although the overall degree of explanatory power declines in comparison with the result from our full sample. The significance is still valid in most cases. In the case of the RMSE analysis in Panel B of Table 10, the result is almost the same as the result in Table 7. Thus, our conclusion is robust over the subsample.

[Insert Table 9 about here]

[Insert Table 10 about here]

With regard to the robustness check for the cross-sectional regression, we only report the result of using the new DRP measure in Table 11. We find the model-free DRP proportion is statistically significant for the variation in adjusted R^2s of level and change regressions.

[Insert Table 11 about here]

Although not reported, we also confirm that the results are qualitatively identical even when we test for the sub-sample period excluding the financial crisis, not dependent on whether we use the PS model-implied DRPs or the model-free DRPs. One exception we note is that the PS DRP proportion is marginally significant for explaining the cross-sectional variation in the explanatory power of change regressions when we exclude the financial crisis period.

Overall, the main findings do not depend on the use of an alternative measure of DRPs and, excluding the financial crisis period, the conclusion is not altered.

5. Conclusion

This paper argues that the presence of DRPs in CDS spreads can be a reason for failure in the structural approach because the DRPs might be related to market-wide factors but not related to firm-specific default factors. While previous empirical studies have extensively addressed the weak explanatory power of the Merton model in terms of average R^2, motivated by the presence of cross-sectional differences in the R^2, we have focused on examining whether the variation is attributable to the amount of DRPs incorporated into CDS spreads.

The research design and the results of the study are threefold. First, we estimate the DRP implicit in the CDS term structure using the methodology suggested by PS. We find that, in terms of the median, DRPs account for approximately 30% of CDS spreads, suggesting that a non-trivial part of CDS spreads is caused by compensation for bearing the risk of unexpected changes in default risk; that is, DRPs. Second, once we identify the individual firm DRPs, we show that they are driven by various aggregate risk premiums observed in the bonds, stocks, and options markets. More interestingly, after controlling for the market-wide risk premiums, the DRPs are unrelated to firm-specific default risk measures such as leverage ratio, historical volatility, and implied volatility, as expected. Finally, we examine whether the DRP is a culpable in weakening the explanatory power of the structural approach in explaining CDS spreads. This hypothesis naturally arises from the finding that CDS spreads contain a significant amount of DRPs, which are unrelated to firm-specific structural variables. To test the hypothesis, we sort all firms based on their DRP proportions. We find strong evidence supporting our hypothesis, showing a monotonically decreasing pattern in adjusted R^2s and statistically significant differences between the extreme groups. Moreover, considering the time-varying effect of DRPs, we sort the firms every month and track the RMSEs of the two extreme groups. Then, we show that the two time series of RMSEs are different with statistical significance. We also find empirical support for our hypothesis in terms of both adjusted R^2s and RMSEs, after controlling for other firm characteristics such as leverage ratio, asset volatility, rating, equity liquidity, and CDS liquidity. Additionally, the cross-sectional regressions show that DRPs are a significant determinant of model performance.

Extensive robustness checks support our results. We use an alternative measure for the DRPs with a model-free approach suggested by Friewald *et al*. (2014). Using the alternative DRPs, we show that the empirical findings remain intact. That is, we confirm monotonically decreasing patterns in explanatory power with DRP proportions and the statistical significance for the difference between extreme two groups based on either adjusted R^2s or RMSEs, even after controlling for other firm-specific characteristics. Analyzing with a subsample that excludes the recent financial crisis period, we also confirm the same results qualitatively.

This study suggests that DRPs may be an important dimension that should be considered when testing structural models empirically. Structural models build on the existence of risk premium. Tests without premiums regarding any risk, especially distress risk, can lead to unsatisfactory performance.

Appendix

A. The pricing of a CDS and ML estimation of the model

Defining the process of the default intensity λ_t^Q under the physical measure and the market process of risk, the formula for a CDS spread at time *t* with maturity τ is

$$CDS_t^Q(\tau) = \frac{L^Q \int_t^{t+\tau} E_t^Q \left[\lambda_u^Q e^{-\int_t^u \left(r_s+\lambda_s^Q\right)ds}\right] du}{\frac{1}{4}\sum_{i=1}^{4\tau} E_t^Q \left[e^{-\int_t^{t+i/4}\left(r_s+\lambda_s^Q\right)ds}\right]}. \tag{14}$$

The numerator represents the protection leg, which is the value of the protection seller's payment in the default event, and r_t denotes the risk-free rate. L^Q represents the loss given default under the risk-neutral distribution and is assumed to be 0.6. When $CDS_t^Q(\tau)$ is multiplied by the denominator, it represents the premium leg with quarterly payments. From the equality of both legs, the CDS spread formula is derived. If the additional assumption that r_t and λ_t^Q are independent is exerted, the CDS spread can be calculated as

$$CDS_t^Q(\tau) = \frac{4L^Q \int_t^{t+\tau} D(t,u) E_t^Q \left[\lambda_u^Q e^{-\int_t^u \lambda_s^Q ds}\right] du}{\sum_{i=1}^{4\tau} D(t, t+i/4) E_t^Q \left[e^{-\int_t^{t+i/4} \lambda_s^Q ds}\right]} \tag{15}$$

where $D(t,u)$ denotes the price of a default-free zero-coupon bond at time t and maturing at time u. Because the expectations in equation (15) are not solved in closed forms, we calculate the expectations numerically using the Crank–Nicolson implicit finite difference method.

Using the formula for pricing a CDS spread, we estimate the parameters for the default intensity process and the market price of risk process from CDS data. One-, five-, and ten-year CDS contracts are used because they are most actively traded. Among the three maturities, five-year contracts are used to invert a CDS spread to the current default intensity λ_t^Q of each date because the five-year maturity is the most quoted spread in almost all firms. We use the derived default intensity for the model prices of

CDSs using the other two maturities, and we assume that there are pricing errors that are the difference between the market CDS spread and the priced CDS spread. The pricing errors in CDSs with one- and ten-year maturities are assumed to follow normal distributions with mean o and standard deviations $\sigma_\epsilon(1)$ and $\sigma_\epsilon(10)$, respectively. That is, the error equation is $\epsilon_t(\tau) = CDS_t(\tau) - CDS_t^Q(\tau)$ for $\tau = 1, 10$, where the error $\epsilon_t(\tau)$ is independent and normally distributed. Then, the joint likelihood of the default intensity and the error can be calculated as $f^P\left(\lambda_t^Q, \epsilon_t \middle| \lambda_{t-1}^Q\right) = f^P\left(\epsilon_t \middle| \lambda_t^Q\right) f^P\left(\lambda_t^Q \middle| \lambda_{t-1}^Q\right)$ where ϵ_t represents the vector with elements of the errors $\epsilon_t(1)$ and $\epsilon_t(10)$. Using the likelihood, parameters $\kappa^Q, \theta^Q, \kappa^P, \theta^P$, σ, $\sigma_\epsilon(1)$, and $\sigma_\epsilon(10)$ for each firm are estimated, and the parameters for the market price of risk δ_0 and δ_1 are calculated from the relation of $\kappa^Q = \kappa^P + \delta_1 \sigma$ and $\kappa^Q \theta^Q = \kappa^P \theta^P - \delta_0 \sigma$. We report the ML estimates of the parameters for 388 sample firms in Table 12.

[Insert Table 12 about here]

B. Regression variables

This section describes the method of variable manipulation used in the regressions and the data sources.

B.1 Firm-specific variables

Leverage ratio (LEV): Leverage ratio is defined by the debt-to-asset ratio. Therefore, the leverage ratio is typically calculated by

$$LEV = \frac{D + PE}{D + PE + E}, \tag{16}$$

where D is a sum of book values of long-term debt and debt in current liabilities, PE denotes the book value of preferred equity, and E denotes the market value of equity. Because the book values are available with quarterly frequency from the COMPUSTAT database, we linearly interpolate the quarterly observations to obtain monthly observations consistent with Ericsson *et al*. (2009). We obtain the market value of equity from the CRSP database.

Historical Volatility (HV): In the structural model, volatility of firm value increases the default probability. Because the volatility of firm value and equity volatility are closely related, historical volatility is widely used to explain variation in credit spreads (e.g., in Ericsson *et al*. (2009), Galil *et al*. (2014)). Historical volatility is calculated as the annualized standard deviation of returns from the previous 250 trading days. We use daily stock returns from CRSP.

Implied Volatility (IV): We test historical volatility and implied volatility as volatility measures. Cao *et al*. (2010) show that implied volatility from put options prevails over historical volatility in explaining CDS spread changes. The implied volatilities of the firms in our sample are obtained from OptionMetrics' standardized options. We use implied volatility of at-the-money put options with 30-day expiration.

Illiquidity (ILLIQ): Illiquidity is the absence of trade in an individual security and can affect stock returns. We use illiquidity as one of the firm characteristics and calculate the measure according to Amihud (2002). From the daily ratio of a stock's absolute return to its dollar volume, we multiply 1,000,000 to the ratio and calculate the monthly average of the value.

CDS liquidity (Depth): Although we use cleaned CDS spreads by Markit, the liquidity of the CDSs may affect the spread values. Markit data have a proxy for the liquidity called depth, which is the number of contributors building spreads each day. Following some papers (Qiu and Yu 2012; Lee *et al*. 2013), we also use the depth as a measure for CDS liquidity.

Credit rating (Rating): We use the average rating provided by Markit where credit ratings range from "AAA" to "CCC." The ratings are averages of Moody's and S&P ratings. To use the ratings in regression analysis, we convert the average ratings to numerical values using the conversion table of Anderson *et al*. (2003). We use the averages of the conversion numbers in the authors' paper because the rating from Markit does not have "+" and "-" levels.

B.2 Market variables

Risk-free rate (RF): Treasury bond yields are considered the risk-free interest rate. Although the yield is a market variable, it can also be considered a factor of the structural model. In Merton's framework, the risk-free rate increases the drift of the firm value process, thus decreasing default probability. We use the 10-year Treasury constant maturity rate from the Federal Reserve.

Variance risk premium (VRP): Variance risk premiums are the difference between implied and realized market volatilities. To quantify the variance risk premium, we use the VIX index as the implied volatility measure and historical sample standard deviation of S&P 500 for realized volatility. The VIX index is a near-term implied volatility calculated from S&P 500 option prices, and we obtain VIX data from the Chicago Board Options Exchange (CBOE). To calculate the sample variation, we use historical 250 trading day returns of the S&P 500 index.

Fama-French three factors (MKT, SMB, HML): MKT represents the market excess return and is calculated as R_m minus R_f. R_m is the value weighted return of all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ. R_f is the one-month Treasury bill rate. SMB is calculated as an average return on small portfolios minus an average return on large portfolios. HML is calculated as an average return on the value portfolios minus an average return on the growth portfolios. All three factors are available on Kenneth French's website.[21]

Market liquidity risk premium (MLIQ): Market-wide liquidity can be considered one of the systematic risk factors in pricing stocks and also a state variable of a market. As a measure of the liquidity risk premium, we use Pástor and Stambaugh's (2003) traded factor, which is the value-weighted return.

Term structure (UTS): Chen *et al*. (1986) show that innovations in economic variables are risk factors and the risks are rewarded. In addition to the relation of the factors with stock returns, Galil *et al*. (2014) test the effect on CDS spreads. The authors found that the factors are significant in several regressions. Among the factors, UTS is the term spread, which is the difference between yields on long-term and short-term bonds. Fama and French (1989) show that the term spread is closely related to business cycles. We calculate this premium as the difference in yields on 20-year and one-year Treasury securities from the Federal Reserve Economic Data (FRED).

Risk premium (UPR): As the other factor of Chen *et al*. (1986), UPR indicates the default premium. It is affected by the economy; therefore, the premium is likely to be high when business conditions are weak. This premium is calculated as the yield of Moody’s seasoned corporate bonds with Baa minus Aaa. The data are obtained from FRED.

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[21] The URL is http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

References

Alexander, Carol, and Andreas Kaeck. 2008. "Regime Dependent Determinants of Credit Default Swap Spreads." *Journal of Banking & Finance* 32 (6): 1008–21.

Amihud, Yakov. 2002. "Illiquidity and Stock Returns: Cross-Section and Time-Series Effects." *Journal of Financial Markets* 5 (1): 31–56.

Andersen, Torben G., and Luca Benzoni. 2010. "Do Bonds Span Volatility Risk in the U.S. Treasury Market? A Specification Test for Affine Term Structure Models." *The Journal of Finance* 65 (2): 603–53.

Anderson, Ronald C., Sattar A. Mansi, and David M. Reeb. 2003. "Founding Family Ownership and the Agency Cost of Debt." *Journal of Financial Economics* 68 (2): 263–85.

Berndt, Antje. 2015. "A Credit Spread Puzzle for Reduced-Form Models." Review of Asset Pricing Studies 5 (1): 48–91.

Berndt, Antje, Robert A. Jarrow, and ChoongOh Kang. 2007. "Restructuring Risk in Credit Default Swaps: An Empirical Analysis." *Stochastic Processes and Their Applications* 117 (11): 1724–49.

Black, Fischer, and Myron Scholes. 1973. "The Pricing of Options and Corporate Liabilities." *The Journal of Political Economy*, 637–54.

Bollerslev, Tim, George Tauchen, and Hao Zhou. 2009. "Expected Stock Returns and Variance Risk Premia." *Review of Financial Studies* 22 (11): 4463–92.

Cao, Charles, Fan Yu, and Zhaodong Zhong. 2010. "The Information Content of Option-Implied Volatility for Credit Default Swap Valuation." *Journal of Financial Markets* 13 (3): 321–43.

Carr, Peter, and Liuren Wu. 2009. "Variance Risk Premiums." *Review of Financial*

Studies 22 (3): 1311–41.

Chen, Long, Pierre Collin-Dufresne, and Robert S. Goldstein. 2009. "On the Relation Between the Credit Spread Puzzle and the Equity Premium Puzzle." *Review of Financial Studies* 22 (9): 3367–3409.

Chen, Hui. 2010. "Macroeconomic Conditions and the Puzzles of Credit Spreads and Capital Structure." *The Journal of Finance* 65 (6): 2171–2212.

Chen, Nai-Fu, Richard Roll, and Stephen A. Ross. 1986. "Economic Forces and the Stock Market." *Journal of Business,* 383–403.

Cochrane, John H., and Monika Piazzesi. 2005. "Bond Risk Premia." *American Economic Review* 95 (1): 138–60.

Collin–Dufresne, Pierre, and Robert S. Goldstein. 2002. "Do Bonds Span the Fixed Income Markets? Theory and Evidence for Unspanned Stochastic Volatility." *The Journal of Finance* 57 (4): 1685–1730.

Collin-Dufresne, Pierre, Robert S. Goldstein, and J. Spencer Martin. 2001. "The Determinants of Credit Spread Changes." *The Journal of Finance* 56 (6): 2177–2207.

Das, Sanjiv R., Darrell Duffie, Nikunj Kapadia, and Leandro Saita. 2007. "Common Failings: How Corporate Defaults Are Correlated." *The Journal of Finance* 62 (1): 93–117.

Das, Sanjiv R., Paul Hanouna, and Atulya Sarin. 2009. "Accounting-Based versus Market-Based Cross-Sectional Models of CDS Spreads." *Journal of Banking & Finance* 33 (4): 719–30.

Díaz, Antonio, Jonatan Groba, and Pedro Serrano. 2013. "What Drives Corporate Default Risk Premia? Evidence from the CDS Market." *Journal of International Money and Finance* 37 (October): 529–63.

Doshi, Hitesh, Jan Ericsson, Kris Jacobs, and Stuart M. Turnbull. 2013. “Pricing Credit Default Swaps with Observable Covariates.” *Review of Financial Studies* 26 (8): 2049–94.

Driessen, Joost. 2005. “Is Default Event Risk Priced in Corporate Bonds?” *Review of Financial Studies* 18 (1): 165–95.

Duffie, Darrell, Andreas Eckner, Guillaume Horel, and Leandro Saita. 2009. “Frailty Correlated Default.” *The Journal of Finance* 64 (5): 2089–2123.

Duffie, Darrell, and Rui Kan. 1996. “A Yield-Factor Model of Interest Rates.” *Mathematical Finance* 6 (4): 379–406.

Eom, Young Ho, Jean Helwege, and Jing-Zhi Huang. 2004. “Structural Models of Corporate Bond Pricing: An Empirical Analysis.” *Review of Financial Studies* 17 (2): 499–544.

Ericsson, Jan, Kris Jacobs, and Rodolfo Oviedo. 2009. “The Determinants of Credit Default Swap Premia.” *Journal of Financial and Quantitative Analysis* 44 (01): 109–32.

Fama, Eugene F., and Kenneth R. French. 1993. “Common Risk Factors in the Returns on Stocks and Bonds.” *Journal of Financial Economics* 33 (1): 3–56.

Friewald, Nils, Christian Wagner, and Josef Zechner. 2014. “The Cross-Section of Credit Risk Premia and Equity Returns.” *The Journal of Finance* 69 (6): 2419-2469.

Galil, Koresh, Offer Moshe Shapir, Dan Amiram, and Uri Ben-Zion. 2014. “The Determinants of CDS Spreads.” *Journal of Banking & Finance* 41 (April): 271–82.

Hackbarth, Dirk, Jianjun Miao, and Erwan Morellec. 2006. “Capital Structure, Credit Risk, and Macroeconomic Conditions.” *Journal of Financial Economics* 82 (3): 519–50.

Harrison, J. Michael, and David M Kreps. 1979. "Martingales and Arbitrage in Multiperiod Securities Markets." *Journal of Economic Theory* 20 (3): 381–408.

Huang, Jing-Zhi, and Ming Huang. 2012. "How Much of the Corporate-Treasury Yield Spread Is Due to Credit Risk?" *Review of Asset Pricing Studies* 2 (2): 153–202.

Jarrow, Robert A., David Lando, and Fan Yu. 2005. "Default Risk and Diversification: Theory and Empirical Implications." *Mathematical Finance* 15 (1): 1–26.

Jones, E. Philip, Scott P. Mason, and Eric Rosenfeld. 1984. "Contingent Claims Analysis of Corporate Capital Structures: An Empirical Investigation." *The Journal of Finance* 39 (3): 611–25.

Joslin, Scott, Marcel Priebsch, and Kenneth J. Singleton. 2014. "Risk Premiums in Dynamic Term Structure Models with Unspanned Macro Risks." *The Journal of Finance* 69 (3): 1197–1233.

Junge, Benjamin, and Anders B. Trolle. 2015. "Liquidity Risk in Credit Default Swap Markets." Working Paper, EPFL and Swiss Finance Institute.

Lee, Jongsub, Andy Naranjo, and Stace Sirmans. 2013. "The Exodus from Sovereign Risk: Sovereign Ceiling Violations in Credit Default Swap Markets." *J Finance, Forthcoming*. http://w.ccfr.org.cn/cicf2013/schedule_files/13_17_2.pdf.

Longstaff, Francis A., Jun Pan, Lasse Heje Pedersen, and Kenneth J. Singleton. 2011. "How Sovereign Is Sovereign Credit Risk?" *American Economic Journal: Macroeconomics* 3 (2): 75–103.

Merton, Robert C. 1974. "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates*." *The Journal of Finance* 29 (2): 449–70.

O'Kane, Dominic. 2011. *Modelling Single-Name and Multi-Name Credit Derivatives*. John Wiley & Sons.

Pan, Jun, and Kenneth J. Singleton. 2008. "Default and Recovery Implicit in the Term Structure of Sovereign CDS Spreads." *The Journal of Finance* 63 (5): 2345–84.

Pástor, Ľuboš, and Robert F. Stambaugh. 2003. "Liquidity Risk and Expected Stock Returns." *Journal of Political Economy* 111 (3): 642–85.

Qiu, Jiaping, and Fan Yu. 2012. "Endogenous Liquidity in Credit Derivatives." *Journal of Financial Economics* 103 (3): 611–31.

Tang, Dragon Yongjun, and Hong Yan. 2010. "Market Conditions, Default Risk and Credit Spreads." *Journal of Banking & Finance* 34 (4): 743–53.

Todorov, Viktor. 2010. "Variance Risk-Premium Dynamics: The Role of Jumps." *Review of Financial Studies* 23 (1): 345-383.

Trolle, Anders B., and Eduardo S. Schwartz. 2009. "Unspanned Stochastic Volatility and the Pricing of Commodity Derivatives." *Review of Financial Studies* 22 (11): 4423–61.

Wang, Hao, Hao Zhou, and Yi Zhou. 2013. "Credit Default Swap Spreads and Variance Risk Premia." *Journal of Banking & Finance* 37 (10): 3733–46.

Zhang, Benjamin Yibin, Hao Zhou, and Haibin Zhu. 2009. "Explaining Credit Default Swap Spreads with the Equity Volatility and Jump Risks of Individual Firms." *Review of Financial Studies* 22 (12): 5099–5131.

Zinna, Gabriele. 2013. "Sovereign Default Risk Premia: Evidence from the Default Swap Market." *Journal of Empirical Finance* 21: 15–35.

Table 1. Explanatory Power of the Merton Variables on CDS Spread Levels and Changes

This table reports the result of regressions of monthly CDS spreads from January 2001 to November 2012. The results of level and change regressions are shown in Panel A and Panel B, respectively. The dependent variable is a CDS spread. The explanatory variables are the leverage ratio (LEV), historical volatility (HV), option-implied volatility (IV), and risk-free rate (RF). We run firm-by-firm time series regressions. Parameter estimates and R^2 are averaged across the firm-by-firm regressions, and associated *t*-statistics (shown in parentheses) are calculated for the average estimates as in Collin-Dufresne *et al*. (2001). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. At the bottom of each panel, the cross-section of R^2s are reported for the fifth, 25th, 50th, 75th, and 95th percentiles.

Panel A: Level Regression			
	M1	M2	M3
Intercept	-73.41**	-22.38	-25.41
	(-2.52)	(-1.38)	(-1.63)
LEV	5.70***	3.97***	3.67***
	(13.93)	(12.10)	(10.16)
HV	1.69***		0.59***
	(10.28)		(4.44)
IV		2.74***	2.45***
		(10.97)	(10.45)
RF	-15.87***	-19.15***	-18.54***
	(-6.17)	(-8.26)	(-8.54)
#Firms	388	388	388
R^2	0.63	0.67	0.72
5th PCTL	0.23	0.28	0.32
25th PCTL	0.52	0.59	0.63
50th PCTL	0.67	0.73	0.76
75th PCTL	0.78	0.81	0.84
95th PCTL	0.87	0.88	0.90

Panel B: Change Regression			
	M1	M2	M3
Intercept	-0.73**	-0.44*	-0.49
	(-2.35)	(-1.87)	(-1.60)
ΔLEV	5.45***	4.39***	4.23***
	(14.13)	(12.61)	(12.08)
ΔHV	1.20***		0.93***
	(8.20)		(6.75)
ΔIV		0.80***	0.74***
		(10.97)	(10.47)
ΔRF	-22.12***	-21.43***	-20.36***
	(-11.15)	(-11.01)	(-10.92)
#Firms	388	388	388
R^2	0.23	0.25	0.27
5th PCTL	0.02	0.02	0.05
25th PCTL	0.11	0.13	0.16
50th PCTL	0.20	0.23	0.26
75th PCTL	0.33	0.35	0.38
95th PCTL	0.49	0.53	0.54

Table 2. Descriptive Statistics for Sample Data

This table shows the descriptive statistics for the sample data. All variables are monthly observations from January 2001 to November 2012. The summary statistics for the CDS-related variables and the firm-specific variables are obtained from individual averages of 388 firms. The CDS-related variables are 5-year CDS spreads (CDS), distress risk premium (DRP), and DRP proportion. The DRP and DRP proportion are calculated using the PS model. The firm-specific variables are the leverage ratio (LEV), historical volatility (HV), option-implied volatility (IV). The statistics for the market-wide variables are calculated from 143 monthly observations. The market-wide variables include the risk-free rate (RF), variance risk premium (VRP), three equity risk premiums (MKT, SMB, and HML), liquidity risk premium (MLIQ), term premium (UTS), and corporate default premium (UPR).

	MEAN	MEDIAN	STD	5^{th} PCTL	95^{th} PCTL
CDS-related variables					
CDS (bps)	162.00	103.61	173.65	34.18	490.44
DRP (bps)	26.70	33.53	118.97	-129.99	180.52
DRP proportion (%)	19.17	37.30	67.57	-76.41	68.86
Firm-specific variables					
LEV (%)	29.24	24.91	18.72	7.06	66.41
HV (%)	38.09	36.60	11.04	23.88	58.30
IV (%)	36.69	35.38	9.93	23.46	54.81
Market-wide variables					
RF (%)	3.85	4.00	0.99	1.83	5.11
VRP (%)	2.13	2.15	6.63	-7.44	13.04
MKT (%)	0.23	0.79	4.72	-8.18	7.72
SMB (%)	0.44	0.17	2.65	-3.72	5.33
HML (%)	0.32	0.22	2.88	-4.36	4.40
MLIQ (%)	0.89	0.51	4.24	-6.52	6.88
UTS (%)	2.47	2.76	1.35	0.00	4.03
UPR (%)	1.16	1.01	0.50	0.73	2.52

Table 3. The Effect of Market-wide Risk Premiums on Distress Risk Premium

This table reports the result of regressions in (6). The dependent variable is either distress risk premium (DRP) (shown in Panel A) or DRP proportion (shown in Panel B), which are calculated using the PS model. The explanatory variables are a set of aggregate risk premiums including the risk-free rate (RF), variance risk premium (VRP), three equity risk premiums (MKT, SMB, and HML), liquidity risk premium (MLIQ), term premium (UTS), and corporate default premium (UPR). All variables are monthly observations from January 2001 to November 2012. The number of firms investigated is 388 for all regressions. Parameter estimates and adjusted R^2 are averaged across firm-by-firm regressions, and associated *t*-statistics (shown in parentheses) are calculated for the average estimates as in Collin-Dufresne *et al*. (2001). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	M1	M2	M3	M4	M5	M6
			Panel A: DRP			
ΔRF	-7.51***					-1.71
	(-3.60)					(-1.31)
ΔVRP		0.37***				0.04
		(2.89)				(0.35)
MKT			-0.64***			-0.51**
			(-3.20)			(-2.55)
SMB			-0.30*			-0.16
			(-1.73)			(-0.83)
HML			0.39**			-0.02
			(2.40)			(-0.12)
MLIQ				-0.46***		-0.32***
				(-3.04)		(-2.72)
ΔUTS					1.05	1.15
					(0.77)	(0.92)
ΔUPR					14.17***	5.35
					(2.88)	(1.38)
Adj. R^2	0.07	0.06	0.16	0.04	0.10	0.25
			Panel B: DRP Proportion			
ΔRF	-2.51***					-1.45***
	(-8.10)					(-3.91)
ΔVRP		0.13***				0.04*
		(4.55)				(1.88)
MKT			-0.20***			-0.12***
			(-6.63)			(-5.90)
SMB			-0.12***			-0.06**
			(-4.74)			(-2.02)
HML			0.00			-0.05**
			(0.06)			(-2.04)
MLIQ				-0.12***		-0.06***
				(-7.97)		(-4.56)
ΔUTS					1.46***	2.06***
					(6.24)	(6.87)
ΔUPR					4.42***	2.17***
					(8.62)	(4.65)
Adj. R^2	0.04	0.04	0.10	0.02	0.03	0.12

Table 4. The Effect of Firm-specific Variables on Distress Risk Premium

This table reports the result of regressions in (7). The dependent variable is either distress risk premium (DRP) (shown in Panel A) or DRP proportion (shown in Panel B), which are calculated using the PS model. The explanatory variables are structural variables including the leverage ratio (LEV), historical volatility (HV), and option-implied volatility (IV). We control for a set of aggregate risk premiums including the risk-free rate (RF), variance risk premium (VRP), three equity risk premiums (MKT, SMB, and HML), liquidity risk premium (MLIQ), term premium (UTS), and corporate default premium (UPR). All variables are monthly observations from January 2001 to November 2012. The number of firms investigated is 388 for all regressions. Parameter estimates and adjusted R^2 are averaged across firm-by-firm regressions and associated *t*-statistics (reported in parentheses) are calculated for the average estimates as in Collin-Dufresne *et al*. (2001). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	M1	M2	M3	M4	M5	M6	M7
				Panel A: DRP			
Firm-specific variables							
ΔLEV	0.86***	0.79***	0.64**	0.27	0.97***	0.73**	0.13
	(2.87)	(2.76)	(2.10)	(0.92)	(3.18)	(2.44)	(0.42)
ΔHV	0.46***	0.33***	0.68***	0.23**	0.33***	0.08	-0.18
	(4.71)	(3.19)	(6.39)	(2.25)	(3.43)	(0.78)	(-1.13)
ΔIV	0.13*	0.12	-0.02	-0.03	0.08	0.12*	-0.01
	(1.77)	(1.60)	(-0.28)	(-0.41)	(1.18)	(1.67)	(-0.18)
Market-wide risk premiums							
ΔRF		-6.27***					-2.69*
		(-4.82)					(-1.87)
ΔVRP			0.51***				0.11
			(5.48)				(1.07)
MKT				-0.73***			-0.60***
				(-5.47)			(-3.84)
SMB				-0.13			0.04
				(-1.22)			(0.33)
HML				0.36*			0.01
				(1.83)			(0.06)
MLIQ					-0.45***		-0.36***
					(-4.23)		(-3.88)
ΔUTS						1.70	2.25**
						(1.49)	(2.05)
ΔUPR						14.16***	11.77***
						(4.68)	(3.36)
Adj.R^2	0.21	0.24	0.22	0.26	0.23	0.25	0.33
				Panel B: DRP Proportion			
Firm-specific variables							
ΔLEV	0.21*	0.18	0.20**	0.08	0.24*	0.20	0.14
	(1.66)	(1.46)	(2.41)	(0.92)	(1.92)	(1.58)	(1.39)
ΔHV	0.13***	0.09***	0.18***	0.07***	0.09***	0.04	-0.02
	(5.57)	(3.68)	(6.29)	(3.27)	(4.12)	(1.43)	(-0.43)
ΔIV	0.06***	0.06***	0.02	0.01	0.05***	0.05***	0.00
	(4.95)	(4.96)	(1.32)	(1.22)	(4.32)	(4.25)	(0.21)
Market-wide risk premiums							
ΔRF		-2.10***					-1.64***
		(-8.20)					(-5.20)
ΔVRP			0.09***				0.00
			(3.29)				(-0.03)
MKT				-0.15***			-0.12***
				(-5.75)			(-3.21)
SMB				-0.11***			-0.05
				(-4.07)			(-1.38)
HML				0.04			-0.01
				(1.50)			(-0.17)
MLIQ					-0.10***		-0.07***
					(-6.19)		(-3.69)
ΔUTS						1.36***	1.98***
						(5.86)	(7.08)
ΔUPR						3.80***	2.55***
						(6.34)	(4.12)
Adj.R^2	0.10	0.12	0.11	0.13	0.10	0.11	0.15

Table 5. The Effect of Distress Risk Premium on the Explanatory Power of Merton Variables

This table shows the result of regressions in (2). The dependent variables are CDS spread changes. The explanatory variables are changes in the structural variables including the leverage ratio (LEV), historical volatility (HV), option-implied volatility (IV), and risk-free rate (RF). All variables are monthly changes from January 2001 to November 2012. We sort sample firms by the average distress risk premium (DRP) proportion calculated using the PS model and assign them to five groups. Group 1 (shown in Panel A) to Group 5 (shown in Panel E) correspond to the lowest to the highest DRP proportion group. Parameter estimates and adjusted R^2 are averaged across firm-by-firm regressions, and associated *t*-statistics (reported in parentheses) are calculated for the average estimates as in Collin-Dufresne *et al*. (2001). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	M1	M2	M3	M4	M5
	Panel A: Group 1 (Lowest DRP Proportion)				
ΔLEV	11.22***	10.47***	7.74***	7.43***	6.86***
	(7.62)	(7.02)	(5.46)	(5.19)	(5.09)
ΔHV		2.10***		1.52***	1.33***
		(6.33)		(5.06)	(4.45)
ΔIV			1.49***	1.39***	1.35***
			(5.84)	(5.49)	(5.39)
ΔRF					-25.89***
					(-4.65)
N	77	77	77	77	77
Adj.R2	0.16	0.19	0.25	0.27	0.29
	Panel B: Group 2				
ΔLEV	7.94***	7.28***	6.29***	5.96***	5.54***
	(9.19)	(8.73)	(9.32)	(8.71)	(8.00)
ΔHV		2.11***		1.70***	1.40***
		(5.37)		(4.94)	(4.22)
ΔIV			0.99***	0.87***	0.79***
			(5.31)	(5.05)	(4.73)
ΔRF					-28.53***
					(-5.08)
N	78	78	78	78	78
Adj.R2	0.18	0.21	0.21	0.23	0.27
	Panel C: Group 3				
ΔLEV	5.31***	4.86***	4.31***	4.07***	3.87***
	(9.17)	(8.73)	(8.03)	(7.72)	(7.48)
ΔHV		1.41***		1.17***	0.94***
		(6.62)		(5.59)	(4.60)
ΔIV			0.69***	0.62***	0.58***
			(7.04)	(6.31)	(5.92)
ΔRF					-15.18***
					(-6.00)
N	78	78	78	78	78
Adj.R2	0.13	0.16	0.17	0.20	0.23
	Panel D: Group 4				
ΔLEV	3.43***	2.98***	2.61***	2.31***	1.92***
	(8.05)	(7.71)	(6.65)	(6.30)	(5.85)
ΔHV		0.88**		0.67*	0.42
		(2.37)		(1.95)	(1.23)
ΔIV			0.60***	0.54***	0.52***
			(6.62)	(7.02)	(7.19)
ΔRF					-14.99***
					(-5.08)
N	78	78	78	78	78
Adj.R2	0.11	0.14	0.15	0.17	0.21

Panel E: Group 5 (Highest DRP Proportion)

ΔLEV	3.90***	3.83***	3.15***	3.12***	2.97***
	(7.21)	(7.33)	(6.24)	(6.26)	(5.98)
ΔHV		1.00***		0.84***	0.56*
		(4.37)		(3.47)	(1.68)
ΔIV			0.50***	0.48***	0.44***
			(4.32)	(4.15)	(3.83)
ΔRF					-17.25***
					(-6.06)
N	77	77	77	77	77
Adj.R2	0.10	0.12	0.14	0.15	0.19

Table 6. The Effect of Distress Risk Premium on the Explanatory Power of Merton Variables: Controlling for Firm Characteristics

This table reports the result of regressions in (10). The dependent variables are CDS spread changes. The explanatory variables are changes in the structural variables including the leverage ratio, historical volatility, option-implied volatility, and risk-free rate. All variables are monthly changes from January 2001 to November 2012. We use nine portfolios formed from the intersection of tercile portfolios sorted by averages of the distress risk premium (DRP) proportion and each firm characteristic including the leverage ratio, historical volatility, option-implied volatility, equity illiquidity, CDS liquidity, and credit ratings. The DRP of each firm is calculated using the PS model. For each portfolio, adjusted R^2 is averaged across firm-by-firm regressions. The averages (L-H) and *t*-statistics (shown in parentheses) are calculated from the difference in adjusted R^2 between the groups with the lowest and the highest DRP proportion. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

DRP proportion	Group by Firm Characteristics		
	Low	Medium	High
	Leverage ratio		
Low	0.21	0.27	0.33
Med	0.21	0.25	0.27
High	0.14	0.22	0.23
L-H	0.07**	0.05*	0.10***
t-statistics	(2.09)	(1.49)	(2.73)
	Historical volatility		
Low	0.22	0.29	0.30
Med	0.19	0.30	0.23
High	0.16	0.22	0.20
L-H	0.06**	0.08**	0.10***
t-statistics	(2.07)	(2.09)	(2.59)
	Implied volatility		
Low	0.21	0.33	0.29
Med	0.19	0.30	0.23
High	0.18	0.20	0.20
L-H	0.04	0.13***	0.09**
t-statistics	(1.28)	(3.59)	(2.21)
	Equity illiquidity		
Low	0.31	0.28	0.26
Med	0.24	0.28	0.19
High	0.21	0.18	0.18
L-H	0.10***	0.10***	0.07**
t-statistics	(2.66)	(3.09)	(2.02)
	CDS liquidity		
Low	0.18	0.34	0.33
Med	0.14	0.26	0.30
High	0.12	0.23	0.22
L-H	0.06**	0.10***	0.11***
t-statistics	(1.82)	(3.18)	(3.37)
	Credit ratings		
Low	0.27	0.28	0.30
Med	0.27	0.24	0.22
High	0.21	0.19	0.18
L-H	0.06*	0.08***	0.11***
t-statistics	(1.56)	(2.68)	(3.03)

Table 7. Test for the Time-varying Effect of Distress Risk Premium on the Explanatory Power of Merton Variables: Controlling for Firm Characteristics

This table reports the results of root-mean-squared errors in (9). The root-mean-squared errors are calculated from regressions in (10). The dependent variables are CDS spread changes. The explanatory variables are changes in the structural variables including the leverage ratio, historical volatility, option-implied volatility, and risk-free rate. All variables are monthly changes from January 2001 to November 2012. To control firm characteristics, we sort sample firms into nine portfolios formed from the intersection of tercile portfolios sorted by the distress risk premium (DRP) proportion and each firm characteristic in each month. The DRP of each firm is calculated using the PS model and the firm characteristics include the leverage ratio, historical volatility, option-implied volatility, equity illiquidity, CDS liquidity, and credit ratings. For each time point, root-mean-squared errors are calculated from the lowest DRP proportion to the highest DRP proportion group. From the time series root-mean-squared errors of the two groups, the averages (L-H) and *t*-statistics (shown in parentheses) from the difference of root-mean-squared errors are calculated for each group sorted by firm characteristics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

DRP proportion	Group by Firm Characteristics		
	Low	Medium	High
		Leverage ratio	
L-H	-0.27***	-0.16***	-0.17**
t-statistics	(-3.15)	(-2.37)	(-2.04)
		Historical volatility	
L-H	-0.23***	-0.23***	-0.15*
t-statistics	(-3.68)	(-3.29)	(-1.56)
		Implied volatility	
L-H	-0.20***	-0.25***	-0.18**
t-statistics	(-2.93)	(-4.08)	(-1.81)
		Equity illiquidity	
L-H	-0.22***	-0.12**	-0.10
t-statistics	(-2.96)	(-1.68)	(-1.12)
		CDS liquidity	
L-H	-0.12*	-0.17***	-0.16**
t-statistics	(-1.59)	(-2.41)	(-2.01)
		Credit ratings	
L-H	-0.17**	-0.18**	-0.10
t-statistics	(-2.00)	(-2.28)	(-1.11)

Table 8. Cross-sectional Relation between Adjusted R^2 and Distress Risk Premiums

This table shows the result of cross-sectional regressions of explanatory power, measured by adjusted R^2, on the average distress risk premium (DRP) proportions. We perform two-pass regressions. The first-pass (time series) regressions are conducted firm-by-firm for either:

$$\text{Level regression: } CDS_{i,t} = \beta_0 + \beta_1 LEV_{i,t} + \beta_2 HV_{i,t} + \beta_3 IV_{i,t} + \beta_4 RF_t + \varepsilon_{i,t},$$

or

$$\text{Change regression: } \Delta CDS_{i,t} = \beta_0 + \beta_1 \Delta LEV_{i,t} + \beta_2 \Delta HV_{i,t} + \beta_3 \Delta IV_{i,t} + \beta_4 \Delta RF_t + \varepsilon_{i,t}.$$

Using the adjusted R^2s obtained from the first-pass regressions as the dependent variables, the second-pass regression is performed by

$$R_i^2 = \alpha + \beta \times \bar{p}_i^{DRP} + \gamma' X_i + \varepsilon_i.$$

Panels A and B show the results using level regression R^2s and change regression R^2s as the dependent variables of the second stage, respectively. The second stage explanatory variables are time series-averaged over the period where each firm's observations are available. The cross-sectional regressions use standardized variables so that the importance of each variable is comparable. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	M1	M2	M3	M4	M5	M6	M7	M8
				Panel A. Level Regression R^2				
$\bar{p}^{DRP}$	-0.21***	-0.21***	-0.21***	-0.21***	-0.21***	-0.21***	-0.21***	-0.17***
	(-4.18)	(-3.95)	(-4.09)	(-4.20)	(-4.16)	(-4.09)	(-4.26)	(-3.32)
Control variables								
LEV		0.014						0.08
		(0.28)						(1.38)
HV			0.03					0.47***
			(0.59)					(2.87)
IV				-0.02				-0.30*
				(-0.40)				(-1.71)
ILLIQ					-0.09*			-0.13**
					(-1.78)			(-2.40)
DEPTH						0.04		-0.002
						(0.74)		(-0.03)
RATING							0.14***	0.23***
							(2.78)	(3.29)
Adj. R^2	0.04	0.04	0.04	0.04	0.05	0.04	0.06	0.09
				Panel B. Change Regression R^2				
$\bar{p}^{DRP}$	-0.27***	-0.20***	-0.25***	-0.25***	-0.26***	-0.23***	-0.26***	-0.16***
	(-5.37)	(-4.08)	(-5.09)	(-5.12)	(-5.35)	(-4.96)	(-5.35)	(-3.45)
Control variables								
LEV		0.23***						0.16***
		(4.50)						(2.89)
HV			0.12**					0.24
			(2.50)					(1.64)
IV				0.10*				-0.05
				(1.95)				(-0.31)
ILLIQ					-0.04			-0.08*
					(-0.79)			(-1.77)
DEPTH						0.38***		0.40***
						(8.39)		(8.59)
RATING							-0.06	0.02
							(-1.30)	(0.35)
Adj. R^2	0.07	0.11	0.08	0.07	0.07	0.21	0.07	0.27

Table 9. Robustness Test for the Effect of Distress Risk Premium on the Explanatory Power of Merton Variables

This table reports the results of the regressions in (10). The dependent variables are CDS spread changes. The explanatory variables are changes in the structural variables including the leverage ratio, historical volatility, option-implied volatility, and risk-free rate. All variables are monthly changes from January 2001 to November 2012 (in Panel A), but the period of the global financial crisis is excluded in Panel B. We use nine portfolios formed from the intersection of tercile portfolios sorted by the average of the distress risk premium (DRP) proportion and each firm characteristic including the leverage ratio, historical volatility, option-implied volatility, equity illiquidity, CDS liquidity, and credit ratings. The DRP of each firm is calculated either using Friewald *et al.*'s (2014) model (shown in Panel A) or the PS model (shown in Panel B). For each portfolio, adjusted R^2 is averaged across firm-by-firm regressions. The averages (L-H) and *t*-statistics (shown in parentheses) are calculated from the difference in the adjusted R^2 between the groups with the lowest and the highest DRP proportion. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: DRP by Friewald *et al*. (2014)				Panel B: Excluding the financial crisis period			
DRP proportion	Group by firm characteristics			DRP proportion	Group by firm characteristics		
	Low	Medium	High		Low	Medium	High
	Leverage ratio				Leverage ratio		
Low	0.23	0.31	0.36	Low	0.19	0.25	0.25
Med	0.18	0.25	0.26	Med	0.13	0.20	0.30
High	0.15	0.18	0.22	High	0.12	0.18	0.19
L-H	0.07***	0.13***	0.15***	L-H	0.07**	0.07**	0.06*
t-statistic	(2.41)	(3.74)	(4.06)	*t*-statistic	(1.94)	(2.15)	(1.66)
	Historical volatility				Historical volatility		
Low	0.25	0.33	0.34	Low	0.16	0.26	0.26
Med	0.17	0.26	0.25	Med	0.12	0.24	0.25
High	0.15	0.17	0.21	High	0.14	0.17	0.17
L-H	0.10***	0.16***	0.12***	L-H	0.02	0.09***	0.09***
t-statistic	(3.21)	(4.22)	(3.40)	*t*-statistic	(0.58)	(2.67)	(2.45)
	Implied volatility				Implied volatility		
Low	0.24	0.34	0.32	Low	0.17	0.29	0.24
Med	0.17	0.26	0.25	Med	0.12	0.24	0.23
High	0.16	0.17	0.20	High	0.16	0.17	0.16
L-H	0.08***	0.16***	0.12***	L-H	0.01	0.13***	0.08**
t-statistic	(2.94)	(4.40)	(3.19)	*t*-statistic	(0.31)	(3.75)	(2.12)
	Equity illiquidity				Equity illiquidity		
Low	0.31	0.32	0.28	Low	0.27	0.24	0.21
Med	0.23	0.21	0.25	Med	0.17	0.24	0.19
High	0.17	0.21	0.17	High	0.21	0.14	0.15
L-H	0.14***	0.11***	0.11***	L-H	0.06**	0.10***	0.06*
t-statistic	(3.93)	(3.06)	(3.03)	*t*-statistic	(1.73)	(3.11)	(1.66)
	CDS liquidity				CDS liquidity		
Low	0.23	0.32	0.34	Low	0.11	0.29	0.30
Med	0.15	0.27	0.25	Med	0.11	0.21	0.27
High	0.11	0.25	0.23	High	0.09	0.19	0.21
L-H	0.12***	0.07**	0.11***	L-H	0.02	0.10***	0.09***
t-statistic	(4.11)	(1.90)	(2.74)	*t*-statistic	(0.73)	(3.05)	(2.92)
	Credit ratings				Credit ratings		
Low	0.32	0.28	0.31	Low	0.23	0.24	0.25
Med	0.27	0.25	0.18	Med	0.26	0.21	0.14
High	0.19	0.17	0.19	High	0.18	0.15	0.16
L-H	0.13***	0.12***	0.12***	L-H	0.05	0.09***	0.08**
t-statistic	(3.48)	(3.77)	(3.10)	*t*-statistic	(1.21)	(2.94)	(2.32)

Table 10. Robustness Test for the Time-varying Effect of Distress Risk Premium on the Explanatory Power of Merton Variables

This table reports the result of root-mean-squared errors in (9). The root-mean-squared errors are calculated from regressions in (10). The dependent variables are CDS spread changes. The explanatory variables are changes in the structural variables including the leverage ratio, historical volatility, option-implied volatility, and risk-free rate. All variables are monthly changes from January 2001 to November 2012 (in Panel A), but the period of the global financial crisis is excluded in Panel B. To control firm characteristics, we sort sample firms into nine portfolios formed from the intersection of tercile portfolios sorted by the distress risk premium (DRP) proportion and each firm characteristic in each month. The DRP for each firm is calculated either using Friewald *et al.*'s (2014) model (shown in Panel A) or the PS model (shown in Panel B). The firm characteristics include the leverage ratio, historical volatility, option-implied volatility, equity illiquidity, CDS liquidity, and credit ratings. For each time point, root-mean-squared errors are calculated from the lowest DRP proportion to the highest DRP proportion group. From the time series root-mean-squared errors of the two groups, the averages (L-H) and *t*-statistics (shown in parentheses) from the difference of root-mean-squared errors are calculated for each group sorted by firm characteristics. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: DRP by Friewald *et al*. (2014)				Panel B: Excluding the financial crisis period			
DRP proportion	Group by firm characteristics			DRP proportion	Group by firm characteristics		
	Low	Medium	High		Low	Medium	High
	Leverage ratio				Leverage ratio		
L-H	-0.22***	-0.24***	-0.35***	L-H	-0.25***	-0.17**	-0.17**
t-statistics	(-3.07)	(-3.68)	(-4.28)	*t*-statistics	(-2.88)	(-2.22)	(-2.04)
	Historical volatility				Historical volatility		
L-H	-0.18***	-0.26***	-0.33***	L-H	-0.23***	-0.24***	-0.14*
t-statistics	(-2.64)	(-3.91)	(-3.96)	*t*-statistics	(-3.80)	(-3.46)	(-1.45)
	Implied volatility				Implied volatility		
L-H	-0.20***	-0.21***	-0.34***	L-H	-0.19***	-0.24***	-0.19**
t-statistics	(-2.89)	(-3.49)	(-3.87)	*t*-statistics	(-2.81)	(-3.78)	(-1.98)
	Equity illiquidity				Equity illiquidity		
L-H	-0.24***	-0.25***	-0.30***	L-H	-0.24***	-0.13*	-0.11
t-statistics	(-3.17)	(-3.93)	(-3.82)	*t*-statistics	(-3.29)	(-1.61)	(-1.16)
	CDS liquidity				CDS liquidity		
L-H	-0.24***	-0.26***	-0.32***	L-H	-0.11*	-0.20***	-0.19***
t-statistics	(-3.12)	(-3.88)	(-4.31)	*t*-statistics	(-1.33)	(-2.70)	(-2.45)
	Credit ratings				Credit ratings		
L-H	-0.28***	-0.31***	-0.21***	L-H	-0.14*	-0.19**	-0.14**
t-statistics	(-3.31)	(-4.56)	(-2.46)	*t*-statistics	(-1.51)	(-2.26)	(-1.71)

Table 11. Robustness Check for the Cross-sectional Regression

This table shows the result of the robustness check of the cross-sectional regressions using an alternative measure of the distress risk premium (DRP) suggested by Friewald *et al*. (2014). We perform two-pass regressions. The first-pass (time series) regressions are conducted firm-by-firm for either:

Level regression: $CDS_{i,t} = \beta_0 + \beta_1 LEV_{i,t} + \beta_2 HV_{i,t} + \beta_3 IV_{i,t} + \beta_4 RF_t + \varepsilon_{i,t}$,

or

Change regression: $\Delta CDS_{i,t} = \beta_0 + \beta_1 \Delta LEV_{i,t} + \beta_2 \Delta HV_{i,t} + \beta_3 \Delta IV_{i,t} + \beta_4 \Delta RF_t + \varepsilon_{i,t}$.

Using the adjusted R^2s obtained from the first-pass regressions as the dependent variables, the second-pass regression is performed by

$$R_i^2 = \alpha + \beta \times \bar{p}_i^{DRP} + \gamma' X_i + \varepsilon_i.$$

Panels A and B show the results using level regression R^2s and change regression R^2s as the dependent variables of the second stage, respectively. The second stage explanatory variables are time series-averaged over the period where each firm's observations are available. The cross-sectional regressions use standardized variables so that the importance of each variable is comparable. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	M1	M2	M3	M4	M5	M6	M7	M8
	Panel A. Level Regression R^2							
$\bar{p}^{DRP}$	-0.24***	-0.23***	-0.24***	-0.24***	-0.24***	-0.24***	-0.23***	-0.22***
	(-4.77)	(-4.57)	(-4.71)	(-4.75)	(-4.81)	(-4.66)	(-4.65)	(-4.18)
Control variables								
LEV		0.03						0.09
		(0.65)						(1.59)
HV			0.05					0.51***
			(1.03)					(3.15)
IV				0.001				-0.36**
				(0.02)				(-2.05)
ILLIQ					-0.09*			-0.14***
					(-1.89)			(-2.71)
DEPTH						-0.01		-0.04
						(-0.11)		(-0.81)
RATING							0.11**	0.19***
							(2.11)	(2.77)
Adj. R^2	0.05	0.05	0.05	0.05	0.06	0.05	0.06	0.10
	Panel B. Change Regression R^2							
$\bar{p}^{DRP}$	-0.30***	-0.26***	-0.29***	-0.29***	-0.30***	-0.22***	-0.31***	-0.18***
	(-6.15)	(-5.33)	(-6.04)	(-6.01)	(-6.16)	(-4.64)	(-6.30)	(-3.76)
Control variables								
LEV		0.24***						0.17***
		(4.93)						(3.24)
HV			0.14***					0.27*
			(2.97)					(1.86)
IV				0.12**				-0.09
				(2.38)				(-0.58)
ILLIQ					-0.05			-0.10**
					(-0.94)			(-2.07)
DEPTH						0.35***		0.37***
						(7.47)		(7.75)
RATING							-0.10**	-0.002
							(-2.07)	(-0.03)
Adj. R^2	0.09	0.14	0.11	0.10	0.09	0.20	0.10	0.27

Table 12. Summary Statistics for Maximum Likelihood Estimates of Model Parameters

This table shows the summary statistics for maximum likelihood (ML) estimates. The ML estimation is carried out for each firm by using monthly term structure observations from January 2001 to November 2012. The term structure we estimate consists of CDS spreads with one-, five-, and ten-year maturities. Following the PS model, κ^P, $\kappa^P\theta^P$, and σ are parameters of a log-normal process under the physical measure in (3). κ^Q and $\kappa^Q\theta^Q$ correspond to those under the risk-neutral measure. The two measures are linked from the specified market price of risk with parameters δ_0 and δ_1. $\sigma_\epsilon(1)$ and $\sigma_\epsilon(10)$ are standard deviations for the pricing errors in CDSs with one- and ten-year maturities. Statistics for mean values of log-likelihood are reported at the bottom.

	MEAN	MEDIAN	STD	5th PCTL	95th PCTL
κ^P	0.8671	0.5322	2.1329	-0.0040	2.5382
$\kappa^P\theta^P$	-4.5954	-2.6644	11.2855	-13.7520	0.1806
σ	0.9838	0.9770	0.2340	0.6747	1.3025
κ^Q	0.0741	0.0772	0.1287	-0.1187	0.2341
$\kappa^Q\theta^Q$	-0.3613	-0.3814	0.5132	-1.0806	0.4748
$\sigma_\epsilon(1)$	0.0038	0.0021	0.0051	0.0006	0.0131
$\sigma_\epsilon(10)$	0.0022	0.0015	0.0024	0.0006	0.0056
δ_0	-4.3101	-2.5663	10.1240	-14.2869	0.6998
δ_1	-0.8818	-0.5082	2.9091	-2.3783	0.1788
Log likelihood	14.59	14.72	2.38	10.31	18.01

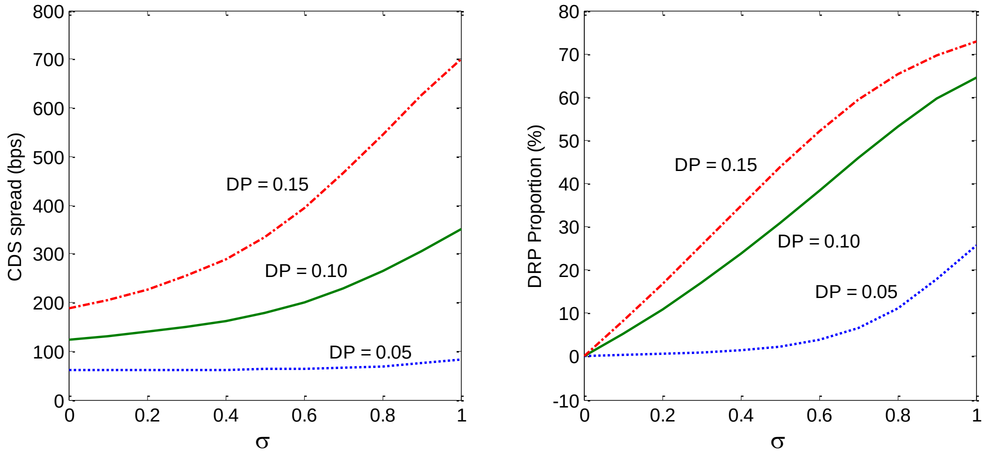

Figure 1. The Effect of Distress Risk on the CDS Spread and DRP Proportion

This figure displays the theoretical CDS spread (left panel) and the distress risk premium (DRP) proportion (right panel) depending on different variation levels of the default intensity process σ from 0 to 1 while keeping the expected default probability (DP) until the maturity of the contract constant. The specification of the default intensity is shown in equation (3), and the CDS spread is calculated by equation (15) for the five-year maturity. We set the current default intensity, λ_t^Q, and the parameters for the market price of risk, δ_0 and δ_1, to be 0.005, -2.906, and -0.619, respectively. The parameter of the mean-reversion rate under the physical measure κ^P, is fixed to 0.637 and the long-term mean parameter θ^P, is adjusted to hold constant the default probability (DP) at 0.05, 0.10, and 0.15.

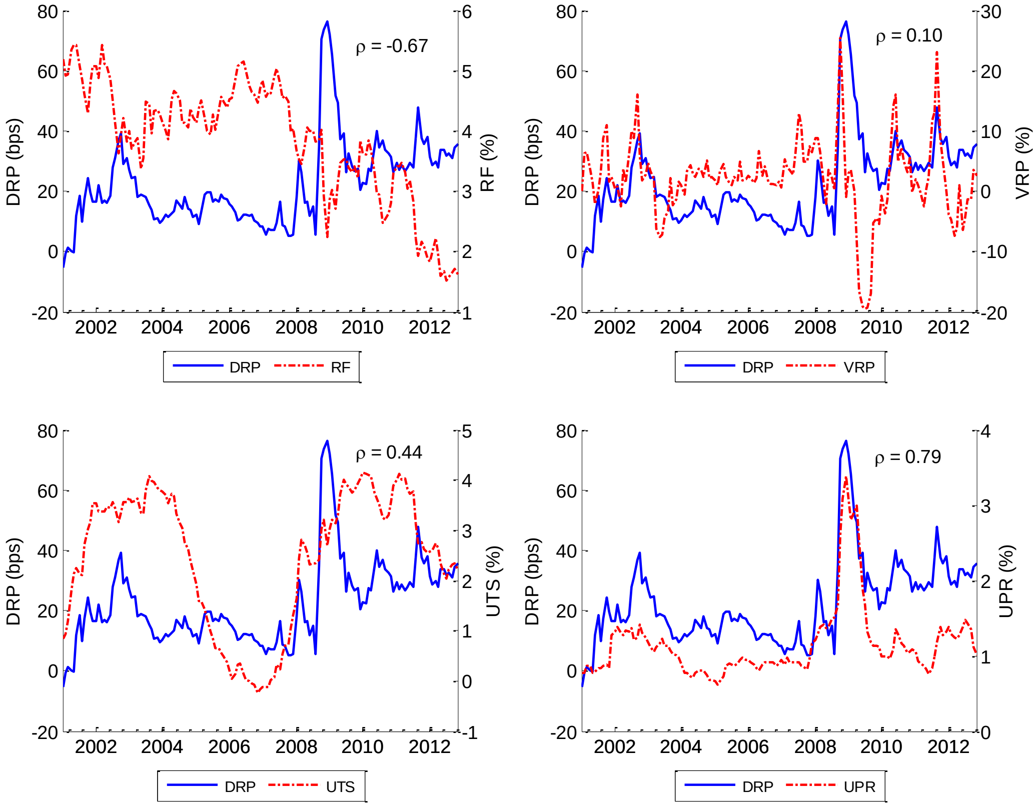

Figure 2. Time Series of the Aggregate Distress Risk Premium and Market-wide Risk Premiums

This figure shows the time series of the aggregate distress risk premium (DRP) and market-wide risk premiums. The DRP is calculated using the PS model. The market-wide risk premiums include the risk-free rate (RF), variance risk premium (VRP), term premium (UTS), and corporate default premium (UPR). All the variables are monthly observations from January 2001 to November 2012. The aggregate DRP is calculated by averaging cross-sectional DRPs in each month. The aggregate DRP is plotted with the solid line. Time series of market-wide risk premiums are plotted with the dashed line.

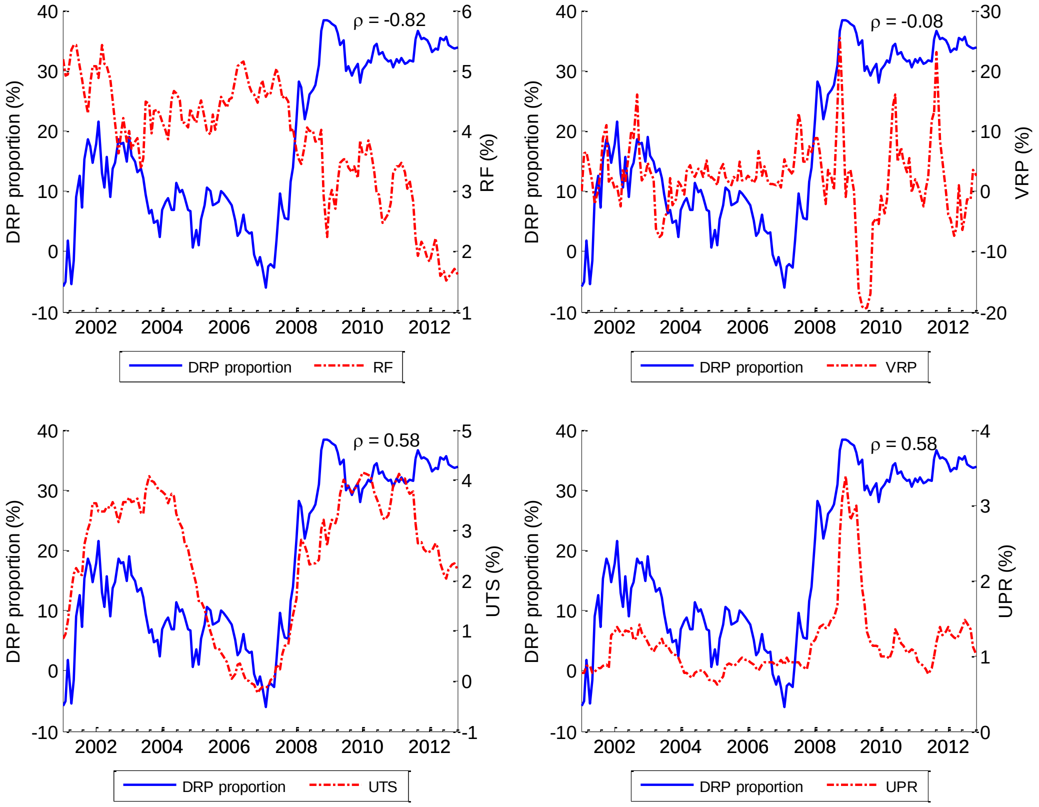

Figure 3. Time Series of the Aggregate Distress Risk Premium Proportion and Market-wide Risk Premiums

This figure shows the time series of aggregate distress risk premium (DRP) proportion and market-wide risk premiums. The DRP is calculated using the PS model. The market-wide risk premiums include the risk-free rate (RF), variance risk premium (VRP), term premium (UTS), and corporate default premium (UPR). All the variables are monthly observations from January 2001 to November 2012. The aggregate DRP proportion is calculated by averaging cross-sectional DRP proportions in each month. The aggregate DRP proportion is plotted with the solid line. Time series of market-wide risk premiums are plotted with the dashed line.

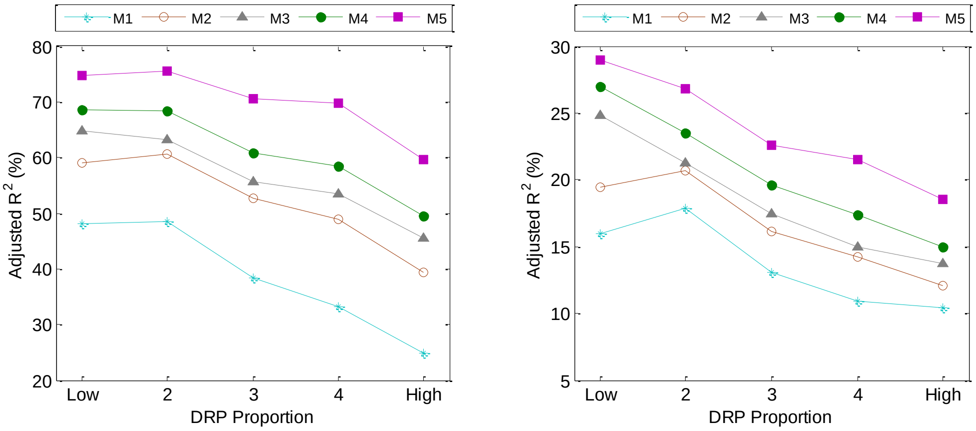

Figure 4. Explanatory Power Change of Merton Variables by Distress Risk Premium

This figure shows average adjusted R^2s of five distress risk premium (DRP) proportion groups. The left panel shows the adjusted R^2s obtained from the level regression of (1). The right panel shows the adjusted R^2s obtained from the change regression of (2). The dependent variables are CDS spreads, and the explanatory variables are the structural variables including the leverage ratio, historical volatility, option-implied volatility, and risk-free rate. All variables are monthly observations from January 2001 to November 2012. We sort sample firms by the average of the DRP proportion calculated using the PS model and assign them to five groups. Group 1 to Group 5 correspond to the lowest to the highest DRP proportion group. Adjusted R^2 are averaged across firm-by-firm regressions. The specifications of the models can be found in Table 5.