Beyond Distress Risk*

Altan Pazarbasi†

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Abstract

I identify a systematic credit risk factor in the Credit Default Swaps (CDS) market. This factor accounts for most of the cross-sectional variation in individual stock returns during 2003–2014. In the cross-section, distressed firms have larger exposures to the systematic credit risk factor, which shrinks positive distress alphas found in recent literature. The systematic credit risk also captures the time-series variation in equity returns, cash flow growth and state of the macroeconomy. A no-arbitrage, dynamic asset-pricing model delivers a structural interpretation for the empirical findings: By investing in distressed firms, investors are exposed to macroeconomic credit shocks beyond firm-specific financial distress risk.

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†Frankfurt School of Finance & Management; E-mail: a.pazarbasi@fs.de

I. Introduction

A large body of literature documents that observed credit spreads are driven by not only firm-specific credit-event risk but also systematic credit risk. Despite the ongoing debate on its source, researchers agree on the larger role of systematic credit risk in generating sizeable credit spreads.[1] On the other hand, most asset-pricing studies focus on the link between *firm-specific* financial distress and the cross-section of equity returns without any emphasis on the systematic nature of defaults. Amid conflicting findings on distress risk premium (i.e., "distress puzzle"), whether and to what extent systematic credit risk is associated with equity returns is an open question. This paper aims to close this gap by providing new insight on the connection between distressed firms and systematic credit risk. Importantly, investors pay attention to the sources (e.g., fundamental vs. discount rate shocks) and dimensions (e.g., cross-sectional vs. time-series effects) of risks that they are exposed to. This paper intends to provide such risk decomposition for distressed firms, with an emphasis on the role of systematic credit risk as a risk channel beyond firm-specific distress.

I use a latent slope factor identified in credit default swaps (CDS) returns to test the effect of systematic credit risk on asset prices. Systematic credit risk indeed matters for asset prices, as the slope factor accounts for the most of cross-sectional variation in stock returns. Firms with distress characteristics (such as high leverage and book-to-market ratios) and higher cash flow riskiness load positively on this slope factor. Such findings emphasize a tight link between distressed firms and systematic credit risk, suggesting a role for systematic credit risk in the risk-based explanation of distress risk premium. Furthermore, the slope factor is highly correlated with the default spread, a commonly used state variable (credit conditions) that predicts future macroeconomic activity. Ultimately, my analysis shows that investors load up more on macroeconomic shocks in credit conditions by investing in distressed firms.

My paper makes three contributions. First, it shows that a latent systematic risk factor in the CDS market is priced in the cross-section of equity returns during 2003–2014. For this purpose, I conduct a principal component analysis to identify a slope factor in CDS portfolio returns on which high (low) CDS return portfolios load positively (negatively). Two-step Fama MacBeth tests reveal

[1] Papers that document the role of systematic credit risk on observed credit spreads include, e.g., Zhou (2001) (default correlations), Duffie, Eckner, Horel, and Saita (2009) (default clustering due to latent state variables), Jarrow and Yu (2001) (counterparty risks), Bai, Collin-Dufresne, Goldstein, and Helwege (2015) (contagion effects).

that the slope factor explains a significant variation in the *entire* cross-section of individual stock returns. Moreover, the slope factor is very similar to another factor I propose, *CRX*, which is the zero-cost portfolio that goes long the highest CDS return portfolio and short on the lowest CDS return portfolio. Loading up on latent systematic credit risk, the CRX factor gives an *equity market* price estimate of 10.4% *per year* during 2003–2014. The redundancy tests show that the CRX factor is mostly orthogonal and not explained by the Fama-French factors. Those results are robust to the exclusion of the financial crises period, as the effect of systematic credit risk in the analysis remains significant.

The second contribution is to demonstrate the empirical link between distressed firms and systematic credit risk. I first show that key proxies for expected default rates, such as market leverage and book-to-market ratios, are increasing with firms' sensitivity to systematic credit risk, that is, the CRX factor. In contrast, firm size is rather U-shaped, with the sensitivity to systematic credit risk, as both the highest and the lowest CRX quantile portfolios are associated with small firm size. Such findings are consistent with Garlappi and Yan (2011) who argue that leverage amplifies the book-to-market effect due to shareholder recovery option in strategic defaults. My findings suggest that the fluctuations in credit conditions are linked not only to the *incidence* of firm-level financial distress but also to the *resolution* of such distress. That is, the co-movement in credit risk premia is another key ingredient in a risk-based explanation of distress risk premium.

Next, I show that distress risk premium can indeed be attributed to systematic credit risk. Recently, Friewald, Wagner, and Zechner (2014) illustrate the Merton (1974) type structural link between equity and CDS returns, the latter being a distress measure that captures both real and risk-neutral probabilities. Similar to Friewald et al. (2014) findings, my analysis reveals distress risk premium with the high-minus-low portfolios sorted on CDS returns earning significant risk-adjusted alphas of 2.9% per month. However, a multi-firm extension of the structural framework motivates the fact that such risk premia are decomposed into firm-specific and systematic components. Indeed, I find that the high-minus-low credit risk portfolio premia shrink by 57% to 1.24% per month when the CRX factor is included in the factor models. Those results are mostly driven by distressed firms. The highest credit risk portfolio also has high exposure to systematic credit risk, which shrinks the factor model portfolio alpha to insignificant levels. Overall, the results contribute to the risk-based explanation for the high performance of distressed stocks. By investing in such stocks, investors load up on both firm-specific distress risk and systematic credit risk.

My third contribution is to highlight the connection between the cash flow fundamentals and the sensitivity to systematic credit risk, which is further linked to the state of the economy, that is, credit conditions. I demonstrate a systematic difference in cash flow growth for stocks with the highest and the lowest sensitivity to the CRX factor. The dividends on stocks with a high CRX-Beta experience a larger drop during deteriorating credit conditions, while stocks with a low CRX-Beta display a rather robust dividend-cycle. Such drop and recovery patterns in dividends suggest that the positive risk premium of systematic credit risk documented by asset-pricing tests is also related to cash flow risk. To formalize this link, I set up and calibrate a structural asset-pricing model that accounts for the dynamics of dividends, fluctuations in credit conditions[2] and CRX risk premia. The model fits well with the observed data, highlighting the key role of fluctuating credit conditions in CRX risk premia. Exposure to cyclical credit risk contributes positively to CRX risk premia, although the firm-specific distress risk is the main driver of expected excess returns. On the other hand, cyclical risk dominates the variation in price-dividend ratio and excess returns. Thus, the model ultimately delivers a structural interpretation for the link between distress risk premium and systematic credit risk. By investing in firms with distress characteristics, investors are not only compensated for firm-level financial distress risk but also exposed to global macroeconomic credit shocks.

A. *Related Literature*

Researchers have examined the systematic nature of credit events to explain corporate debt prices as well as high co-movement in credit spreads. Extensions of structural models, such as Zhou (2001) and Hull, Predescu, and White (2010), mostly aim to incorporate the joint probability of default as a systematic channel in asset pricing. Another strand of the literature proposes reduced form (default intensity) models, which investigate unobserved covariates beyond structural model risk factors (e.g., leverage, volatility) that determine conditional default probabilities. This literature has focused on explaining correlated changes in corporate default probabilities (see Das,

[2] Shocks to financial intermediary leverage would be an alternative channel that gives rise to the systematic credit risk premia. However, CRX's correlation with the leverage factor of Adrian, Etula, and Muir (2014) is rather low (-0.37) compared to its correlation with the Moody's default spread (0.83). The redundancy tests in Section IV.D also point out a large CRX risk premia that is not captured by the intermediary leverage factor.

Freed, Geng, and Kapadia (2002)) via counterparty risk (e.g., Jarrow and Yu (2001)), contagion-type non-diversifiable jump risk (e.g., Benzoni, Collin-Dufresne, Goldstein, and Helwege (2015), and Bai et al. (2015)) or latent state variables (e.g., Duffie et al. (2009)). Although those papers have already documented the role of non-diversifiable credit risk on observed credit spreads, whether such systematic credit risk is also associated with equity returns is still an open question. This paper uses an extension of the structural model only for illustrative purposes, without aiming to estimate the model. Thus, my estimates of systematic credit risk emerge only from econometric specifications.

I contribute to the empirical literature on asset pricing related to systematic distress risk, starting with Chen, Roll, and Ross (1986) and Fama and French (1993). Those seminal papers show that *the returns or innovations* of some variations of default spread are priced in the cross-section of equity returns. Contrary to my findings, however, the default risk premia in those papers are rather small. On the other hand, conditional asset-pricing models in, for example, Jagannathan and Wang (1996) and Petkova and Zhang (2005) demonstrate the role of *the level* of default spread in time-series of equity returns, particularly in predicting conditional betas and risk premia.[3] Yet, the relation of systematic distress risk to other stock-related factors or firm fundamentals is rather unexplored. Recently, Anginer and Yildizhan (2018) show that stocks with higher exposures to a systematic default risk measure have higher excess returns, which are nonetheless subsumed by Fama-French risk factors. In contrast to Anginer and Yildizhan (2018)'s credit risk premia implied by sorted equity returns, my CDS-based factor is orthogonal to Fama-French factors. My analysis also quantifies the decomposition as well as the asset pricing patterns of firm-specific distress risk and systematic credit risk, rather than just highlighting the distinction.

Several studies analyze the effect of firm-level distress risk on equity returns. Notable empirical contributions include Dichev (1998), Griffin and Lemmon (2002), Vassalou and Xing (2004), Campbell, Hilscher, and Szilagyi (2008), Chava and Purnanandam (2010), and Avramov, Chordia, Jostova, and Philipov (2013). Most evidence demonstrates that highly distressed firms have *lower* returns against conventional risk-based explanations, suggesting a so-called "distress risk puzzle". Such puzzling findings can be boiled down to the definition, measurement or proxies of financial

[3]Note that the common CDS factor in this paper is highly correlated with *the level* of default spread rather than its innovations. This suggests that the systematic credit risk premium can also be attributed to the future investment opportunity set or cash flow growth, as further shown in the paper.

distress risk, which are mostly based on observed default likelihood indicators.[4] More recently, Friewald et al. (2014) argue that distress proxies based only on real (observed) *or* risk-neutral probabilities are not informative on expected stock returns. They derive a simple structural framework, which implies that equity and credit risk premia depend on both the real *and* risk-neutral risk probabilities captured by CDS returns.[5] Indeed, their analysis shows that firms sorted by their *firm-specific* CDS-implied risk measures have higher equity returns, hence distress risk premium is positive and in line with risk-based explanation. I extend Merton's structural framework to a multi-firm setting, emphasizing the eminent role of default dependencies in driving expected equity returns. My findings on the entire equity cross-section indicate that the relevance of *global* CDS-implied information goes beyond distress risk of the firms with traded CDS contracts.

The theoretical literature on distress risk has aimed to reconcile conflicting findings. Examples of such papers include Garlappi, Shu, and Yan (2006), Gomes and Schmid (2010), and George and Hwang (2010). Ozdagli (2012) argues that stock returns are increasing in risk-neutral probabilities of default, which is driven by cash flow riskiness due to the exposure to systematic risk. My paper provides empirical evidence for the connection between cash flow heterogeneity and systematic risk. Unlike Ozdagli (2012), I also provide a source of systematic risk, a macroeconomic credit shock, in an asset-pricing model. My paper also relates to Garlappi and Yan (2011), who demonstrate the role of resolution of financial distress on distress risk and expected stock returns.

A growing body of literature has focused on linking CDS-related information to stock prices. Notable examples are found in Acharya and Johnson (2007), Han, Subrahmanyam, and Zhou (2017), Qiu and Yu (2012), and Lee, Naranjo, and Sirmans (2017). I am unaware of any work in this area that identifies common CDS risk factors through principal component or factor analysis. Popular in literature on term structure of interest rates, principal component analysis has also been explored to extract factors in other asset classes such as sovereign bonds (Longstaff, Pan, Pedersen, and Singleton (2011)), currencies (Lustig, Roussanov, and Verdelhan (2011)), and equities (Clarke (2017).

The remainder of the paper is organized as follows: Section II illustrates the relation between

[4]For example, Hilscher and Wilson (2017) demonstrate the failure of credit ratings to capture the systematic variation in default probabilities, emphasizing the distinction between idiosyncratic and systematic default risk.

[5]The static link between real-world and risk-neutral default probabilities and the average market price of risk is also discussed in Duffie and Singleton (2003) and Berg (2010).

equity risk premia and systematic credit risk. Section III describes the data. Section IV explores credit risk factor and its cross-sectional pricing in equity returns. Section V discusses the link between CRX and firm fundamentals, such as firm characteristics, risk-adjusted returns, and cash flows. Section VI provides a dynamic asset-pricing model that connects empirical findings on cash flow dynamics and systematic credit risk. Section VII concludes. The appendices provide additional data descriptions, derivations, and technical details.

II. Linking Systematic Credit Risk to Equity Returns

In this section, I present a simple model to illustrate the mechanism behind systematic credit risk and its relation to equity risk premium. Building on the insight in Friewald et al. (2014), the model demonstrates the inverse relation between equity and CDS returns to motivate the use of CDS-implied information in empirical analysis in subsequent sections. In contrast to Friewald et al. (2014), I extend the Merton model to a multi-firm framework with asset correlations. This approach highlights the decomposition of CDS-equity relation into firm-specific and systematic components, the latter being extracted from CDS returns.

A. The Setup

In my illustrative model, the dynamics of asset value $V_{i,t}$ of each firm i under $\mathbb{P}$- and $\mathbb{Q}$-measure are given by

$$dV_{i,t} = \mu_i V_{i,t} dt + \sigma_i V_{i,t} dW_{i,t}^{\mathbb{P}}\,, \tag{1}$$

$$dV_{i,t} = r V_{i,t} dt + \sigma_i V_{i,t} dW_{i,t}^{\mathbb{Q}}\,, \tag{2}$$

where μ_i and σ_i are the drift and volatility of the stochastic processes for firm i. Each firm also has zero-coupon debt D_i payable at time-to-maturity T. In multi-firm extensions of the Merton model, default dependencies are commonly captured by asset correlations. Following Vasicek (1991) and Hull et al. (2010), I decompose each $W_{i,t}$ into two independent Brownian motions with a common component F_t and firms specific component $B_{i,t}$, as follows:

$$dW_{i,t}^{\mathbb{P}} = \rho_i dF_t^{\mathbb{P}} + \sqrt{1-\rho_i^2}\, dB_{i,t}^{\mathbb{P}}\,, \tag{3}$$

$$dW_{i,t}^{\mathbb{Q}} = \rho_i dF_t^{\mathbb{Q}} + \sqrt{1-\rho_i^2}\, dB_{i,t}^{\mathbb{Q}}\,. \tag{4}$$

The parameter ρ_i captures the asset correlation that measures the default dependency of firm i.[6]

B. Risk Premia

The conditional default probabilities (i.e., the probability of $V_{i,t+T} < D_i$ given realization f of common component) under real and risk-neutral measure, $CPD_{i,t}^{\mathbb{P}}$ and $CPD_{i,t}^{\mathbb{Q}}$, are given by[7]

$$CPD_{i,t}^{\mathbb{P}} = \Phi\left(\frac{ln(D_i/V_{i,t}) - (\mu_i - \frac{1}{2}\sigma_i)T - \rho_i f \sigma_i}{\sigma_i\sqrt{T}\sqrt{1-\rho_i^2}}\right), \tag{5}$$

$$CPD_{i,t}^{\mathbb{Q}} = \Phi\left(\frac{ln(D_i/V_{i,t}) - (r - \frac{1}{2}\sigma_i)T - \rho_i f \sigma_i}{\sigma_i\sqrt{T}\sqrt{1-\rho_i^2}}\right). \tag{6}$$

Combining 5 and 6 yields the market price of risk λ_i for firm i, which becomes

$$\lambda_i = \frac{\mu_i - r}{\sigma_i} = \left(\Phi^{-1}(CPD_{i,t}^{\mathbb{Q}}) - \Phi^{-1}(CPD_{i,t}^{\mathbb{P}})\right)\frac{\sqrt{1-\rho_i^2}}{\sqrt{T}}\,. \tag{7}$$

The implications of Equation 7 are twofold. First, the compensation per unit of risk for each firm i is associated with both risk-neutral and physical default probabilities. In other words, as in the single firm case, multi-firm risk premia cannot be captured by one of the default probabilities alone. Second, and more notably, the compensation per unit of risk for each firm depends on the asset correlation. Thus, cross-sectional risk premia that investors demand beyond the expected default risk depend on a common risk associated with default dependencies, hence the systematic credit

[6] Equivalently, the asset correlation between firm i and j is given by $\rho_i\rho_j$. Thus, correlations arise from a single systematic risk factor.

[7] See Appendix B for derivations.

risk. More formally, the market price of risk for firm i can be decomposed into two parts as follows:

$$\lambda_i = \lambda_i^0 + \lambda_i^\rho \,, \tag{8}$$

where λ_i^0 is the market price of risk when asset correlations are ignored (i.e., $\rho_i \to 0$), and λ_i^ρ is the price of risk purely driven by default dependency, that is, the difference between the total market price of risk and λ_i^0. Intuitively, λ_i^0 is the credit-event risk premium that investors demand beyond the expected loss given default due only to an independent credit event. Then, λ_i^ρ is another type of risk premium that compensates investors for firm's exposure to the systematic credit risk.[8]

A multi-firm extension of the Merton model preserves the link between equity and credit returns shown in Friewald et al. (2014). The Merton-type model typically assumes both equity and CDS contracts are contingent claims on each firm's asset value. Consequently, the market price of risk on both claims is equivalent to the risk premium implied by the asset value process. The derivations in Appendix C show that the equity and credit Sharpe ratios are inversely related as follows:

$$\lambda_{E,i} = \frac{\mu_{E,i} - r}{\sigma_{E,i}} = \lambda_i = -\frac{\mu_{S,i}^{\mathbb{P}} - \mu_{S,i}^{\mathbb{Q}}}{\sigma_{S,i}} = -\lambda_{S,i} \,, \tag{9}$$

where $\mu_{E,i}$ ($\mu_{S,i}^{\mathbb{P}}$) and r ($\mu_{S,i}^{\mathbb{Q}}$) are the instantaneous expected returns on equity (CDS) under $\mathbb{P}$- and $\mathbb{Q}$-measure, respectively. $\sigma_{E,i}$ and $\sigma_{S,i}$ are the instantaneous equity and CDS volatility. Notably, the equity and credit Sharpe Ratios depend on default dependencies via the market price of risk, λ_i. Thus, analogous of Equation 8 implies the following:

$$\lambda_{S,i} = \lambda_{S,i}^0 + \lambda_{S,i}^\rho \,, \tag{10}$$

where $\lambda_{S,i}^0$ is the CDS Sharpe Ratio when asset correlations are ignored. Thus, expected equity returns are related to both firm-specific credit events and default dependencies as follows:

$$\lambda_{E,i} = -\lambda_{S,i}^0 - \lambda_{S,i}^\rho \,, \tag{11}$$

$$\mu_{E,i} - r = -\sigma_{E,i}\lambda_{S,i}^0 - \sigma_{E,i}\lambda_{S,i}^\rho \,. \tag{12}$$

[8]In this Merton-type framework, all firms are subject to the same pricing kernel. Thus, the compensation demanded beyond expected default risk is assumed to be risk-adjusted compensation. The point of this exercise is to show that default dependencies matter, even if such systematic risk is not a part of the pricing kernel.

Equation 12 suggests that excess returns are related to CDS-implied information for both firm-specific credit events and systematic credit risk premia. The second term on the right hand side of Equation 12 implies that the CDS market possesses information on correlation-related credit-implied market price of risk that drives the excess equity returns. To the extent that asset correlations are associated with latent systematic factors in credit markets, as documented in credit risk literature, Equation 12 shows that all equity returns must also be driven by their sensitivity to those systematic credit risk factors, no matter what their firm-specific credit-event risks are. Moreover, if systematic credit risk can be extracted as common risk factors in the CDS market, firms' sensitivities to those factors can be linked to equity returns, regardless of whether those firms have traded CDS contracts or not. Guided by these insights, I explore the pricing relation between systematic credit risk factors and the entire cross-section of stock returns in Section IV.

III. Data

I obtain daily spreads for USD-denominated CDS contracts from Markit Group Database in Wharton Research Data Services (WRDS) for the period from January 2003 to September 2014. I only use CDS contracts with five-year maturity, since these contracts are the most liquidly traded, as discussed in Lee et al. (2017). In line with previous literature on USD-denominated CDS contracts, only the contracts with the modified-restructuring (MR) clause — the market convention before the CDS Big Bang protocol took place in April 2009 — and the contracts with the no-restructuring (NR) clause — the current market standard — are gathered. These eliminations result in 351,513 observations of CDS spreads for 2,493 firms.

I calculate monthly CDS returns following the industry standard practice, which has been recently adopted by academic literature, for example, Berndt and Obreja (2010), Friewald et al. (2014), and Lee et al. (2017). Mainly, monthly CDS returns are computed following Lee et al. (2017), and fitting a hazard rate of Berndt and Obreja (2010) for each monthly CDS spread. The discount factors are fitted from USD Libor money market deposits and swap rates term structure (one month to 10 years). The USD Libor/swap rate data is obtained from the Federal Reserve Database. More details on CDS return calculations are provided in Appendix D. Table I provides the descriptive statistics on CDS spreads and monthly returns over the sample time period from

January 2003 to September 2014.

I gather monthly stock returns from the Center for Research in Security Prices (CRSP) Database in WRDS. In line with the literature, I only obtain US stock returns with share code equal to 10 or 11, and that are traded in NYSE, AMEX, or NASDAQ. I also eliminate small stocks with a price less than $5 or stocks with a return series of fewer than 36 months. This leaves me 421,877 equity return observations of 4,329 firms. The returns on Fama-French factors — namely the market portfolio (MKT), value portfolio (HML), the size portfolio (SMB), the profitability portfolio (RMW), the investment portfolio (CMA) and the risk-free rate(RF) are from Professor Kenneth French's website.[9] Table I also provides the descriptive statistics for monthly stock returns in the sample time period.

I construct firm characteristics by combining quarterly accounting data from COMPUSTAT in WRDS with monthly equity market data from CRSP. More details for the selection and construction of firm characteristics are given in Section V.

IV. Credit Risk Factor in Stock Returns

In this section, I analyze whether systematic credit risk is priced in the cross-section of stock returns, First, I propose a simple asset-pricing model that uses systematic credit risk as a risk factor. Then, by utilizing the principal components analysis, I extract the latent credit risk premium that gives rise to CDS returns. Finally, I test whether extracted credit risk factors are significant determinants of equity prices by performing the cross-sectional asset-pricing tests of Fama and MacBeth (1973).

A. Methodology

As the arbitrage pricing theory (APT) of Ross (1976) suggests, average returns on a cross-section of equities can be explained by their exposure to a number of factor risk premia that capture common variations among individual stock returns. I hypothesize that the Credit Risk Factor is such a factor, which should also explain, and hence can be extracted from, CDS Returns, by definition. I define stock and CDS return generating processes for each firm i as follows:

[9] I thank Professor French for providing this data on his website.

$$R_{i,t} = \alpha_i + \beta_i F_t + \theta_i CRF_t + \epsilon_{i,t} \, , \tag{13}$$

$$CDS_{i,t} = a_i + b_i CRF_i + u_{i,t} \, , \tag{14}$$

where R is the excess stock returns, F is a set of factors (previously shown or theorized by literature, e.g., market portfolio, Fama and French (1993), or Fama and French (2015) factors), CRF is a latent credit risk factor that captures credit risk premium, and CDS is the CDS return series. If APT holds, the following should also hold. (See e.g., Huberman and Wang (2005).)

$$E[RX_{i,t}] = \beta_i \lambda_F + \theta_i \lambda_{CRF} \, , \tag{15}$$

$$E[CDSX_{i,t}] = b_i \lambda_{CRF} \, , \tag{16}$$

where $RX_{i,t}$ and $CDSX_{i,t}$ denote the corresponding excess returns and λ_j denotes the risk premia for the set of factors and credit risk factor. Note that APT holds for CDS returns; that is, Equation 14 to Equation 16 should follow from APT, although credit risk factor CRF is a latent factor. To the extent to my knowledge, there is no theoretical or empirical model to extract the risk premium that captures the common variation in excess CDS returns. A common approach to extract a latent factor structure in asset returns is the principal component analysis.

B. Principal Component Analysis on CDS Portfolios

The principal component analysis (PCA) on monthly CDS returns shows that two components capture large variation in CDS returns. Since PCA depends on a larger time dimension compared to asset dimension, I first form decile CDS return portfolios for further analysis. Thus, at each month, the CDS returns of each firm are grouped into the aforementioned decile CDS portfolios based on their return levels (Low:1 to High:10). Then I perform PCA on those decile CDS portfolios to extract principal components.

Table II shows that CDS portfolio returns can be represented in terms of two factors. The first two principal components of the portfolio returns explain 94% of the variation in CDS portfolio returns. Interestingly, the PCA results are qualitatively similar to those found in the literature on term structures of bonds or currencies. The first principal component gives rise to 64% of common variation in CDS portfolio returns, and all portfolios load almost equally on it. In the literature on bonds and currencies, such a component with equal loadings is interpreted as a *level* factor. The second principal component explains 30% of common variation, and its loadings increase monotonically along with portfolio returns. In the literature on bonds and currencies, such a component with increasing loadings is interpreted as a *slope* factor. Therefore, CDS portfolio returns can be explained by the level and slope factors, which can ultimately be tested and used in APT framework for equities.

Since economic intuition of principal components is not obvious, it is helpful to propose other risk factor candidates that covary with principal components and potentially explain CDS portfolio returns. Inspired by the work of Lustig et al. (2011) on currency returns, I propose and construct another risk factor, CRX, as the difference between the return on the highest CDS return portfolio and on the lowest CDS return portfolio. Like all similarly constructed risk factors, CRX has an economic interpretation as being the payoff to a zero-cost portfolio that loads positively on the CDS risk premium. Since CRX is monotonic along with portfolio returns, it is expected to be highly correlated with the *slope* factor.

Table III shows that CRX factor is highly correlated with the second principal component, as expected. The correlation of CRX with the second component is 0.91. Other than the second principal component and the risk-free rate, CRX has very low correlation with Fama and French (2015) factors that potentially explain the cross-section of stock returns. Thus, CRX is a viable candidate to have an additional power in an APT setting, although low correlation also suggests that CRX has low likelihood to absorb Fama-French factor effects.

C. Cross-Sectional Asset Pricing

I estimate factor prices and beta loadings of the APT model discussed in Section IV.A by following the Fama and MacBeth (1973) two-step cross-sectional method. In the first step, I run a time-series regression of returns on the factors to estimate stock beta loadings. In the second step, I run a cross-sectional regression of average returns on the betas to estimate factor risk premia. To remedy the error-in-variables problem, I apply the Shanken (1992) correction in standard errors. I use individual stocks as test assets, following Ang, Liu, and Schwarz (2017).

First, I describe the results obtained using principal components as factors. Table IV reports the estimates of market price of risk (λ) and adjusted R^2 of the second pass regression that measures the overall fit of the cross-sectional model. (See e.g., Jagannathan and Wang (1996) and Petkova (2006)). I provide the test results for two model specifications: a model with market (MKT) factor and a model with Fama-French factors of market (MKT), size (SMB) and value (HML). In both specifications, the loadings on the second principal component, that is, the slope factor of CDS returns, appear as an important cross-sectional determinant of average stock returns. Under Shanken correction, the t-statistics for the hypotheses $H_0 : \lambda_{PC2} = 0$ are 2.397 in the model with equity market return (Panel A), and 2.51 in the model with all three Fama-French factors (Panel B). Both tests are rejected at a 1% significance level. On the other hand, the prices of risk for the first principal component is not significant in the cross-section of stock returns. Surprisingly, none of the three Fama-French factor loadings represents a significant determinant in the cross-section of stock returns. The adjusted R^2 of 16.1% and 21.0% of both model specifications is relatively high, considering only three or five factor variables are used to explain over 4,000 test assets. In an unreported result, the Fama-French three-factor model (without principal components) has an adjusted R^2 of 17.7% over the sample time period. Hence, the specification in Panel B has 3.3% more explanatory power, due to inclusion of the second principal component, that is, the slope factor of CDS returns. Those results imply that the systematic credit risk is priced in average equity returns over the sample time period.

Although the price of risk of the second principal component is significant, its magnitude does not necessarily have an economic interpretation or significance. Thus, I also conduct the asset-pricing tests (as well as the subsequent empirical analysis in this paper) with the CRX factor, which has a high correlation with the slope factor of CDS portfolio returns, as shown in Section IV.B. Table V reports the test results obtained for the models with Fama-French three and five factors together with the CRX factor. In each panel, the market price of risks of all Fama-French factors except the size factor are insignificant. On the other hand, in Panels A, B, and C, the CRX explains the cross-section of stock returns significantly. Under the Shanken correction, high t-statistics lead to reject the hypothesis that the effect of CRX on average stock returns is essentially zero. Based on five-factor model estimates, the market price of CRX risk is 0.87% *per month*, or 10.44% *per annum*. APT implies that the market price of risk of each factor is also its average excess return. Thus, an asset with a beta of one to CRX, which consequently loads positively to the systematic credit risk, earns 10.44% per year on average for taking such risk. Moreover, the adjusted R^2 of the model with three Fama-French factors and the CRX factor is 21.4%, which indicates 3.7% more explanatory power over the unreported three-factor Fama-French model with the adjusted R^2 of 17.7%. The results on models with the CRX factor provide, a more intuitive demonstration for the significant pricing of systematic credit risk in the cross-section of equity returns over the sample time period.

A natural criticism would be whether the pricing estimates overemphasize the effect of a rare financial crises. For robustness, I conduct the two-step Fama MacBeth procedure for all specifications, while excluding the period of financial turmoil between 2007 and 2009. The magnitude and significance of Fama-French factors do not change when the financial crises period is excluded, although the market price of risk estimate for the CRX factor indeed drops by 20% to 0.70% *per month*, or 8.4% *per annum*. Yet, high t-statistics still suggest that the CRX is a significant cross-sectional determinant of equity returns. It seems that systematic credit risk is priced in stock returns even if the period of financial crises is ignored.

D. *The CRX as Another Factor*

In the spirit of Fama and French (2015), I explore whether the CRX factor is actually related to five Fama-French factors. Indeed, the asset-pricing test results in Table V, and the correlation statistics in Table III suggest that the CRX factor is mostly orthogonal to Fama-French factors. Here, I go one step further and examine how much additional return is captured by each factor after other factors are accounted for. Put differently, I investigate whether any factor effects are subsumed by the other factor returns.

Table VI shows the regressions of the monthly returns of each factor on the other five factors from January 2003 through September 2014. For Mkt, SMB, HML, and CMA factors, the intercepts (excess returns unexplained by other factors) are insignificant with low t-statistics. In each of the Mkt, SMB, HML and CMA regressions, other factors subsume the factor effects with a positive or negative slope with significant t-statistics. The regressions of the profitability factor indicates that the RMW factor has a positive covariance with HML but negative slopes for Mkt and SMB, consistent with Fama and French (2015) results. However, these significant slopes don't explain away the profitability factor. RMW provides 0.5% *per month* excess return (the intercept) versus the other factors with significant t-statistics.

In the CRX regressions, the CRX is largely orthogonal to other factors ($R^2 = 13.3\%$), with a negative correlation to HML factor. Unlike most other Fama-French factors, exposure to the CRX factor cannot be explained away by other factors. The intercept is large at 2.3% *per month*, thus the excess returns of CRX factor are not captured by its exposures to Fama-French factors. On the other hand, an unreported result highlights that CRX has high correlation(-0.37) to the shocks to intermediary leverage. When the leverage factor of Adrian et al. (2014) is added to the redundancy CRX regressions, the R^2 rises to 22%. Though, the CRX premia is not subsumed by the leverage factor as the intercept still remains at 2.3% per month. That is, a large portion of CRX risk premia is not explained away by the shocks to financial intermediary leverage, either. Together with asset-pricing test results in Section IV.C, the factor redundancy regressions show that CRX arises as a new risk factor, explaining average cross-sectional stock returns, at least during 2003–2014.

V. The Relation of the CRX and Firm Fundamentals

A. The CRX and Firm Characteristics

Previous sections show that the CRX has a role in explaining average stock returns. However, this doesn't necessarily mean that the CRX improves the description of average returns for any *portfolio*. Hence, summarizing the key characteristics of firms with high/low sensitivity of the CRX factor is of importance. Firms with higher sensitivity to the CRX, hence systematic credit risk, are more likely to be "fragile" to deteriorating credit conditions due to for example, default clustering, contagion effects, or credit cycles. If, for example, those fragile firms are financially distressed firms, they could be smaller, have higher leverage, have lower profitability and have lower credit ratings.

Table VII reports the mean and median characteristics of CRX quantile portfolios. Quantile 1 contains low CRX-beta portfolios, while Quantile 5 consists of stocks with high CRX loadings. To construct firm characteristics, I combine quarterly accounting data from COMPUSTAT in WRDS with monthly equity market data from CRSP. The profitability (NIMTA) and cash liquidity (CASHMTA) ratios are constructed following Campbell et al. (2008). Net debt repayment (NDRepay) and Expected Default Frequency (EDF) is defined following Gomes, Grotteria, and Wachter (2017). Market value (MV), market leverage ratio (Mlevg), investment ratio (Inv), book-to-market ratio (BM), and earnings-price ratio (E/P) are the standard measures in the literature. Ratings are integer numbers assigned to firms' domestic long-term issuer credit rating (AAA=1, AA+=2, . . . , C=21, D=22). I describe the details on the construction of these characteristics in Appendix A.

The results reveal that CRX loadings are increasing with market leverage and book-to-market ratios. This increasing pattern is much stronger for median statistics in Panel B of Table VII. Structural models imply higher *expected* default rates when default boundaries (hence, market leverage) are higher or firm values (hence, market-to-book ratios) are lower. Therefore, such increasing pattern suggest that firms with higher sensitivity to systematic credit risk have also higher expected default rates, that is, distress risk. As argued by Friewald et al. (2014) and Ozdagli (2012), *physical* default probabilities (proxied by either credit ratings or EDF measures) do not capture such high *expected* default rates. Neither market leverage/BM ratios nor CRX quantile portfolios are monotonically related to credit ratings/EDFs, which exhibit rather U-shaped pattern from Quantile 1 to 5. Similarly, size (MV) also displays a non-monotonic U-shaped pattern. Therefore, it seems smaller stocks with low credit ratings are more responsive to credit risk fluctuation. However, the positive or negative impact of such fluctuations depends on whether firms hold high leverage or have lower market values, hence their distress levels.

Exposure to systematic credit risk has generally no direct relation to firm characteristics other than leverage and book-to-market ratio. There is very little dispersion in firm profitability and cash liquidity, which are the main determinants of physical default probability in Campbell et al. (2008). CRX quantile portolios do not diverge in debt repayments, either. Thus, in contrast to Gomes et al. (2017), the variation in credit quality is not linked to cyclical fluctuations. Similarly, investment ratios do not display any monotonic patterns across CRX quantile portfolios.

Table VII also sheds new light on the findings of Griffin and Lemmon (2002) and Vassalou and Xing (2004), who document a stronger book-to-market effect in highly levered stocks. The results suggest that the leverage and book-to-market effects would also be linked to firms' higher sensitivity to the shocks in credit conditions. This is somewhat consistent with Garlappi and

Yan (2011) theoretical framework in which leverage amplifies the book-to-market effect through the *shareholder recovery* option in strategic defaults. The fluctuations in credit conditions would provide the necessary environment to trigger strategic defaults for distressed firms, while those firms would recover (part of) the residual firm value upon the resolution of financial distress when the credit conditions get milder. However, Garlappi and Yan (2011) prediction of hump-shaped relationship between earnings-price ratios and *physical* default probabilities (e.g., credit ratings) contradicts Table VII. This is another indication that real default probabilities alone do not capture expected default rates, and thus any sensitivity to systematic credit risk. In the next section, the link between the real *and* risk-neutral default probabilities and the systematic credit risk is further investigated.

B. The CRX and Distress Risk Premium

Here, I analyze the cross-sectional relationship between firms' stock returns and distress risk using portfolio sorts. The model illustration in Section II highlights that the risk premia are associated with both risk-neutral and physical default probabilities, hence portfolio sorts based solely on one of the default probabilities are uninformative. Following Friewald et al. (2014), I sort firms based on their *realized* excess CDS returns into quantile portfolios at the end of each month and calculate *contemporaneous* equal and value-weighted excess returns.[10] $P1$ contains firms with the lowest CDS returns, hence lowest distress risk, and $P5$ contains firms with the highest CDS returns.

Panel A in Tables VIII and IX present results of regressions on three Fama-French factors for equal-weighted and value-weighted portfolios, respectively. Those results are qualitatively similar to findings of Friewald et al. (2014) for firms sorted by estimates of their Credit Risk Premia (CRP) measure. Particularly, High minus Low ($P5 - P1$) portfolios deliver significantly positive Fama-French three-factor alphas. The results in Panel A suggest that the risk-adjusted excess return for buying high and selling low credit risk equal-weighted (value-weighted) portfolios is 2.90%(2.46%) per month. Displaying a non-monotonic pattern in loadings, Fama French factors have limited

[10] Note that Friewald et al. (2014) use default risk measures constructed from estimations of *expected* CDS returns at time t based on information at time $t-1$. Here, the realized CDS returns at time t are used as a proxy for expected CDS returns at time t, hence distress risk at time $t-1$. Therefore, sorting stocks with respect to distress risk at time $t-1$ is equivalent to sorting with respect to CDS returns at time t, given that CDS returns are good enough proxy.

explanatory power over credit risk sorted portfolios. Only the loadings on the Market factor is significant for each quantile portfolio. Factor loadings for the Market, SMB, and HML factors are insignificant for high minus low credit risk portfolio. Overall, those results confirm the link between credit and equity returns, implying a positive risk premium for firms with high distress risk.

However, the illustrative model in Section II has another insight. Equation 7 indicates that distress risk premium estimates can be decomposed into two parts: firm-level credit event risk premium and systematic credit risk premium. In Section IV, I demonstrate CRX as a (latent) systematic credit risk factor, which is also priced in equity returns. Moreover, Section V.A highlights the fact that distressed firms are highly loaded to the CRX factor. Therefore, I further explore the extent to which systematic credit risk drives distress risk premia found in Panel A of Table VIII and IX.

Panel B in Tables VIII and IX present the results of regressions on three Fama-French factors and the CRX factor for equal-weighted and value-weighted portfolios, respectively. Those results reveal that there is non-monotonic pattern in loadings on the CRX factor across portfolios $P1$ to $P5$. The loadings on the CRX factor is positive and significant for both equal-weighted and value-weighted portfolios of only high credit risk $P5$. This implies that firms with high distress risk are most prone to systematic credit risk, consistent with the findings in Section V.A. The effect of systematic credit risk is strong for $P5$ portfolios, for which three-factor model alphas shrink to statistically and economically insignificant levels. When the CRX is added to the factor model in Panel B, the model alphas for the high-risk portfolio in Panel A drops from 1.65% to 0.04% per month for equal-weighted portfolios (Table VIII) and from 1.57% to 0.38% for value-weighted portfolios (Table IX). Those results suggest that high compensation for high distressed stocks is, in fact, for their high exposure to the systematic credit risk.

Controlling for systematic credit risk also diminishes high minus low credit risk portfolio premia. Panel B of Table VIII reports 1.24% per month risk-adjusted returns for high-minus-low ($P5-P1$) equal-weighted portfolios. This represents a 57% drop from an alpha level of 2.90% per month for the equal-weighted $P5-P1$ portfolios in Panel A. However, the risk-adjusted return for high-minus-low portfolio remains statistically significant. Thus, systematic credit risk factor appears to have subsumed more than half, but not all, of distress risk premia. The pattern of risk-adjusted returns for value-weighted portfolios in Table IX is qualitatively similar. For value-weighted $P5-P1$

portfolios, the three-factor model alpha drops to 1.0% per month. Overall, those results imply that the excess performance of high distressed stocks can be attributed to their exposure to systematic credit risk as much as their firm-level distress risk.

The results indicate that the distress alphas are associated with exposures to common sources of risk. In other words, by investing high-minus-low distressed risk portfolios, investors load up on common credit risk. With that in mind, positive risk-adjusted performance of distressed stocks has another risk-based explanation: Investors demand higher compensation for non-diversifiable systematic (correlated) defaults, to which highly distressed stocks have higher betas.

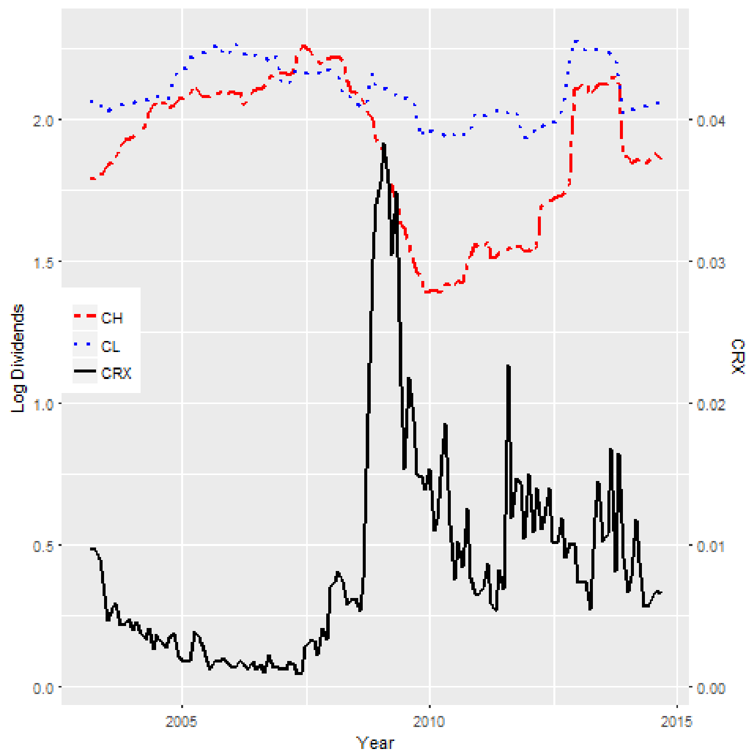
C. The CRX and Cash Flow Risk

Finally, I explore the connection between cash flows of CRX quantile portfolios and the CRX factor by plotting log dividends on CRX quantile portfolios. I use CRSP's monthly cumulative and ex-dividends together with the price data from January 2003 to December 2014. Dividends for each stock are computed from the difference between cum- and ex-dividend returns, multiplied by the previous month's ex-dividend price. To remove seasonality in dividends, I follow Koijen, Lustig, and Nieuwerburgh (2017) and construct annualized dividends by finding the trailing dividends sum of the past 12 months. Figure 1 presents the plot for the highest *(CH)* and the lowest*(CL)* CRX quantile portfolios as well as the time-series of the CRX factor. It is worthy to note that both high and low quantile portfolios distribute considerable amounts of dividends. The time-series average of log dividends does not differ much across CH (1.86) and CL (2.09) portfolios, whereas the average dividend yields for both CH and CL portfolios are 1.11%. Thus, CH (CL) stocks are not necessarily value (growth) stocks despite their high (low) book-to-market ratios.[11]

Figure 1 provides evidence for the heterogeneity in dividends for CRX quantile portfolios. The dividends on CH stocks are substantially more sensitive to the CRX factor, which captures the elevated systematic credit risk. In contrast, the dividends on CL stocks are less sensitive to credit conditions. In fact, the CH dividends started to drop as early as mid-2007 and continue their slump long after the peak of the financial crises until 2010. However, CL dividends display a rather robust pattern even during financial crises. The findings are consistent with Ozdagli (2012), who argues

[11]In fact, the highest (lowest) book-to-market quantile corresponds to the average BM of 1.96 (0.03) during the sample time period (not reported).

Figure 1. Log Dividends vs. CRX Factor : 2003-2014



that the distress risk premium results from firms' heterogenous cash flow risks captured by risk-neutral default probabilities. Here, a positive risk premium for high CRX-Beta portfolios appears to be connected to cash flow riskiness. The recovery pattern in dividends as credit conditions get milder (as seen from dropping CRX) may also be attributed to the shareholder recovery option in financially distressed firms. As argued by Garlappi and Yan (2011), the risk premium for distress risk can be attributed not only to the incidence of financial distress but also to the resolution of such distress. In Section VI, I will further formalize the empirical relationship between cash flows and systematic distress risk, shown in Figure 1.

VI. A Dynamic Asset-Pricing Model with Credit Risk

In the spirit of Koijen et al. (2017), I set up and calibrate a dynamic asset-pricing model that demonstrates the empirical link among systematic credit risk, equity returns, and cash flows, shown in Figure 1. With a single state variable, the model aims to match the dynamics of dividend growth, credit conditions, and CRX risk premia, providing a structural interpretation for asset prices. This setup is chosen to emphasize the role of systematic credit risk as both a pricing kernel state variable and a source of cash flow heterogeneity during the sample time period. Using an exogenously specified affine pricing kernel, I impose minimal structure necessary to match the observed moments by only ruling out arbitrage possibilities among equity portfolios.

A. Setup

Let the default spread (the difference between the Moody's BAA yield and the 10-year Treasury bond yield) be the only state variable s_t that measures the good/bad credit environment. I define s_t as an autoregressive process with autocorrelation ρ_s, and ϵ^s_{t+1} as a priced shock to the state variable. Higher values of s_t are a signal of elevated systematic credit risk, representing deteriorating credit conditions.

$$s_{t+1} = \rho_t s_t + \sigma_s \epsilon^s_{t+1} \tag{17}$$

The asset space is given by i $\in \{CH, CL, Mkt\}$, where CH is the highest quintile CRX-Beta portfolio, CL is the lowest quantile CRX-Beta portfolio, and Mkt is the market portfolio. Then, log dividend growth, which depends on the state of the economy, is specified as follows:

$$\begin{aligned} \Delta d^i_{t+1} &= \delta_i + \gamma_{di} s_t + \sigma_{di}\epsilon^d_{t+1} - \sigma_{vi}\epsilon^v_{t+1}\,, \\ v^i_{t+1} &= \mu_i + \rho_v v^i_t + \sigma_{vv}\epsilon^v_{t+1}\,, \end{aligned} \tag{18}$$

where d_i represents log dividends. Innovations ϵ^d_{t+1} and ϵ^v_{t+1} are Gaussian shocks with unit standard deviations. Following Bekaert, Engstrom, and Xu (2017), v_t is defined as the latent "financial" cash flow uncertainty. Shocks to v_t capture the changes in the conditional variance of fundamentals not spanned by aggregate dividend shocks. This specification allows me to incorporate firm-specific financial default risks priced in the economy, which has been documented in distress risk literature as well as in this paper. The financial uncertainty is correlated with dividend growth through σ_{vi} parameter. Since any default should diminish dividends, the sign before σ_{vi}, the sensitivity to financial uncertainty shocks, is negative.[12] I set $\sigma_{vM} = 0$ to allow a single source of dividend risk

[12] To allow tractability and the ease of estimation, I use a simplified version of financial cash flow uncertainty in Bekaert et al. (2017). Indeed, a richer model would define corporate loss rate as an autoregressive function, which also spans macroeconomic state, macroeconomic shocks, and firm-level financial uncertainty shocks. In such a setup, dividend growth would be negatively related to such a loss rate. Note that, in Bekaert et al. (2017), the most variation

for market portfolio, which leads to a market-beta interpretation for aggregate dividend shocks.

The model allows the state of macroeconomy, that is, systematic default risk, to affect the conditional mean of dividend growth process. The parameter γ_{di} captures any heterogenity in cash flow riskiness. The pattern in Figure 1 suggests that high value in s_t is related to lower dividend growth for CH stocks. Thus, the model would capture such patterns when $|\gamma_{dCH}| > |\gamma_{dCL}|$. (Notice that high values of s_t represent a bad state.) Unlike Bekaert et al. (2017), the state variable does not influence the conditional volatility of dividend growth process.

The pricing kernel M_t is a stochastic process, which implies that $E_t[M_{t+1}R_{i,t+1}] = 1$ for all assets i. I propose an exponential affine pricing kernel, similar to the stochastic discount factors used in term structure literature (e.g. Duffie and Kan (1996), Dai and Singleton (2002)). I assume all independent shocks in the economy are priced. That is, the log stochastic discount factor $m_{t+1} = log(M_{t+1})$ is given by

$$-m_{t+1} = r_f + \frac{1}{2}\Lambda_t'\Lambda_t + \Lambda_t'\epsilon_{t+1}\,, \tag{19}$$

where r_f is the risk-free rate and the vector $\epsilon_{t+1} = [\epsilon^d_{t+1}, \epsilon^s_{t+1}, \epsilon^v_{t+1}]^T$. The 3 x 1 vector of market prices of risk is affine in systematic default state s_t, as follows:

$$\Lambda_t = \Lambda_0 + \Lambda_1 s_t \tag{20}$$

B. *Asset Pricing*

The setup with an affine pricing kernel implies a log price-dividend ratio that is affine in state variables (as in Bekaert, Engstrom, and Xing (2009), Lettau and Wachter (2011), and Koijen et al. (2017) among others). Formally, the log price-dividend ratio for portfolio i is given by[13]

$$pd_i = A_i + B_i s_t\,, \tag{21}$$

in loss rate comes from independent uncertainty shocks rather than macroeconomic effects.

[13] See Appendix E for derivations

where

$$B_i = \frac{\gamma_{di} - \Lambda_1(1)\sigma_{di} + \Lambda_3(1)\sigma_{vi}}{1 - \kappa_{1i}\rho_s}, \qquad \kappa_{1i} = \frac{exp(\overline{pd})}{exp(\overline{pd}) + 1}. \tag{22}$$

The sign of B_i coefficient is non-trivial, as it depends on cash flow heterogeneity parameter γ_{di} as well as two prices of risk parameters, although price-dividend ratios are expected to be pro-cyclical, with negative B_i. In a bad credit environment (high s_t), prices are lower hence the expected returns are higher. There are two effects of an increase in systematic credit risk on price-dividend ratio. As seen in Figure 1, the cash flow effect is expected to be pro-cyclical with negative γ_{di}, at least for CH portfolios. This would allow for high variability in price-dividend ratios if the total discount rate effect captured by the price of risk parameters are also procyclical as expected. In other words, cash flow and discount rate effects are expected to reinforce each other in this setup.

The conditional equity risk premium on portfolio i is given by

$$E_t[rx^i_{t+1}] = \Lambda_0(1)\sigma_{di} + \Lambda_0(2)\kappa_{1i}B_i\sigma_s - \Lambda_0(3)\sigma_{vi} \quad + \quad (\Lambda_1(1)\sigma_{di} - \Lambda_3(1)\sigma_{vi})\, s_t\,. \tag{23}$$

Similar to Koijen et al. (2017), the equity risk premium for each portfolio has an unconditional and time-varying component. As discussed above, the equity risk premium varies countercyclically with respect to systematic credit risk s_t, thus $\Lambda_1(1)\sigma_{di} - \Lambda_3(1)\sigma_{vi}$ should be positive. Higher realizations of s_t (a bad state of the economy) leads to higher equity risk premia. Past asset-pricing literature has already demonstrated the positive risk premium for aggregate dividend risk, that is, $\Lambda_1(1)\sigma_{di} > 0$. Bekaert et al. (2017) find the financial cash flow uncertainty countercyclical, implying that $-\Lambda_3(1)\sigma_{vi} < 0$ for my model.

The unconditional equity risk premium for each portfolio i has three distinct components: compensations for aggregate dividend risk, cyclical risk, and financial uncertainty risk. On the one hand, excess return differences among portfolios can have a high market-beta explanation due to higher sensitivity to aggregate dividend shocks. On the other hand, the sensitivity of cyclical risks captured by B_i can also drive the excess return differences. For example, the data implies $|\gamma_{dCH}| > |\gamma_{dCL}|$ for cash flow effects, suggesting $|B_{CH}| > |B_{CL}|$ even if the total discount rate effects for these portfolios do not differ much. In fact, CH portfolios have higher co-variation with systematic default risk by definition, so it is natural to expect higher discount rate effects and $|B_i|$, thus higher excess portfolio returns for portfolio CH in general. However, empirical results of this paper emphasize that CH and CL portfolios are also distinct in terms of their distressed firm characteristics, hence their dividend growth sensitivity σ_{vi} to financial uncertainty shocks. Thus, relative importance of cyclical risk would also depend on the payoffs for bearing financial uncertainty risk. Nonetheless, the model aims to compare and contrast how large and significant the magnitudes of those distinct risk compensations are.

It is worthy to note that I will allow market portfolio to have non-zero sensitivity to cyclical shocks, $B_M \neq 0$, unlike Koijen et al. (2017)). This specification is crucial in order to allow discount rate shocks into the market and hence match the variation in P/D ratios. It is also realistic to let the market risk premium depend on the (only) state of the economy s_t. However, this approach will also incorporate cyclical risk as a part of market return. That is, *all* cyclical risks will be attributed to market exposures, although the model is still useful for its main purpose: disentangling the relative impact of three different components of unconditional equity risk premium.

C. Calibration

I calibrate the model to provide a reasonable fit to the data for market portfolio and two other equity portfolios. The model specification includes the processes for the state variable, the dividend growth, and the price of risk. As a proxy for the state variable, I use the Moody's 10-year spread of BAA bonds relative to 10-year Treasury yield. The dividend parameters are calibrated on dividends data presented in Section V.C. The price of risk variables are then jointly determined by the equity returns and volatility for CRX-quantile portfolios and the market portfolio.

The state variable s_t is de-meaned and standardized. I set the persistence parameter ρ_s state variable as 0.9654 to match the first-order autocorrelation of the default spread for monthly data. Given those variables, the autoregressive process has $\sigma_s = 0.26$. Dividend parameters of each portfolio are calibrated to match first and second centered moments of dividend growth. The parameters of γ_{di}, which determine the conditional means of dividend growths, are chosen to match the slope coefficients of the regressions between dividend growth and lagged state variable, that is, the default spread. As suggested in Figure 1, CH portfolios have higher cash flow riskiness, which is captured by $\gamma_{dCH} = -0.0107$, compared to cash flow heterogeneity of other two portfolios,

$\gamma_{dM} = -0.00236$ and $\gamma_{dCL} = -0.0006$. Note that $|\gamma_{dCH}| > |\gamma_{dCL}|$ generates differential cash flow effects, being one of the mechanisms that can be attributed to return and volatility disparity of these portfolios.

The parameter σ_{dM} is chosen to exactly match the unconditional volatility of market dividend growth of 1% per month in the data. In contrast, it is less straightforward to calibrate the dividend shocks for CH and CL portfolios due to the existence of financial uncertainty shocks. The unconditional dividend growth volatility of CH and CL portfolios are much higher, 4.6% and 2.8%, respectively. Thus, I set slightly higher parameter values for $\sigma_{dCH} = 1.5\%$ and $\sigma_{dCHL} = 2.0\%$. I set $\sigma_{dCH} < \sigma_{dCHL}$ due to the fact that CH portfolios have higher market beta. Note that much higher parameter values for dividend shocks would overstate the covariance of those portfolios with market portfolio. The conditional volatilities of financial uncertainty shocks in dividend growth process are set as $\sigma_{vCH} = 4.37\%$, $\sigma_{vCH} = 1.92\%$, matching exactly the unconditional volatility of CH and CL portfolio dividend growths not spanned by dividend shocks. $\sigma_{vCH} > \sigma_{vCL}$ is consistent with the notion that CH firms possess distress characteristics, hence are more prone to firm-specific financial uncertainty shocks.

Given parameter values for dividend growth and state variable processes, I calibrate price of risk parameters in two steps. In the first step, I set $\Lambda_1(1) = 0.4955$ and $\Lambda_1(3) = 0.07615$ by minimizing the sum of squared fitting errors for the volatility of each portfolio return. Note that the positive parameter value for $\Lambda_1(1)(\Lambda_1(3))$ captures procyclical (countercyclical) nature of aggregate dividend (financial uncertainty) risk, as expected. In the second step, I find the values for the remaining market price of risk parameters by exactly matching the unconditional mean excess returns of each portfolio to the expected value of conditional equity risk premia given by Equation 23. I simply solve a system of three equations to recover three parameter values for $\Lambda_0(1) = 0.18068$, $\Lambda_0(2) = -0.12534$, and $\Lambda_0(3) = -0.28503$. Table X summarizes these parameter choices.

D. Asset-Pricing Implications

Panel A in Table XI presents moment statistics implied by model parameter values. Log excess return of each portfolio is fit exactly since Λ_0 parameters are set to solve these moments analytically. The model produces the volatility of market portfolio excess returns (4.38% in the model vs. 4.37% in the data), the volatility of CH portfolio excess returns (8.4% in the model vs. 8.02% in the data), and the volatility of CL portfolio excess returns (5.10% in the model vs. 5.16% in the data). However, the market beta of CH and CL portfolios are slightly overstated. The maximum annual Sharpe Ratio impled by the model is 1.32. This value is higher than the highest Sharpe Ratio (1.24) for CH portfolios in the sample. Overall, I conclude that the model parameters match reasonably well with the observed first and second moment of portfolio returns data.

Matching the moments of log price-dividend ratio is rather difficult for affine class of models, especially with a single state variable. The difficulty mostly lies in the persistence of the price-dividend ratio (see, e.g., Campbell and Cochrane (1999)). The model produces a higher mean of price-dividend ratios for each portfolio. The volatility of market pd ratio is reasonably fit, 16.53% in the model, compared to 16.90% in the data. However, the volatility of pd ratios for CH and CL portfolios are measured with noise. Typically, the volatility and persistence of pd ratios can be increased by a richer model with more than one state variable. Yet such a model would be more complicated with multiple sources of discount rate shocks. In contrast, a key goal of this exercise is to demonstrate the effect of the fluctuations in the global credit risk environment when it is the only source of macroeconomic risk.

Panels B and C in Table XI present unconditional return and variance decompositions implied by the model. The relative contribution of cyclical risk is substantial for each portfolio. Thus, the return dynamics of each portfolio is determined by the cash flow sensitivity to macroeconomic shocks, that is, the systematic credit risk. The model implies the highest compensation for cyclical risk (0.88% per month) for CH portfolios, consistent with their higher beta to the CRX factor. Yet the model generates a larger portion of unconditional returns for CH-CL portfolios through their exposure to financial uncertainty risk. In other words, the model suggests that distress characteristics of CH firms account for most of the superior returns over CL portfolios. Although systematic credit risk still plays a role in accounting for the cross-section of stock returns, the compensation for such macroeconomic risk is rather limited.

In contrast, macroeconomic fluctuations have a profound impact on the variation of each portfolio return. The unconditional variance of portfolio returns is mostly driven by the exposure to cyclical risk. CH portfolios have higher sensitivity to macroeconomic shocks, thus they display higher return variation during the sample time period. Note that the state variable dynamics are the only source of discount rate variation in the model. Thus, the model suggests that CH portfolios with high γ_{dCH} have higher sensitivity to discount rate effects. This is consistent with the fact that incidences of default and Sharpe Ratios covary in the boom and bust cycles. (see, e.g., Chen, Collin-Dufresne, and Goldstein (2008)) That is, both default rates and discount rates are high (low) during a bad (good) state of the economy. Structural model implies that the higher returns for distress firms come with a cost of higher volatility, even though the return and volatility components have different sources of risk. By investing in distressed firms, investors are exposed to macroeconomic credit shocks beyond the firm-level financial uncertainty risk.

VII. Conclusion

Consistent with the multi-firm extension of structural models, I provide evidence that a common slope factor in CDS returns is also related to equity returns. Firms with distress characteristics and firms with high distress risk measures have larger exposures to this slope factor. These findings emphasize another risk-based explanation for positive risk-adjusted performance of distressed stocks. I also show that the equity risk premia in such distressed firms are connected to high sensitivity of their cash flows to the macroeconomic activity, particularly credit conditions. A standard affine asset-pricing model reproduces the return and volatility patterns of distressed firms, providing an economic interpretation of the slope factor and distress risk premia through the connections among equity returns, cash flow dynamics, and the fluctuations in credit conditions: The distress risk premia reflects compensation for both firm-level distress risk and macroeconomic risks.

My results suggest a key role of systematic credit risk in explaining both cross-section and time-series of stock returns. Future work should investigate whether a similar affine model with systematic credit risk can explain corporate bond and equity returns jointly. Furthermore, the economic mechanism behind the effect of systematic credit risk in discount rate variation remains an open question. One interesting avenue would be to link business cycles with credit cycles, as in Gomes et al. (2017). Chen et al. (2008) also demonstrated that a stochastic risk aversion due to habit-type preferences can jointly explain time-variation in credit spreads and equity returns. However, default correlations and contagion effects in credit markets can be other mechanisms with different implications on asset prices. Future work should bring default correlations inside models to fully understand the consequences of default clustering or contagion.

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Table I

Summary Statistics

This table presents the summary statistics of variables used in this study. Data are monthly from January 2003 to December 2011. CDS data are provided by Markit; stock returns are from CRSP. The sample period is 01/2003-09/2014. N refers to the number of firm-month observations.

Variables	Mean	Std.Dev	Min	Median	Max	N
CDS Spread (bps)	256.414	725.333	0.5	104.819	45650.4	351513
CDS Return (%)	-0.005	2.041	-164.3	0.001	225.9	351513
Change in CDS Spread (bps)	-4.673	252.187	-21307.5	0.068	18634.9	351513
Stock Return (%)	1.679	12.499	-86.8	1.010	1349.5	421877

Table II

Principal Components

This table presents the principal component loadings on sorted CDS portfolios. The last row indicates the percentage of the total variance explained by each component. CDS data are provided by Markit. The sample period is 01/2003-09/2014.

Portfolio	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10
1	0.143	-0.448	-0.818	0.241	-0.097	-0.185	-0.083	0.009	0.022	0.009
2	0.297	-0.374	0.074	0.145	0.381	0.576	0.396	-0.177	-0.256	-0.123
3	0.311	-0.339	0.286	0.088	0.277	-0.013	-0.263	0.335	0.575	0.331
4	0.337	-0.275	0.333	0.014	-0.005	-0.430	-0.366	-0.019	-0.410	-0.462
5	0.379	-0.134	0.179	-0.119	-0.452	-0.235	0.319	-0.463	0.007	0.465
6	0.387	0.072	-0.054	-0.242	-0.482	0.210	0.257	0.456	0.230	-0.424
7	0.354	0.235	-0.181	-0.275	-0.050	0.379	-0.507	0.102	-0.395	0.376
8	0.324	0.319	-0.190	-0.198	0.290	-0.007	-0.171	-0.562	0.432	-0.319
9	0.310	0.347	-0.150	-0.064	0.461	-0.448	0.418	0.327	-0.197	0.152
10	0.248	0.410	0.080	0.849	-0.181	0.077	-0.065	-0.015	0.009	-0.006
% Var	0.643	0.297	0.039	0.014	0.004	0.002	0.001	0.000	0.000	0.000

Table III

Principal Components vs. Factors — Correlation Table

This table presents the correlations among Fama French factors, market (MKT),size (SMB), value (HML), profitability (RMW) and investment (CMA), the first two principal components PC1 and PC2, and CRX factor based on high-minus-low CDS portfolios. CDS data are provided by Markit. Fama-French factors are from the Kenneth French website. The sample period is 01/2003-09/2014.

	Mkt	SMB	HML	RMW	CMA	RF	CRX	PC1	PC2
Mkt	1.00	0.48	0.35	-0.54	0.08	-0.09	-0.07	0.56	-0.15
SMB		1.00	0.25	-0.45	0.14	-0.06	0.01	0.30	-0.01
HML			1.00	-0.20	0.41	0.03	-0.21	0.23	-0.20
RMW				1.00	-0.23	0.02	0.05	-0.40	0.09
CMA					1.00	-0.07	-0.05	-0.05	0.02
RF		-				1.00	-0.49	-0.15	-0.51
CRX							1.00	0.11	0.91
PC1								1.00	-0.00
PC2									1.00

Table IV

Stock Level Risk Premium Estimates — Principal Components

This table presents the Fama MacBeth cross-sectional regression results of two-pass regression test using the excess returns on 4,329 US stocks and principal components of the CDS returns.The full-sample factor loadings are computed in one multiple time-series regression in the first stage. Then, the loadings are used as the independent variables in the second stage. The risk premium coefficients are monthly estimates. Panel A presents results for the model with Excess Market Return (MKT), Principal Component 1 (PC1), and Principal Component 2 (PC2). Panel B presents results for the model including the Fama-French factors of market (MKT),size (SMB) and value (HML) as well as principal components. The adjusted R^2 follows Jagannathan and Wang (1996) and Petkova (2006). The first set of t-statistics, indicated by FM t-stat, stands for the Fama MacBeth estimate. The second set, indicated by SH t-stat, adjusts for errors-in-variables and follows Shanken (1992). For each panel, the sample period is from February 2003 to September 2014.

Panel A: The Model with MKT and Principal Components

	λ_0	λ_{Mkt}	λ_{PC1}	λ_{PC2}	Adj.R^2
Estimate	0.009	0.004	0.198	0.633	0.161
FM t-stat	5.736	1.060	0.767	3.882	
SH t-stat	3.664	0.655	0.476	2.397	

Panel B: The Model with Fama-French Factors and Principal Components

	λ_0	λ_{Mkt}	λ_{SMB}	λ_{HML}	λ_{PC1}	λ_{PC2}	Adj.R^2
Estimate	0.009	0.004	0.005	-0.003	0.153	0.603	0.210
FM t-stat	5.562	0.881	2.310	-1.262	0.598	3.914	
SH t-stat	3.717	0.567	1.486	-0.817	0.387	2.510	

Table V

Stock Level Risk Premium Estimates — CRX Factor

This table presents the Fama-MacBeth cross-sectional regression results of two-pass regression test using the excess returns on 4,329 US stocks and Credit Risk Factor (CRX) derived from high-minus-low CDS return portfolios. The full-sample factor loadings are computed in one multiple time-series regression in the first stage. Then, the loadings are used as the independent variables in the second stage. The risk premium coefficients are monthly estimates. Panel A presents results for the model with Excess Market Return (MKT) and the CRX factor. Panels B and D present results for the model that includes the three Fama-French factors of market (MKT), size (SMB) and value (HML) as well as the CRX. The models in Panels C and E also include profitability (RMW) and investment (CMA) factors. The adjusted R2 follows Jagannathan and Wang (1996) and Petkova (2006). The first set of t-statistics, indicated by FM t-stat, stands for the Fama-MacBeth estimate. The second set, indicated by SH t-stat, adjusts for errors-in-variables, and follows Shanken (1992). For Panels A, B and C, the sample period is from February 2003 to September 2014. Panels C and E exclude the period 2007–2009.

Panel A: The Model with MKT and the CRX Factor

	λ_0	λ_{Mkt}	λ_{CRX}	Adj.R^2
Estimate	0.009	0.004	0.009	0.162
FM t-stat	5.73	1.05	3.32	
SH t-stat	5.73	0.97	3.11	

Panel B: The Model with Fama-French Three Factors and the CRX Factor

	λ_0	λ_{Mkt}	λ_{SMB}	λ_{HML}	λ_{CRX}	Adj.R^2
Estimate	0.0087	0.0035	0.0047	-0.0033	0.0085	0.214
FM t-stat	5.54	0.88	2.16	-1.32	3.43	
SH t-stat	5.54	0.81	1.99	-1.24	3.19	

Panel C: The Model with Fama-French Five Factors and the CRX Factor

	λ_0	λ_{Mkt}	λ_{SMB}	λ_{HML}	λ_{RMW}	λ_{CMA}	λ_{CRX}	Adj.R^2
Estimate	0.0086	0.0036	0.0046	-0.0034	-0.0016	0.0004	0.0087	0.218
FM t-stat	6.08	0.93	2.17	-1.40	-0.99	0.33	3.71	
SH t-stat	6.08	0.86	1.99	-1.31	-0.90	0.31	3.43	

Panel D: The Model with Fama-French Three Factors and the CRX Factor(Excl.2007–2009)

	λ_0	λ_{Mkt}	λ_{SMB}	λ_{HML}	λ_{CRX}	Adj.R^2
Estimate	0.0082	0.0039	0.0048	-0.0024	0.0067	0.167
FM t-stat	4.98	1.18	2.35	-1.12	3.05	
SH t-stat	4.98	1.06	2.14	-1.03	2.79	

Panel E: The Model with Fama-French Five Factors and the CRX Factor (Excl. 2007–2009)

	λ_0	λ_{Mkt}	λ_{SMB}	λ_{HML}	λ_{RMW}	λ_{CMA}	λ_{CRX}	Adj.R^2
Estimate	0.0086	0.0034	0.0049	-0.0026	-0.0018	-0.0001	0.0070	0.170
FM t-stat	5.17	1.07	2.41	-1.22	-1.18	-0.10	3.36	
SH t-stat	5.17	0.95	2.19	-1.11	-1.07	-0.09	3.05	

Table VI

CRX vs. Fama-French Factors: Redundancy Tests

This table presents the redundancy regressions using Fama and French (2015) factors and the CRX factor. In each regression test, the monthly returns of one factor are regressed on the remaining five factors. Mkt is the excess market return, SMB is the size factor, HML is the value factor, RMW is the profitability factor, and CMA is the investment factor. Coefficients are the regression slopes. T-statistics are based on Newey and West (1994) heteroskedasticity and autocorrelation consistent standard errors with optimal lag. R^2 is the regression R-squares. The CRX is derived from high-minus-low CDS return portfolios. Five Fama-French factors are from the Kenneth French website. The sample period is 01/2003–09/2014.

		Intercept	Mkt	SMB	HML	RMW	CMA	CRX	R^2
CRX									
	Coef.	0.023	0.051	0.212	-0.262	-0.032	-0.117		0.133
	t-stat	3.234	0.926	1.135	-1.816	-0.206	-0.322		0.133
Mkt									
	Coef.	0.009		0.135	0.878	-0.828	-0.623	0.100	0.457
	t-stat	1.548		0.973	4.415	-2.993	-1.894	0.571	0.457
SMB									
	Coef.	-0.002	0.054		0.047	-0.363	0.048	0.167	0.188
	t-stat	-0.715	0.836		0.578	-1.512	0.207	1.384	0.188
HML									
	Coef.	0.002	0.378	0.051		0.329	0.774	-0.222	0.495
	t-stat	0.419	2.440	0.685		2.615	3.729	-0.916	0.495
RMW									
	Coef.	0.005	-0.198	-0.218	0.183		-0.370	-0.015	0.322
	t-stat	4.343	-4.035	-1.667	2.080		-0.994	-0.356	0.322
CMA									
	Coef.	0.002	-0.089	0.017	0.258	-0.221		-0.033	0.279
	t-stat	0.806	-1.610	0.209	3.929	-1.252		-0.324	0.279

Table VII

CRX Portfolios: Characteristics

This table presents the quarterly characteristics of CRX quantile portfolios. *Q1* contains stocks with the lowest CRX loadings, and *Q5* contains the highest. The characteristics include market value (MV), market leverage ratio (Mlevg), investment ratio (Inv), Net debt repayment (NDRepay), book-to-market ratio (BM), profitability (NIMTA), cash liquidity (CASHMTA), earnings-price ratio (E/P), credit ratings(Rating) and Expected Default Frequency(EDF). The sample period is 01/2003–09/2014. All variables are constructed using quarterly COMPUSTAT data. Variable descriptions are in Appendix A.

Panel A: Average Statistics

Quantile	MV	Mlevg	Inv	NDRepay	BM	NIMTA	CASHMTA	E/P	Rating	EDF
Q5	707.3	0.286	0.146	-0.068	0.702	-0.008	0.171	0.012	13.037	0.040
Q4	2024.8	0.252	0.138	-0.025	0.623	0.003	0.147	0.031	11.503	0.023
Q3	3756.0	0.219	0.131	-0.012	0.567	0.008	0.136	0.043	10.101	0.008
Q2	3778.6	0.232	0.124	-0.013	0.594	0.007	0.134	0.058	9.599	0.009
Q1	1099.8	0.230	0.148	-0.055	0.593	-0.000	0.161	0.027	12.120	0.021

Panel B: Median Statistics

Quantile	MV	Mlevg	Inv	NDRepay	BM	NIMTA	CASHMTA	E/P	Rating	EDF
Q5	259.4	0.221	0.101	-0.001	0.557	0.004	0.103	0.013	13.500	0.000
Q4	622.7	0.196	0.101	-0.003	0.536	0.008	0.097	0.020	12.000	0.000
Q3	936.4	0.165	0.099	-0.003	0.506	0.010	0.088	0.023	10.000	0.000
Q2	979.9	0.175	0.088	-0.004	0.535	0.009	0.089	0.026	9.000	0.000
Q1	370.1	0.170	0.104	-0.003	0.520	0.007	0.108	0.017	13.000	0.000

Table VIII

Returns on Equal-Weighted Stock Portfolios Sorted by CDS Returns

This table presents asset-pricing test results using excess returns of Equal-Weighted Stock Portfolios Sorted by CDS Returns. I sort 565 stocks (which have quoted CDS spreads) based on their realized CDS returns into quantile portfolios. $P1$ contains stocks with lowest realized CDS returns, and $P5$ contains the highest. Panel A presents regression estimates for the model with the Fama-French factors of market (MKT), size (SMB) and value (HML). Panel B presents regression estimates for the model including the Fama-French factors of market (MKT), size (SMB) and value (HML) as well as the CRX factor. Values in parentheses are t-statistics based on Newey-West (1994) heteroskedasticity and autocorrelation consistent standard errors with optimal lag. For each panel, the sample period is from February 2003 to September 2014.

Panel A: The Model with Fama-French Factors

	P1	P2	P3	P4	P5	P5-P1
FF alpha	-0.0137	0.0011	0.0046	0.0061	0.0165	0.029
	(-7.9626)	(0.9842)	(4.3614)	(5.8692)	(4.9338)	(7.9361)
Mkt beta	1.2836	1.0257	0.9715	0.9885	1.2282	-0.0518
	(19.0442)	(27.3647)	(40.6034)	(31.3006)	(29.1136)	(-0.6468)
SMB beta	0.3488	0.1452	0.1421	0.2051	0.5706	0.2235
	(5.1898)	(3.0392)	(2.1658)	(3.9475)	(3.2473)	(1.2322)
HML beta	0.3627	0.0168	0.0312	0.0845	0.4744	0.1071
	(3.9677)	(0.2159)	(0.4780)	(1.1923)	(2.6908)	(0.6998)

Panel B: The Model with Fama-French Factors and the CRX Factor

	P1	P2	P3	P4	P5	P5-P1
CRX alpha	-0.0139	-0.0007	0.0010	0.0043	0.0004	0.0124
	(-6.6765)	(-0.4985)	(0.7174)	(3.1881)	(0.1060)	(5.0193)
Mkt beta	1.2838	1.0268	0.9737	0.9896	1.2382	-0.0415
	(19.0685)	(22.7736)	(37.6578)	(30.1985)	(30.4724)	(-0.6992)
SMB beta	0.3480	0.1392	0.1301	0.1991	0.5166	0.1678
	(5.2163)	(3.3886)	(2.0007)	(3.7722)	(4.0432)	(1.3778)
HML beta	0.3648	0.0332	0.0640	0.1011	0.6220	0.2593
	(3.9778)	(0.4516)	(1.2795)	(1.6679)	(6.8519)	(1.9110)
CRX beta	0.0092	0.0725	0.1449	0.0733	0.6520	0.6727
	(0.1872)	(1.2084)	(3.1619)	(1.6934)	(6.5370)	(11.2405)

Table IX

Returns on Value-Weighted Stock Portfolios Sorted by CDS Returns

This table presents asset-pricing test results using excess returns of Value-Weighted Stock Portfolios Sorted by CDS Returns. I sort 565 stocks (which have quoted CDS spreads) based on their realized CDS returns into quantile portfolios. $P1$ contains stocks with lowest realized CDS returns, and $P5$ contains the highest. Panel A presents regression estimates for the model with the Fama-French factors of market (MKT), size (SMB) and value (HML). Panel B presents regression estimates for the model including the Fama-French factors of market (MKT), size (SMB) and value (HML) as well as the CRX factor. Values in parentheses are t-statistics based on Newey-West (1994) heteroskedasticity and autocorrelation consistent standard errors with optimal lag. For each panel, the sample period is from February 2003 to September 2014.

Panel A: The Model with Fama-French Factors

	P1	P2	P3	P4	P5	P5-P1
FF alpha	-0.0100	0.0008	0.0057	0.0088	0.0157	0.0246
	(-5.9253)	(0.5988)	(4.0419)	(8.2440)	(7.7919)	(6.1890)
Mkt beta	1.1434	0.8546	0.8614	0.8416	1.1479	0.0081
	(19.4861)	(17.2684)	(23.3475)	(19.8297)	(15.9395)	(0.0829)
SMB beta	-0.0516	-0.1186	-0.1262	0.0038	0.1486	0.2020
	(-0.8107)	(-1.9514)	(-2.6499)	(0.0656)	(2.1398)	(1.6829)
HML beta	0.4452	0.0790	-0.0871	0.0519	0.3580	-0.0918
	(3.7357)	(0.8151)	(-1.4162)	(0.6970)	(3.9929)	(-0.4137)

Panel B: The Model with Fama-French Factors and the CRX Factor

	P1	P2	P3	P4	P5	P5-P1
CRX alpha	-0.0081	-0.0003	0.0028	0.0085	0.0038	0.0100
	(-4.0805)	(-0.1916)	(1.6252)	(7.0833)	(1.0045)	(2.2512)
Mkt beta	1.1422	0.8553	0.8631	0.8418	1.1552	0.0171
	(18.4759)	(17.3035)	(24.0712)	(20.0107)	(23.9636)	(0.1794)
SMB beta	-0.0453	-0.1221	-0.1359	0.0028	0.1086	0.1531
	(-0.7091)	(-2.0622)	(-2.8433)	(0.0468)	(1.1405)	(1.1951)
HML beta	0.4280	0.0888	-0.0607	0.0547	0.4674	0.0416
	(3.6374)	(0.9237)	(-1.0690)	(0.7313)	(4.0943)	(0.2345)
CRX beta	-0.0763	0.0433	0.1167	0.0120	0.4833	0.5896
	(-1.6266)	(0.8387)	(1.6955)	(0.3770)	(3.4491)	(6.5777)

Table X

Parameters of the Model

This table presents model parameter values calibrated to observed data for the portfolios i $\in \{CH, CL, Mkt\}$ in 2003–2014. The model is calibrated at a monthly frequency. All parameter values are in monthly terms.

$$
\begin{aligned}
s_{t+1} &= \rho_t s_t + \sigma_s \epsilon^s_{t+1} \\
\Delta d^i_{t+1} &= \delta_i + \gamma_{di} s_t + \sigma_{di} \epsilon^d_{t+1} - \sigma_{vi} \epsilon^v_{t+1} \\
v^i_{t+1} &= \mu_i + \rho_v v^i_t + \sigma_{vv} \epsilon^v_{t+1} \\
-m_{t+1} &= r_f + \frac{1}{2} \Lambda'_t \Lambda_t + \Lambda'_t \epsilon_{t+1} \\
\Lambda_t &= \Lambda_0 + \Lambda_1 s_t
\end{aligned}
$$

	ρ_s	σ_s			
State Variable	0.9654	0.26			
	γ_{dM}	σ_{dM}			
Market Portfolio	-0.00236	0.01			
	γ_{dCH}	σ_{dCH}	σ_{vCH}		
CH Portfolio	-0.0107	0.015	0.0437		
	γ_{dCL}	σ_{dCL}	σ_{vCL}		
CLPortfolio	-0.0006	0.02	0.01922		
	$\Lambda_0(1)$	$\Lambda_0(2)$	$\Lambda_0(3)$	$\Lambda_1(1)$	$\Lambda_1(3)$
Market Price of Risk	0.18068	-0.12534	-0.28503	0.49555	0.07615

Table XI

Asset-Pricing Implications

This table presents portfolio moments, return and variance decomposition implied by the parameter values. Panel A reports the annualized mean and standard deviation of portfolio variables in the model and in the data. Moments of portfolio returns reported are monthly. Moments of price-dividend ratios reported are monthly but based on trailing sum of dividends over the past 12 months. The maximum Sharpe Ratio is annualized. Panels B and C report the unconditional return and variance decompositions for each portfolio. The sample time period is 2003–2014.

Panel A: Impled Moments

Moment	Data	Model	Moment	Data	Model
$E(rx^{Market})$	0.00716	0.00716	$E(pd_{Market})$	3.91944	4.957484
$E(rx^{CH})$	0.02399	0.02399	$E(pd_{CH})$	4.55362	5.664220
$E(rx^{CL})$	0.01447	0.01447	$E(pd_{CL})$	4.69764	4.983314
$\sigma(rx^{M})$	0.04374	0.043841	$\sigma(pd_{Market})$	0.16903	0.165366
$\sigma(rx^{CH})$	0.08022	0.084098	$\sigma(pd_{CH})$	0.49564	0.274835
$\sigma(rx^{CL})$	0.05159	0.051074	$\sigma(pd_{CL})$	0.20906	0.167838
β_{CH}	1.51005	1.637641	Max. Sharpe		1.32
β_{CL}	1.04016	1.056483			

Panel B: Return Decomposition

	Dividend Growth Risk $(\Lambda_0(1)\sigma_{di})$	**Cyclical Risk** $(\Lambda_0(2)\kappa_{1i}B_i\sigma_s)$	**Financial Uncertainty Risk** $(-\Lambda_0(3)\sigma_{vi})$	**Total**
Market Portfolio	0.18%	0.53%	–	0.7%
CH Portfolio	0.27%	0.88%	1.25%	2.4%
CL Portfolio	0.36%	0.54%	0.55%	1.45%

Panel C: Variance Decomposition

	Dividend Growth Risk (σ_{di}^2)	**Cyclical Risk** $(\kappa_{1i}^2 B_i^2 \sigma_s^2)$	**Financial Uncertainty Risk** (σ_{vi}^2)	**Total**
Market Portfolio	0.01%	0.18%		0.19%
CH Portfolio	0.02%	0.49%	0.19%	0.70%
CL Portfolio	0.04%	0.18%	0.04%	0.26%

Appendix A. Data Description

This appendix provides a detailed description of variable construction. All variables are constructed using quarterly COMPUSTAT data.

Market Value of Equity (MV): Market Value (MV) is determined by Shares Outstanding ($cshoq$) times Price Close ($prccq$)

Market Leverage (MLevg): Market Leverage is given by

$$MLevg_t = \frac{BV\ of\ Debt_t}{MV_t},$$

where BV of Debt is determined by short-term debt ($dlcq$) plus long-term debt ($dlttq$) and MV is the market value of equity.

Investment (Inv): Investment is determined by

$$Inv_t = \frac{CAPEX_t - PSALE_t}{PPE_t},$$

where CAPEX is capital expenditures ($capxy$), PSALE is sale of property ($sppey$) and PPE is the book value of property plant and equipment ($ppentq$).

Book-to-Market Ratio (BM): Book-to-Market ratio (BM) is book value of equity ($ceqq$) divided by the market value of equity (MV).

Profitability (NIMTA): Following Campbell et al. (2008), profitability is determined by

$$NIMTA_t = \frac{NI_t}{MV\ of\ Assets_t},$$

where NI is the net income (ibq) and MV of Assets is the Market Value of Total Assets given by the market value of equity (MV) plus the book value of debt ($dlcq + dlttq$).

Cash Liquidity (CASHMTA): Following Campbell et al. (2008), cash liquidity is given by

$$CASHMTA_t = \frac{CASH_t}{MV\ of\ Assets_t},$$

where CASH is the cash and short-term investments (*cheq*) and MV of Assets is the Market Value of Total Assets given by the market value of equity (MV) plus the book value of debt ($dlcq + dlttq$).

Debt Repayment (NDRepay): FollowingGomes et al. (2017), debt repayment is calculated by

$$NDRepay_t = \frac{\Delta BE_t - \Delta BA_t}{BA_{t-1}},$$

where ΔBE_t is the change in the book value of equity at quarter t, ΔBA_t is the change in the book value of assets at quarter t, and BA_{t-1} is the book value of assets in the previous quarter.

Earnings-Price Ratio (E/P): Earnings-Price ratio is calculated by earnings divided by the market value of equity (MV). Earnings is the net income (*ibq*) plus deferred taxes (*txditcq*) minus preferred dividends (*dvpy*).

Credit Rating: (Rating:) Firms' S&P credit ratings are obtained from COMPUSTAT's Domestic Long-Term Issuer Credit Rating (*splticrm*) data item. Rating is determined by assigning integer numbers to the firms' S&P credit ratings, that is, AAA=1, AA+=2,.....C=21, D=22.

Appendix B. Conditional Default Probabilities

In this section, I will derive the conditional default probabilities for firms in multi-firm Merton-type model. In single-firm Merton model with zero-coupon debt with face value D and time-to-maturity T, the probability of default for a firm i under the physical measure $PD^{\mathbb{P}}_{i,t}$ (i.e., the probability that $Prob(V_{i,t+T} < D_i)$) is given by

$$PD_{i,t}^{\mathbb{P}} = P(V_{i,t+T} < D_i) = P\left(\frac{W_{i,t+T} - W_{i,t}}{\sqrt{T}} < \frac{ln(D_i/V_{i,t}) - (\mu_i - \frac{1}{2}\sigma_i)T}{\sigma_i\sqrt{T}}\right). \quad \text{(B1)}$$

In multiple-firm framework, the default probabilities are conditional on the default dependencies, that is, asset correlations. Thus, the conditional default probabilities is obtained as the probability of $V_{i,t+T} < D_i$ conditional on the realization f of common component under the physical measure. Then, the conditional default probability for a firm i under the physical measure $CPD_{i,t}^{\mathbb{P}}$ becomes

$$CPD_{i,t}^{\mathbb{P}} = [PD_{i,t}^{\mathbb{P}}/\Delta F_t = f] = P(V_{i,t+T} < D_i/\Delta F_t = f) \quad \text{(B2)}$$

$$= P\left(\frac{W_{i,t+T} - W_{i,t}}{\sqrt{T}} < \frac{ln(D_i/V_{i,t}) - (\mu_i - \frac{1}{2}\sigma_i)T}{\sigma_i\sqrt{T}} \Big/ \Delta F_t = f\right) \quad \text{(B3)}$$

$$= P\left(\rho_i\left(\frac{F_{t+T} - F_t}{\sqrt{T}}\right) + \sqrt{1-\rho_i^2}\left(\frac{B_{i,t+T} - B_{i,t}}{\sqrt{T}}\right) < \frac{ln(D_i/V_{i,t}) - (\mu_i - \frac{1}{2}\sigma_i)T}{\sigma_i\sqrt{T}} \Big/ \Delta F_t = f\right) \quad \text{(B4)}$$

$$= P\left(\left(\frac{\rho_i f}{\sqrt{T}}\right) + \sqrt{1-\rho_i^2}\left(\frac{B_{i,t+T} - B_{i,t}}{\sqrt{T}}\right) < \frac{ln(D_i/V_{i,t}) - (\mu_i - \frac{1}{2}\sigma_i)T}{\sigma_i\sqrt{T}}\right) \quad \text{(B5)}$$

$$= P\left(\frac{B_{i,t+T} - B_{i,t}}{\sqrt{T}} < \frac{ln(D_i/V_{i,t}) - (\mu_i - \frac{1}{2}\sigma_i)T}{\sigma_i\sqrt{T}\sqrt{1-\rho_i^2}} - \frac{\rho_i f}{\sqrt{T}\sqrt{1-\rho_i^2}}\right). \quad \text{(B6)}$$

Since $\frac{B_{i,t+T}-B_{i,t}}{\sqrt{T}}$ follows standard normal distribution, the conditional default probability under the physical risk measure is obtained as

$$CPD_{i,t}^{\mathbb{P}} = \Phi\left(\frac{ln(D_i/V_{i,t}) - (\mu_i - \frac{1}{2}\sigma_i)T - \rho_i f \sigma_i}{\sigma_i\sqrt{T}\sqrt{1-\rho_i^2}}\right). \quad \text{(B7)}$$

The conditional default probability under the risk-neutral risk measure can be found analogously as

$$CPD_{i,t}^{\mathbb{Q}} = \Phi\left(\frac{ln(D_i/V_{i,t}) - (r - \frac{1}{2}\sigma_i)T - \rho_i f \sigma_i}{\sigma_i\sqrt{T}\sqrt{1-\rho_i^2}}\right). \quad \text{(B8)}$$

Appendix C. Equity and Credit Return Dynamics

Here, I provide the link between expected return and volatility for equity and credit (CDS) claims in a multi-firm framework. The derivations exactly follow the single-firm framework results of Friewald et al. (2014), since the unconditional asset processes in single-firm and multi-firm settings are identical.

In a multi-firm Merton-type structural model, the asset value V_i for firm i under physical and risk-neutral measure are defined as[14]

$$\begin{aligned} dV_i &= \mu_i V_i dt + \sigma_i V_i dW_i^{\mathbb{P}} \,, \\ dV_i &= r V_i dt + \sigma_i V_i dW_i^{\mathbb{Q}} \,. \end{aligned} \tag{C1}$$

Firm default dependencies can be captured by decomposing W_i into two independent Brownian motions with a common component F_i and firms specific component B_i, as follows:

$$dW_i^{\mathbb{P}} = \rho_i dF^{\mathbb{P}} + \sqrt{1-\rho_i^2} dB_i^{\mathbb{P}} \,, \tag{C2}$$

$$dW_i^{\mathbb{Q}} = \rho_i dF^{\mathbb{Q}} + \sqrt{1-\rho_i^2} dB_i^{\mathbb{Q}} \,. \tag{C3}$$

Thus, asset values in C1 become

$$dV_i = \mu_i V_i dt + \sigma_i V_i (\rho_i dF^{\mathbb{P}} + \sqrt{1-\rho_i^2} dB_i^{\mathbb{P}}) \,, \tag{C4}$$

$$dV_i = r V_i dt + \sigma_i V_i (\rho_i dF^{\mathbb{Q}} + \sqrt{1-\rho_i^2} dB_i^{\mathbb{Q}}) \,. \tag{C5}$$

I first consider the equity claim. In the Merton framework, equity represents a European call option written on a firm's assets with strike equal to the firm's zero-coupon debt D_i and time-to-maturity T. Then, given the equity is a function of both V_i and t. Applying Ito's lemma to $E_i = f(t, V_i)$ under both measures yields the following:

[14] I suppress time subscripts for ease of notation.

$$\frac{dE_i}{E_i} = \frac{\frac{\partial E_i}{\partial dt} + \mu_i V_i \frac{\partial E_i}{\partial V_i} + \frac{1}{2}\sigma_i^2 V_i^2 \frac{\partial^2 E_i}{\partial V_i^2}}{E_i} dt + \sigma_i \frac{\frac{\partial E_i}{\partial V_i} V_i}{E_i} (\rho_i dF^{\mathbb{P}} + \sqrt{1-\rho_i^2} dB_i^{\mathbb{P}})\,, \tag{C6}$$

$$\frac{dE_i}{E_i} = \frac{\frac{\partial E_i}{\partial dt} + r V_i \frac{\partial E_i}{\partial V_i} + \frac{1}{2}\sigma_i^2 V_i^2 \frac{\partial^2 E_i}{\partial V_i^2}}{E_i} dt + \sigma_i \frac{\frac{\partial E_i}{\partial V_i} V_i}{E_i} (\rho_i dF^{\mathbb{Q}} + \sqrt{1-\rho_i^2} dB_i^{\mathbb{Q}})\,. \tag{C7}$$

The instantaneous expected returns and volatility on equity under $\mathbb{P}$- and $\mathbb{Q}$-measures are defined similar to single-firm case. For a firm i, those are given by

$$\begin{aligned} \mu_{E,i} &= E^{\mathbb{P}}\left[\frac{dE_i}{E_i}\right] = \frac{\frac{\partial E_i}{\partial dt} + \mu_i V_i \frac{\partial E_i}{\partial V_i} + \frac{1}{2}\sigma_i^2 V_i^2 \frac{\partial^2 E_i}{\partial V_i^2}}{E_i}\,, \\ \sigma_{E,i} &= \sqrt{Var^{\mathbb{P}}\left[\frac{dE_i}{E_i}\right]} = \sigma_i \left[\frac{V_i}{E_i}\frac{\partial E_i}{\partial V_i}\right]\,. \end{aligned} \tag{C8}$$

Under the $\mathbb{Q}$-measure, instantaneous expected equity return and volatility for firm i are given by

$$\begin{aligned} r &= E^{\mathbb{Q}}\left[\frac{dE_i}{E_i}\right] = \frac{\frac{\partial E_i}{\partial dt} + r V_i \frac{\partial E_i}{\partial V_i} + \frac{1}{2}\sigma_i^2 V_i^2 \frac{\partial^2 E_i}{\partial V_i^2}}{E_i}\,, \\ \sigma_{E,i} &= \sqrt{Var^{\mathbb{Q}}\left[\frac{dE_i}{E_i}\right]} = \sigma_i \left[\frac{V_i}{E_i}\frac{\partial E_i}{\partial V_i}\right]\,. \end{aligned} \tag{C9}$$

Combining C8 and C9 equates firm i's equity and asset Sharpe Ratio (market price of risk) as follows:

$$\lambda_{E,i} = \frac{\mu_{E,i} - r}{\sigma_{E,i}} = \frac{\mu_i - r}{\sigma_i} = \lambda_i\,. \tag{C10}$$

Now consider the CDS contract as a credit claim. In the Merton framework, a European put option written on a firm's assets with strike equal to the firm's zero-coupon debt D_i and time-to-maturity T is a hedge against default event. Following Friewald et al. (2014), I consider a CDS contract as a credit insurance with premium S^T, the CDS Spread, which a protection buyer holds until a default event or contract expiration. Both being default protection hedges at maturity T, the CDS contract and put option P_i have the same value. Then the CDS spread with continuous premium payments is given by the following:

$$S_i^T = \frac{r}{1-e^{-}rT} P_i \,, \tag{C11}$$

which implies that the CDS spread is a function of V_i. Analogous to the equity claim, applying Ito's lemma under $\mathbb{P}$- and $\mathbb{Q}$-measures and combining yields the following:

$$\mu_{S,i}^{\mathbb{P}} - \mu_{S,i}^{\mathbb{Q}} = \mu_i - r\left[\frac{V_i}{S_i}\frac{\partial S_i}{\partial V_i}\right] , \tag{C12}$$

$$\sigma_{S,i} = \sigma_i\left[\frac{V_i}{S_i}\left|\frac{\partial S_i}{\partial V_i}\right|\right] . \tag{C13}$$

Since $\partial S_i/\partial V_i$ refers to the put option's delta, which is less than zero, this follows:

$$\lambda_{S,i} = \frac{\mu_{S,i}^{\mathbb{P}} - \mu_{S,i}^{\mathbb{Q}}}{\sigma_{S,i}} = -\frac{\mu_i - r}{\sigma_i} = -\lambda_i \,, \tag{C14}$$

and thus $\lambda_{E,i} = -\lambda_{S,i}$.

Appendix D. CDS Return Computation

Here, I give a technical summary for CDS valuation and return computation. Mainly I follow the approaches of Lee et al. (2017) and Friewald et al. (2014), which are also the industry standard practices. Since CDS valuation is well-documented in academic papers, I instead give you a summary. Please check the aformentioned papers for derivations and further details, if necessary.

A CDS with a five-year time-to-maturity has two legs in valuation. Premium Leg refers to the discounted value of the sequence of risk premium payments for the contract. Protection Leg refers to the one-time payment *contingent* to the event of default. Following Lee et al. (2017) we can define premium leg for five-year maturity CDS contract given the quoted spread S_0 as follows:

$$PremiumPV = S_0 * RPV01(t_0, t_{21}) \tag{D1}$$

$$\begin{aligned} RPV01(t_0, t_{21}) = & \sum_{n=1}^{21} \Delta(t_{n-1}, t_n) Z(t_0, t_n) Q(t_0, t_n) \\ & + \sum_{n=1}^{21} \frac{1}{2} \Delta(t_{n-1}, t_n) Z(t_0, t_n) (Q(t_0, t_{n-1}) - Q(t_0, t_n)), \end{aligned} \tag{D2}$$

where t_i represents quarterly payment dates of a five-year contract, t_0 being the valuation date, $\Delta(t_{n-1}, t_n)$ is the corresponding accrual factor for the time period $[t_{n-1}, t_n]$, $Z(t_0, t_n)$ is the risk-free discount factor for the time period $[t_0, t_n]$, and $Q(t_0, t_n)$ is the survival probability for the time period $[t_0, t_n]$. With the same notation, and assuming a constant loss given default (1-R), Protection Leg is given by

$$ProtectionPV = (1 - R) \sum_{n=1}^{21} Z(t_0, t_n)(Q(t_0, t_{n-1}) - Q(t_0, t_n)). \tag{D3}$$

Combining two legs, the mark-to-market value of a five-year short protection position of a CDS with a unit \$1-notional at t_0 becomes

$$V(t_0) = S_0 * RPV01(t_0, t_{21}) - (1 - R) \sum_{n=1}^{21} Z(t_0, t_n)(Q(t_0, t_{n-1}) - Q(t_0, t_n)). \tag{D4}$$

With this valuation framework, CDS return with a unit \$1-notional can be defined. For a seller of a CDS protection at time t_0 who unwinds the position at time t' by buying a protection on the same reference entity and the same maturity date, the CDS return becomes

$$CDSReturn(t_0, t') = -(S(t') - S(t_0)) * RPV01(t', t_{21}). \tag{D5}$$

I compute monthly CDS returns using Equation D. I follow Lee et al. (2017) and Friewald et al. (2014) and fit US Libor and swap rates to the Nelson-Siegel-Svenson curve, and then use those fitted values to construct the risk-free discount factors, $Z(t_0, t_n)$, for each month. To obtain the survival probabilities $Q(t_0, t_n)$ for each contract at each month, I follow Berndt and Obreja (2010) and use the following formulas for five-year maturity CDS contracts:

$$Q(t_0, t_n) = e^{\lambda(t_n - t_0)} \,, \tag{D6}$$

$$\lambda = 4log\left(1 + \frac{S(t_0)}{4R}\right) \,. \tag{D7}$$

where recovery rate is assumed as $R = 0.6$.

Appendix E. Structural Model Derivations

This section provides the derivations for the equilibrium stock prices and related moments used in the calibration exercise. The economy is defined by a single-state variable, a log stochastic discount factor, and the processes of dividend growth and latent financial uncertainty for an asset space i $\in \{CH, CL, Mkt\}$ as follows:

$$\begin{aligned}
s_{t+1} &= \rho_t s_t + \sigma_s \epsilon^s_{t+1} \,, \\
\Delta d^i_{t+1} &= \delta_i + \gamma_{di} s_t + \sigma_{di} \epsilon^d_{t+1} - \sigma_{vi} \epsilon^v_{t+1} \,, \\
v^i_{t+1} &= \mu_i + \rho_v v^i_t + \sigma_{vv} \epsilon^v_{t+1} \,, \\
-m_{t+1} &= r_f + \frac{1}{2} \Lambda'_t \Lambda_t + \Lambda'_t \epsilon_{t+1} \,, \\
\Lambda_t &= \Lambda_0 + \Lambda_1 s_t \,.
\end{aligned}$$

<u>Price-Dividend Ratios</u>

The log price-dividend ratio for portfolio i is affine in state s_t such that

$$pd_i = A_i + B_i s_t \,, \tag{E1}$$

where

$$B_i = \frac{\gamma_{di} - \Lambda_1(1)\sigma_{di} + \Lambda_3(1)\sigma_{vi}}{1 - \kappa_{1i}\rho_s}, \qquad \kappa_{1i} = \frac{exp(\overline{pd})}{exp(\overline{pd}) + 1} \,. \tag{E2}$$

The proof follows Campbell-Shiller return decomposition as in Koijen et al. (2017). The log return identity is given by

$$
\begin{aligned}
R_{t+1} &= \frac{P_{t+1}+D_{t+1}}{P_t} = \left(\frac{P_{t+1}/D_{t+1}+1}{P_t/D_t}\right)\frac{D_{t+1}}{D_t}\,, \\
ln(R_{t+1)} &= ln\left(\frac{P_{t+1}}{D_{t+1}}+1\right) - ln\left(\frac{P_t}{D_t}\right) + ln\left(\frac{D_{t+1}}{D_t}\right)\,, \\
r_{t+1} &= ln(1+exp(pd_{t+1})) + \Delta d_{t+1} - pd_t \\
&\approx ln(1+exp(\overline{pd})) + \frac{exp(\overline{pd})}{exp(\overline{pd})+1}(pd_{t+1}-\overline{pd}) + \Delta d_{t+1} - pd_t \\
&= \kappa_0 + \kappa_1 pd_{t+1} + \Delta d_{t+1} - pd_t\,,
\end{aligned}
$$

where κ_0, κ_1 are given by

$$
\begin{aligned}
\kappa_0 &= ln(1+exp(\overline{pd})) - \kappa_1\overline{pd}\,, \\
\kappa_1 &= \kappa_{1i} = \frac{exp(\overline{pd})}{exp(\overline{pd})+1}\,.
\end{aligned}
$$

Using the conjecture for price-dividend ratio and dividend growth process, the Euler equation $E_t[M_{t+1}R_{i,t+1}] = 1$ for pricing kernel M_t results in the following:

$$
\begin{aligned}
1 &= E_t[M_{t+1}R_{i,t+1}] \\
0 &= ln(E_t[M_{t+1}R_{i,t+1}]) \\
&= E_t(m_{t+1}) + \frac{1}{2}Var_t(m_{t+1}) + E_t(r_{t+1}) + \frac{1}{2}Var_t(r_{t+1}) + Cov_t(m_{t+1}, r_{t+1}) \\
&= -r_f + E_t[\kappa_0 + \kappa_1 pd_{t+1} + \Delta d_{t+1} - pd_t] + \frac{1}{2}Var_t(\kappa_1 pd_{t+1} + \Delta d_{t+1}) \\
&\quad + Cov(-\Lambda_t'\epsilon_{t+1}, \kappa_1 pd_{t+1} + \Delta d_{t+1}) \\
&= -r_f + \kappa_0 + \kappa_1(A + B\rho_s s_t) + \delta + \gamma_d s_t - A - Bs_t + \frac{1}{2}\kappa_1^2 B^2\sigma_s^2 + \frac{1}{2}\sigma_d^2 + \frac{1}{2}\sigma_v^2 \\
&\quad - \Lambda_0(1)\sigma_d - \Lambda_0(2)\kappa_1 B\sigma_s + \Lambda_0(3)\sigma_v - (\Lambda_1(1)\sigma_d - \Lambda_1(3)\sigma_v)\, s_t
\end{aligned}
$$

This system of equations implies

$$0 = -r_f + \kappa_0 + (\kappa_1 - 1)A + \delta + \frac{1}{2}\kappa_1^2 B^2 \sigma_s^2 + \frac{1}{2}\sigma_d^2 + \frac{1}{2}\sigma_v^2 - \Lambda_0(1)\sigma_d - \Lambda_0(2)\kappa_1 B\sigma_s + \Lambda_0(3)\sigma_v$$
$$0 = B(\kappa_1\rho_s - 1) + \gamma_1 - \Lambda_1(1)\sigma_d + \Lambda_1(3)\sigma_v$$

Rearranging terms gives the following price-dividend ratio coefficients for each portfolio i as follows:

$$A_i = \frac{-r_f + \kappa_{0i} + \delta_i + \frac{1}{2}\kappa_{1i}^2 B_i^2 \sigma_s^2 + \frac{1}{2}\sigma_{di}^2 + \frac{1}{2}\sigma_{vi}^2 - \Lambda_0(1)\sigma_{di} - \Lambda_0(2)\kappa_{1i} B_i \sigma_s + \Lambda_0(3)\sigma_{vi}}{1 - \kappa_{1i}} \tag{E3}$$
$$B_i = \frac{\gamma_{di} - \Lambda_1(1)\sigma_{di} + \Lambda_1(3)\sigma_{vi}}{1 - \kappa_{1i}\rho_s} \tag{E4}$$

Stock Returns and Volatilities

The log equity risk premium for each portfolio i is given by

$$\begin{aligned} E_t[rx_{t+1}^i] &= Cov(-m_{t+1}, r_{t+1}^i) = Cov(\Lambda_t' \epsilon_{t+1}, \kappa_{1i} pd_{t+1}^i + \Delta d_{t+1}^i) \\ &= Cov(\Lambda_t' \epsilon_{t+1}, \kappa_{1i} B_i \rho_s \sigma_s \epsilon_{t+1}^s + \sigma_d i \epsilon_{t+1}^d - \sigma_v i \epsilon_{t+1}^v) \\ &= \Lambda_0(1)\sigma_{di} + \Lambda_0(2)\kappa_{1i} B_i \sigma_s - \Lambda_0(3)\sigma_{vi} \quad + \quad (\Lambda_1(1)\sigma_{di} - \Lambda_3(1)\sigma_{vi})\, s_t \end{aligned} \tag{E5}$$

For standardized state variable s_t, the unconditional first moment of log equity risk premium used in calibration exercise is then given by

$$E(rx^i) = E[E_t[rx_{t+1}^i]] = \Lambda_0(1)\sigma_{di} + \Lambda_0(2)\kappa_{1i} B_i \sigma_s - \Lambda_0(3)\sigma_{vi}\,. \tag{E6}$$

The second centered moment of stock returns are found by:

$$\begin{aligned} Var(r_{t+1}^i) &= E[(r_{t+1}^i - E_t[r_{t+1}^i])^2] \\ &= E[(\kappa_{1i} B_i \sigma_s \epsilon_{t+1}^s + \sigma_{di}\epsilon_{t+1}^d - \sigma_{vi}\epsilon_{t+1}^v)^2] \\ \sigma^2(r^i) &= \kappa_{1i}^2 B_i^2 \sigma_s^2 + \sigma_{di}^2 + \sigma_{vi}^2\,. \end{aligned} \tag{E7}$$

For convenience, I choose to calibrate excess return volatility rather than the return volatility using equation E7.

Similarly, the covariance of the portfolio returns is given by

$$\begin{aligned} Cov(r_{t+1}^{i}, r_{t+1}^{Mkt}) &= Cov[(\kappa_{1i} B_i \sigma_s \epsilon_{t+1}^{s} + \sigma_{di} \epsilon_{t+1}^{d} - \sigma_{vi} \epsilon_{t+1}^{v}), (\kappa_{1M} B_M \sigma_s \epsilon_{t+1}^{s} + \sigma_{dM} \epsilon_{t+1}^{d})] \\ &= \sigma_{dM} \sigma_{di} + \kappa_{1M} B_M \kappa_{1i} B_i \sigma_s^2 \,. \end{aligned} \tag{E8}$$

Then, the model-implied market betas are simply the market covariance in (E8) divided by the model-implied variance given by (E7) for market portfolio.