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Systemic Credit Risk Premium: Insights from Credit Derivatives Markets

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Abstract

This study examines the market-implied premiums for bearing systemic credit risk by analyzing credit derivatives on the CDX North American Investment Grade portfolio from September 2005 to March 2021. We construct *systemic credit risk premium* (SCRP) as the difference between the observed prices of multi-name super-senior tranches and their synthetic counterparts valued from historical asset correlations implied by single-name CDS spreads. Our findings show that the fitted SCRP surged during the 2007-2009 financial crisis, remained stable for a period, declined gradually after 2016, and spiked again during the COVID-19 shock. The empirical analysis highlights that the estimated SCRP has significant implications for asset pricing, particularly in affecting investment opportunities for U.S. stock investors during periods of financial instability.

Keywords — Credit Default Swap (CDS); CDS Index (CDX); Reference Tranche Rate; Systemic Credit Risk Premium

JEL — C63; G01; G12; G17

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1. Introduction

Market participants face the risk of encountering correlated defaults, as corporate defaults tend to cluster Das et al. (2007); Duffie et al. (2009). Given the significant impact of a potential cluster of correlated defaults on the entire system Giesecke and Kim (2011), investors generally require significant premiums to account for the risk of default correlation dynamics. Gaining insight into the default dependence and the associated premium movements is both an intellectually stimulating task and an important step toward understanding systemic risk, financial stability, and cross-market asset pricing implications Bhansali et al. (2008); Azizpour et al. (2011); Driessen et al. (2009); Bondarenko and Bernard (2023).

In this study, we construct, estimate and investigate *systemic credit risk premium* (SCRP), which reflects the extra compensation that investors demand for holding assets exposed to the risk of a cascade of defaults across multiple investments, leading to systemic losses that are more severe than expected based on individual credit risk alone. SCRP is a form of the credit risk premium that depends on the joint behavior of the underlying assets and highlights the inter-dependencies among them. In essence, SCRP addresses the risk premium for a borrower's defaults triggering other borrowers' defaults, particularly if these defaults are correlated due to common exposures or contagion effects.

We aim to extract the dynamics of SCRP based on the portfolio-wide default risk premium after controlling for the individual default risk premium. Through this analysis, potential approaches for distinguishing the portfolio default risk premium into two distinct components, namely the individual default risk premium and the systemic credit risk premium, can be identified. The former component focuses on the possibility of a single asset failing, while the latter relates to the probability of multiple assets failing simultaneously. The structured credit market's overall perception of joint loss distribution for the reference entities in the index can be deduced by examining the quotes of single-name Credit Default Swap (CDS) and multi-name CDS index (CDX) tranche spreads. Accordingly, our study employs both CDS and CDX tranche rates to isolate the individual default risk premium at the portfolio level.

To the best of our knowledge, the existing literature has not clearly addressed these issues; thus, this paper fills this gap. For example, Giesecke and Kim (2011) develop dynamic measures of systemic risk, defining it as the conditional probability of correlated failures in the financial sector, based on a dynamic hazard model for accurate out-of-sample forecasts of the U.S. term structure of systemic risk, while not examining the dynamic premium for bearing systemic risk. Azizpour et al. (2011) examine the premiums associated with correlated default risk using corporate default data and CDX market rates. They compare the actual default event intensity with the risk-neutral intensity of CDX market rates. In contrast, our methodology compares CDX tranche spreads to hypothetically synthesized tranche spreads derived solely from CDS spreads. Li and Zinna (2014) study systemic bank credit risk using a multivariate credit risk model and CDS values to examine the compensation for default risk as systemic risk and bank-specific risk. Although they show that their estimated systemic credit risk is related to the CDX spread, they use the CDS market data alone to estimate the premium. The study by Huang (2020) explores correlated default risk and premiums in CDS of six major U.S. banks from 2002 to 2018, finding that the estimated conditional variance is asymmetric and leptokurtic, with positive shocks increasing variance more than negative ones. Notably, the CDS-implied conditional correlations have remained high since the financial crisis, in contrast to declining stock correlations, indicating persistent systemic risk in the banking sector. Our approach differs in that we employ both CDS and CDX market data to isolate the SCRP, while controlling for the individual credit risk premiums across the 125 index constituents.

Admittedly, participants in the single-name CDS market also require significant premiums to compensate for systemic credit risks Markose et al. (2012); Paddrik et al. (2016). However, as shown in Amato and Gyntelberg (2005), different CDX tranches exhibit different price sensitivities to the time-varying default correlations. Consequently, the SCRP captured by CDS spreads (or, equivalently, CDX index spreads) alone differs from the spreads across CDX tranches with different attachment and detachment points. Bhansali et al. (2008) show that the senior and super-senior tranches have high exposures to the systemic factor. The spreads for the super-senior tranche reflect the market price of bearing systemic tail (or economic catastrophe) risk, as the super-senior tranche investors face losses only in the event of a shock triggering the nearly simultaneous default of a substantial number of firms in the economy Berndt and Obreja (2010). In addition, Azizpour et al. (2018) find that CDX investors require risk premiums for bearing clustered default risk and part of the risk premiums for senior CDX tranches can be attributed to contagion risk.

Accordingly, our study focuses specifically on the *super-senior* tranche spreads of the CDX North American Investment Grade (CDX.NA.IG), which serve as a proxy for the systemic credit risk premium. In this context, the SCRP is positively associated with the senior tranche spread. This positive relationship arises because the realization of super-senior tranche losses is limited to extreme scenarios, making the corresponding SCRP specific to the senior tranche a meaningful measure of the market's perception of the prevailing systemic credit risk. We focus on 5-year maturity, on-the-run CDS and CDX products to mitigate liquidity concerns in our analysis. In the end, we analyze the 5-year super-senior tranche at the tranche-swap spread level, rather than the correlation level, to circumvent model risk across tranches and maturities.

The implication of SCRP has considerable academic significance in finance. It is also pertinent for policymakers who utilize credit market signals to make decisions. Consequently, its importance is highlighted by events such as the global financial crisis and the COVID-19 pandemic, which illustrate how market participants perceive systemic risk and how financial sector issues can impact the real sector or vice versa. The 2007-9 global financial crisis demonstrated that risk management at the individual financial firm level is insufficient and underscored the need for macroprudential supervision to ensure the holistic management of systemic risk. The recent downturn in financial markets due to the COVID-19 pandemic highlights the possibility of future similar scenarios, even with the potential resolution of the pandemic-related adverse feedback loop.

This paper makes a unique and significant contribution to the literature by directly estimating the SCRP and examining how market participants perceived major recent crises, including the global financial crisis and the COVID-19 pandemic. Tarashev and Zhu (2008) show the pricing of correlated default risk premiums using the CDS and CDX market data. They extract the risk-neutral probability of default and physical asset return correlations from single-name CDS spreads and compare them to correlations obtained using CDX tranche spreads. Nevertheless, our study utilizes CDS spreads to produce artificial tranche spreads, which we then compare directly to market-traded CDX tranche spreads to extract the time-series implications of SCRP. The SCRP units are the same as market-traded instrument units, allowing for a more direct interpretation of SCRP. Unlike the extraction of implied correlation, the calculation of the spread exhibits a lower sensitivity to model risk, and its theoretical range lacks an upper bound, making it more practical and adaptable in times of market instability.

Our fitted SCRP is inferred from structured credit market data that encompasses real-time market price information offering forward-looking indications of default likelihood and the related premiums associated with the underlying names in the portfolio. As such, the estimated SCRP provides the benefit of being more directly linked to the system-wide credit risk premium, in contrast to measures extrapolated from other markets, such as the equity market. Driessen et al. (2009) show the market price of correlation risk inferred from the equity options market data. Using S&P100 index options and individual equity options on all components, their paper demonstrates that the index variance risk premium can be decomposed into an individual variance risk premium and a correlation risk premium. Bondarenko and Bernard (2023) explore options written on individual stocks and their associated index to identify a dependence structure that can illuminate the return distribution of the index. To this end, they introduce the concept of model-free dependence recovery (MFDR), leveraging options on the S&P 500 index and nine industry sectors, particularly those traded as ETF options. Our approach is similar in that it uses the multi-name CDX tranche spreads and the single-name CDS of the reference entities that make up the CDX to decompose the portfolio default risk premium into an individual default risk premium and a SCRP. However, the SCRP, estimated from credit derivatives directly related to corporate default, can be seen as a conceptually more relevant measure of the system-wide systemic credit risk premium than the correlated risk premium derived from equity options. Rodríguez-Moreno and Peña (2013) estimate market-based systemic risk measures by using data on interbank interest rates, stock prices, and credit derivatives, suggesting that measures based on CDS spreads outperform measures based on interbank rates or stock market prices.

Furthermore, our empirical analysis sheds light on the cross-market implications for asset pricing, revealing that the estimated SCRP is vital as a significantly priced risk factor in the investment opportunities available to U.S. stock investors, particularly during times of financial instability. Our findings highlight the significant impact of SCRP on the equity market, thereby establishing a link between the equity market and the structured credit derivatives market. More specifically, this paper empirically analyzes how U.S. equity market participants perceive SCRP information extracted from the credit derivatives market. While the analyses in Kitwiwattanachai and Pearson (2015) and Huang (2020) focused on discrepancies between CDS-implied and equity return correlations, we conduct an in-depth analysis to assess whether the fitted SCRP, extracted from credit market data, is perceived as a significantly priced risk factor in the equity market, during crises and in normal periods. Related to our approach, Collin-Dufresne et al. (2024), using multivariate affine transformation analysis, explore several aspects of the joint dynamics of CDX and S&P 500 (SPX) options while showing that the credit and equity markets are not fully integrated. Our analysis shows that, after controlling for Fama and French's three factors and a momentum factor in both time-series and cross-sectional regressions, stock market participants demand additional compensation for taking on systemic credit risk, primarily when the financial system is vulnerable as a whole. These findings demonstrate that the estimated SCRP is an important cross-market pricing factor affecting stock investors' decisions during periods of financial instability.

2. Motivation

This section outlines our research objectives, introduces the concept of market-implied SCRP in credit derivatives, and explains how to apply the fitted SCRP in a cross-market asset pricing framework.

2.1. Main objectives

The aim of this study is to extract the time-series dynamics of the SCRP by analyzing portfolio-wide default risk premiums while controlling for individual credit risk premiums, using single-name CDS spreads and multi-name CDX tranche spreads. In conceptual terms, the SCRP estimation approach is relevant to the trading strategy of premiums on default timing correlation through combining individual CDS contracts and CDX tranche swap contracts. This strategy aims to reduce the risk of correlated defaults adversely affecting the overall portfolio while simultaneously hedging against the risk of individual reference entity defaults. CDX tranche swaps allow investors to take positions on a reference entity portfolio's credit risk, enabling them to hedge against the risk of a cluster of defaults in the index. In contrast, CDS contracts protect against the individual reference entity default, allowing market participants to hedge against idiosyncratic default risk. Market participants can trade default timing correlation by taking long positions in CDX tranche swaps and short positions in CDS individual reference entity contracts within the portfolio.

The paper examines the systemic credit risk premium by exploring the estimated SCRPs derived from the market prices of credit derivatives directly associated with corporate default events. We employ the CDX senior tranche swap price as the portfolio default risk premium to obtain a more pertinent estimation of the systemic credit risk premium. Tranches are structured products that allow investors to take positions on a specific portion of the underlying credit risk. In a synthetic collateralized debt obligation (CDO), the tranche is determined by the attachment point at which the loss begins and the detachment point at the maximum loss point the tranche can afford. Among CDO tranches, the highest-rated and lowest-risk tranche is called the senior tranche. If there are any defaults or losses on the underlying assets, the senior tranche is the last to experience these losses, as all other tranches bear the losses first. Therefore, the price of senior tranches may reflect the market's assessment of the systemic credit risk. In this regard, Seo and Wachter (2018) explain CDX senior tranche spread levels in terms of a time-varying probability of economic disaster.

Furthermore, we extend our analysis of the SCRPs, estimated from credit market data, by exploring how equity market investors perceive systemic credit risk, thereby expanding the scope of our investigation beyond the credit market. The objective is to investigate whether equity market participants demand compensation for the fitted SCRP, regarding it as a risk factor that affects changes in portfolio returns in the equity market. If the SCRP factor is significantly priced in the equity market, we can conjecture that the cross-market asset pricing implications of the estimated SCRP are significant, particularly with respect to the investment opportunities accessible to stock investors.

2.2. Identifying the systemic credit risk premium

We extract the dynamics of SCRPs as the difference between the market price of CDX senior tranches and the valuation of artificially generated tranches comprising the same CDS contracts as the CDX reference entities. The magnitude and time series behavior of the discrepancy reflect the market-implied perception of systemic credit risk over time. If investors require compensation for taking the risk of excessively clustering defaults in the system, the market tranche rate should exceed the artificially generated tranche rate.

In principle, the approach adopted for estimating SCRPs entails the disentanglement of individual default risk premiums from portfolio default risk premiums, accomplished through the use of both single-name and multi-name credit derivative securities. A CDS is a derivative financial instrument that allows investors to hedge against the individual default risk of an underlying asset associated with individual credit risks, such as corporate bonds or loans. As a CDS contract refers to an instrument on a single reference entity, the single-name CDS market price data may primarily provide the unconditional risk-neutral probability of the default of an individual reference entity for its remaining maturity at a given point in time. This is insufficient for capturing the systemic credit risk premium, which incorporates a conditional set of information regarding the risk-neutral probability of observing clustered defaults of multiple entities at the portfolio level. In this regard, market-based information derived from the CDX tranche spreads, as a specific category of CDOs, can be considered a valuable supplement for capturing the compensation demanded by investors for bearing the portfolio-wide systemic credit risk. The CDX swap contracts are traded in the form of an index, which is a basket of multiple CDS contracts and tranches. Tranches are segments created from a pool of securities and classified according to the scope of CDO loss compensation. The market price of a CDX tranche swap contains information regarding individual default risk and systemic credit risk premiums, as it is composed of multiple reference entities.

Therefore, SCRPs can be extracted from the portfolio default risk premium by controlling the individual default risk premium through the association between the individual and the portfolio-wide default risk premiums, representing the perception of a correlated default risk of a product consisting of multiple assets. To control for the individual default risk premium, we artificially construct time series of senior tranche spreads using CDS spreads by matching the reference entities with the CDS index tranche swap contracts. Each time, these artificial senior tranches can be created with inverted marginal default probabilities and physical correlation. We define them as *reference* tranches and compare them to market tranche spreads for extracting SCRP. Since the individual default probabilities are inverted from the CDS spreads observed in the market, we can effectively correct the impact of the individual default risk premium on the CDX tranche spreads.

2.3. Cross-market asset pricing implications

The nature of SCRP dynamics should be time-varying, as its magnitude and direction change over time. The time-varying risk factor could manifest only in certain periods and is not present in others. As the SCRPs signify the compensation level for taking on systemic credit risk by design, they may more prominently impact equity returns as a priced risk factor during economic downturns when the systemic credit risk is relatively high but less so in economic expansions. In this context, our empirical study employs various indices designed to differentiate between stable and distressed periods, including the Chicago Fed National Activity Index (CFNAI), the St. Louis Fed Financial Stress Index (STLFSI), and the Office of Financial Research Financial Stress Index (OFRFSI), to examine whether

SCRPs have divergent impacts on equity returns during these different periods.[1]

Our inter-market empirical analysis employs the fitted SCRPs sourced from credit market information to investigate how equity market investors view systemic credit risk. In other words, our asset-pricing study presumes that the credit-market-implied SCRP can be viewed as an external risk factor affecting investment opportunities in the stock market in the sense that risk premiums in other markets could be a significant risk factor in the stock market. Cross-market risk factors have long been recognized as important drivers of stock market returns, as evidenced in studies such as Chen et al. (1986) and Fama and French (1993), among many others. These inter-market factors, including the *default spread* and *term spread* inferred from bond market data, have been shown to significantly impact stock market investments. CDS spreads are closely tied to corporate bond yields, particularly when the reference entity in the CDS contract matches the issuer of the risky bond. CDS spreads often reflect the excess of the bond yields of the reference entity over the risk-free rate, as highlighted in Hull et al. (2004), because both are affected by the same underlying credit risk.

Recent research, such as Friewald et al. (2014), further highlights the importance of these inter-market risk factors by demonstrating that the credit risk premium estimated from CDS spreads contains information about stock prices not captured by traditional risk factors. Specifically, they show that firms' stock returns tend to increase with the credit risk premium, as reflected in the term structure of CDS spreads. Collin-Dufresne et al. (2024) employ the multivariate affine transformation analysis to capture several aspects of the joint dynamics of CDX and S&P 500 (SPX) options, showing that the credit and equity markets are not fully integrated. While the studies by Kitwiwattanachai and Pearson (2015) and Huang (2020) examined the differences between CDS-implied and equity return correlations, our analysis goes further by investigating whether the estimated SCRP, derived from credit market data, is recognized as a significant risk factor in equity markets, both during times of crisis and under normal conditions.

[1] The CFNAI is a monthly economic indicator that comprehensively measures overall economic activity and inflationary pressures in the United States. The STLFSI is a weekly index that monitors the stress level of the U.S. financial system using a range of financial indicators, whereas the OFRFSI is a stress index covering the global scope and is updated daily to track stress levels in financial systems.

3. Model Framework

In this section, we introduce our model framework for capturing the time-varying dynamics of SCRPs and outline the methodologies used to estimate these premiums based on the implied information from the credit derivatives market data. We consider a portfolio of n credit sensitive positions, e.g., the CDX.NA.IG index has $n = 125$ constituents. In our analysis, we fix a statistical data-generating probability measure denoted as $\mathbf{P}$. For the valuation of both single-name and multi-name credit derivatives in the absence of arbitrage opportunities, we further introduce a fixed risk-neutral probability measure $\mathbf{Q}$, which is equivalent to $\mathbf{P}$ and is associated with a constant risk-free rate $r > 0$.[2]

3.1. CDS-implied dependence structure

Our model specification aims to capture the time-series patterns of SCRP across single-name and multi-name credit market participants. Specifically, we extract individual distance-to-default values from single-name CDS spreads at each time point, focusing on the evolution of their cross-sectional correlation structure. Motivated by Kitwiwattanachai and Pearson (2015) based on Merton (1974) and Black and Cox (1976), our structural credit risk model aims to infer the correlation dynamics of distance-to-defaults based on the market-quoted CDS spreads. Specifically, we presume that the risk-neutral dynamics of a firm's asset value (V) follows a geometric Brownian motion specified as

$$d \log V(t) = (r - \sigma^2/2)dt + \sigma dW(t) \ ,$$

where W is a standard Brownian motion under $\mathbf{Q}$. Default occurs when the asset value hits a boundary. For a parsimonious model specification, we adopt the *base model*[3] of Kitwiwattanachai and Pearson (2015), by assuming that the $\mathbf{Q}$-

[2]The assumption of a constant risk-free rate facilitates our calibration procedure. Empirical studies related to credit derivatives markets commonly assume a constant risk-free rate for computational tractability, as evidenced by several works such as Driessen (2005), Pan and Singleton (2008), Carr and Wu (2011), Oh and Patton (2018), and many others.

[3]Kitwiwattanachai and Pearson (2015) explore various default boundary dynamics, including generalized growth rates, mean-reverting leverage ratios, and stochastic boundary models, and

dynamics of the boundary process $B(t)$ at time t is given by $B(t) = B(0)e^{\left(r-0.5\sigma^2\right)t}$. Then, by applying Theorem 3.7.1 of Shreve (2004), the **Q**-density of default time is derived as a function of the distance-to-default, represented by $m \geq 1$, taking the form of

$$q(m,t) = \frac{m}{t\sqrt{2\pi t}} \times e^{\frac{-m^2}{2t}} \ .$$

This default time density is used to calculate the present value of the cash flow stream associated with a CDS contract, specifying a contractual agreement between a protection buyer and a protection seller. In the context of CDS valuation, the contract consists of two main components: the default leg, also known as the protection leg, and the premium leg. The default leg represents the protection seller's obligation to make a payment upon default of the reference entity, while the premium leg represents the periodic payments made by the protection buyer to the protection seller.

The present value of the payments on the default leg of a CDS is given by

$$\Lambda_1(m,\ell,r) = \ell \int_0^T q(m,t)v(t)dt \ ,$$

where $v(t)$ is the present value of \$1 received at time t and ℓ is the loss rate.[4] The present value of the premium leg is obtained by multiplying the fair CDS spread, denoted by $S(m,\ell,r)$, with the risky present value of a basis point (RPV01) of the CDS contract, which is given by

$$\Lambda_2(m,r) = \int_0^T q(m,t)g(t)dt + \left(1 - \int_0^T q(m,t)dt\right) g(T) \ ,$$

where $g(t) = \frac{1}{4}\sum_{j:0<u_j\leq t} e^{-ru_j}$ is the cumulative present value as of time t of the quarterly payments at the rate of \$1 per year on the payment dates between t and u, and captures the premiums paid on these dates. Subsequently, the fair CDS spread with its time-to-maturity T can be obtained by equating the present values

find that the correlation estimates are reasonably similar across these specifications. We adopt the base model for its parsimonious specification, minimizing the number of parameters to reduce overfitting and ensure a more tractable and reliable calibration.

[4]We assume a constant loss rate (ℓ), which is a common simplification in the relevant literature, for the feasibility of our model fitting procedure; e.g., refer to Longstaff et al. (2005), Chen et al. (2008), Chen et al. (2013) and Li and Zinna (2014) for similar treatment.

of the cash flow streams implied by default and premium legs, or equivalently

$$S(m,\ell,r) = \frac{\Lambda_1(m,\ell,r)}{\Lambda_2(m,r)} \ .$$

At each time point t, we observe a market-quoted CDS spread and infer the distance-to-default, $m(t)$, by calibrating our model to be consistent with CDS spread data. Recall that the computational feasibility of parameter calibration is facilitated by our assumption of a constant r and ℓ, as the CDS spread is then a one-to-one function of the distance-to-default m. As Itô's lemma implies that $dm(t) = dW(t)$, we can derive the stochastic differential equation of the CDS spread dynamics in the form of

$$\begin{aligned} dS(m(t)) &= \frac{\partial S}{\partial m} dW(t) + \frac{1}{2}\frac{\partial^2 S}{\partial m^2} dt \\ &= b_1(S(t))dW(t) + \frac{1}{2} b_2(S(t))dt \ , \end{aligned}$$

where $b_1(S) = \frac{\partial S}{\partial m}$ and $b_2(S) = \frac{\partial^2 S}{\partial m^2}$ are the first and second order derivatives of S with respect to m, respectively. Since $S(m)$, $\frac{\partial S}{\partial m}$ and $\frac{\partial^2 S}{\partial m^2}$ are one-to-one functions of m, we approximate the first derivative $b_1(S)$ and the second derivative $b_2(S)$ based on the third-order polynomial fitting of the CDS spread, respectively. Through this process, the past trajectory of the implied distance-to-default $m(t)$ can be extracted from the CDS spread data based on the relationship given by

$$dm(t) = dW(t) = \frac{dS(t) - \frac{1}{2} b_2(S(t))dt}{b_1(S(t))} \ .$$

To quantify the statistical behaviors of the CDS-implied asset correlations under $\mathbf{P}$, we incorporate the dynamic information flow observed from the CDS market regarding the co-movement of asset returns. This is achieved in our study by adopting the DCC-GARCH(1,1) approach, following the model specifications proposed by Tse and Tsui (2002) and Engle (2002). It is worth noting that analogous methodologies have been extensively employed in recent literature, as they effectively capture the dynamic nature of market conditions better than unconditional correlations containing only static information. Based on the DCC-GARCH modeling approach, Cho and Parhizgari (2009) analyzed the impact of the 1997 East Asian financial crisis on the stock markets of eight countries to investigate contagion effects. Celık (2012) used a DCC-GARCH model to test the existence of financial contagion among the foreign exchange markets of several emerging and developed countries during the U.S. subprime crisis. DCC-GARCH models are also used to measure systemic risk. Girardi and Ergün (2013) used a DCC-GARCH model to estimate CoVaR, originally proposed by Adrian and Brunnermeier (2016), the Value-at-Risk of the financial system conditional on an institution being in financial distress. Brownlees and Engle (2017) used a DCC-GARCH model to define SRISK to measure financial firms' contributions to systemic risk.

Specifically, on a daily basis, we introduce the statistical correlation between the CDS-implied returns of the underlying assets for any two firms i and j, denoted by $\rho_{ij}(t)$, as

$$\rho_{ij}(t) \triangleq Corr^{\mathbf{P}}\left(\Delta \log V_i(t), \Delta \log V_j(t)\right) = Corr^{\mathbf{P}}\left(\Delta m_i(t), \Delta m_j(t)\right) \tag{1}$$

on each date t. Subsequently, we form the $(n \times n)$ correlation matrix

$$\Sigma(t) = \Big(\rho_{ij}(t)\Big)_{1 \leq i,j \leq n} \ ,$$

representing the statistically observed conditional correlations between the cross-firm innovations of the distance-to-defaults. As illustrated by Equation (1), the matrix $\Sigma(t)$ equivalently captures the observed $\mathbf{P}$-dynamics of the pairwise correlations among the CDS-implied asset returns.

In our DCC-GARCH(1,1) model framework, we consider a vector of the demeaned daily distance-to-default innovations $\mathbf{y}(\mathbf{t}) = \Big(y_1(t), \cdots, y_n(t)\Big)^{\top}$ specified as

$$\mathbf{y}(t) = \mathbf{H}(t)^{1/2}\ \mathbf{z}(t)\ ,$$

where $\mathbf{H}(t)$ is the date-t conditional variance-covariance matrix of $\mathbf{y}(t)$, $\mathbf{H}(t)^{1/2}$ is obtained by a Cholesky factorization of $\mathbf{H}(t)$, and $\mathbf{z}(t)$ is a random vector with a zero mean and an identity covariance matrix of order n. In turn, we posit

$$\mathbf{H}(t) = \Big(\rho_{ij}(t)\sqrt{h_i(t)h_j(t)}\Big)_{1 \leq i,j \leq n} \ ,$$

where $\rho_{ij}(t)$ is a conditional correlation and, for $\omega_i > 0, \alpha_i \geq 0, \beta_i \geq 0$ with $\alpha_i + \beta_i < 1$, we have

$$h_i(t) = w_i + \alpha_i y_i^2(t-1) + \beta_i h_i(t-1) \quad i = 1, \ldots, n$$

representing the conditional variance of $y_i(t)$ under the GARCH(1,1) model. Furthermore, we assume that the conditional correlation matrix $\Sigma(t) = \Big(\rho_{ij}(t)\Big)_{1\leq i,j\leq n}$ can be expressed as $\Sigma(t) = A^\star(t)^{-1}\ A(t)\ A^\star(t)^{-1}$, where the dynamics of $A(t) = \Big(a_{ij}(t)\Big)_{1\leq i,j\leq n}$ can be expressed as

$$A(t) = \Big(a_{ij}(t)\Big)_{1\leq i,j\leq n} = (1-\alpha-\beta)\bar{A} + \alpha \mathbf{z}(t-1)\mathbf{z}^\top(t-1) + \beta A(t-1)$$

for non-negative scalar parameters α and β satisfying $\alpha + \beta < 1$ to ensure stationarity along with

$$A^\star(t) = \operatorname{diag}\left(\left(\sqrt{a_{ii}(t)}\right)_{1\leq i\leq n}\right)$$

and $\bar{A}$ as the unconditional covariance matrix of devolatized residuals $\Big(y_i(t)/\sqrt{h_i(t)}\Big)_{i=1,\ldots,n}$. To reflect market participants' perceptions, we forecast a one-step-ahead conditional correlation matrix $\Sigma(t+1)$ from estimated DCC-GARCH(1,1) and use it as input value to evaluate the *reference* tranche spread.[5]

3.2. Extracting the SCRP estimates

Notice that the **P**-correlation dynamics, reflecting the statistically estimated asset-correlation structure inferred from the time-series evolution of the CDS spreads alone, cannot fully address the systemic credit risk premium implied by the market-observed CDX tranche spreads. In this vein, we wish to assess credit market participants' perception of systemic credit risk by comparing market-quoted CDX (senior) tranche spreads with corresponding *reference* tranche spreads constructed using a statistically estimated asset dependence structure. To ensure consistency with the single-name assumption of risk-neutral dynamics of asset

[5]We fit the DCC-GARCH(1,1) model to our dataset by maximizing the log-likelihood function. This is done by employing the *dccfit* function provided as a built-in module in the R package *rmgarch*; refer to Ghalanos (2022) for details. The sample average of estimates for α and β are 0.0096 and 0.9009, with sample standard deviation of 0.0119 and 0.2073, respectively.

value following a geometric Brownian motion, we extend this framework to the multi-name level when calculating the reference tranche spreads.

This entails integrating the statistically estimated asset-return correlation structure, enabling us to infer the risk-neutral dynamics of the underlying asset value specified as a geometric Brownian motion, for tractable pricing purposes. Accordingly, we assess the reference tranche spreads, serving as the counterparts to the market-quoted tranche spreads, while consistently assuming the risk-neutral dynamics of a name's asset value by using the estimated **P**-correlation matrix as an input.[6] We adopt the Monte Carlo simulation method to numerically compute the first passage time of a multivariate geometric Brownian motion. This is accomplished through a joint simulation of the distance-to-default processes for a portfolio comprising n assets. A constituent defaults when its distance-to-default process reaches zero, and we count the number of defaults in the portfolio for a given horizon.

More specifically, at each time t, we obtain the statistically estimated correlation matrix $\Sigma(t)$ from the **P**-observed movements of the extracted distance-to-defaults, which are obtained by inverting the CDS pricing formula under the **Q**-geometric Brownian motion framework. To ensure a simulation procedure that is both cohesive and unified with our pricing model, we generate the correlated default times based on the statistically estimated correlation matrix $\Sigma(t)$, assuming it remains constant throughout the simulation horizon between time t and $t + T$. On the subsequent date $t+1$, we re-estimate $\Sigma(t+1)$ using the DCC-GARCH(1,1) model, considering it as a time-invariant input over the next simulation horizon between $t + 1$ and $t + 1 + T$, and so forth. This approach imposes a hypothetical interdependence structure among the *risk-neutral* default times of different entities to generate the reference tranche spreads, which cannot capture all the premiums for taking correlated defaults reflected in the CDX tranche spreads. Our objective is to examine the time-series dynamics of the discrepancy between market-quoted and reference (senior) tranche spreads.

Having simulated a sequence of the *ordered* default times, $(\tau_k)_{k=0}^{n}$, in the reference

[6] In contrast, the market-quoted tranche is based on the risk-neutral dynamics of reference entities combined with **Q**-correlation matrix.

portfolio of firms, where $0 = \tau_0 < \tau_1 < \tau_2 < \cdots < T$, we use them to estimate the exposure of an investor selling default protection on the CDX tranche swap contract.[7] The joint default times generate the *default counting process*

$$N_t = \sum_{k \geq 1} 1_{\{\tau_k \leq t\}} \ ,$$

which counts the number of defaults in the portfolio. The loss process

$$L_t = \sum_{k \geq 1} \ell_k 1_{\{\tau_k \leq t\}}$$

for $\ell_k \in (0,\ 1]$ records the cumulative financial loss due to defaults until t, where the jump times of L_t are identical to those of N_t. In our analysis, we assume that the loss rates, which specify the jump sizes of L_t at each of the default times, are all $\ell_k = \ell$ for all $k \geq 1$; i.e., $L_t = \ell N_t$, which is consistent with the assumption in the CDS valuation.

A tranche of a synthetic CDO is a swap contract specified by a lower attachment point $\underline{K} \in [0, 1)$ and an upper attachment point $\overline{K} \in (\underline{K}, 1]$, where $K = \overline{K} - \underline{K}$ is the tranche width. The protection seller agrees to cover all losses due to default in the reference portfolio, provided these losses are realized between $\underline{K}n$ and $\overline{K}n$. In exchange, the protection buyer pays the protection seller an upfront fee at inception and a quarterly spread payment, both of which are negotiated at contract inception. With the convention that the portfolio loss at the contract inception is equal to zero, the cumulative tranche loss at post-inception time t is given by the call spread on the portfolio loss taking the form of

$$U_t = (L_t - \underline{K}n)^+ - (L_t - \overline{K}n)^+ \ .$$

The default leg of a tranche swap is a stream of payments that cover portfolio losses as they occur, given that the cumulative losses are larger than Kn but do not exceed it. The protection buyer pays the upfront payment FKn at inception with the upfront rate F, and $SC_m(Kn - U_{t_m})$ at each date t_m, where S is the tranche spread and $C_m = 0.25$ is the day count fraction for quarterly payments.

[7] For simplicity in notation, we assume that the simulation horizon is from time 0 to T.

The fair tranche swap spread at time t equates the two leg present values satisfying

$$(\text{Fair Tranche Spread}) = \frac{E^{\mathbf{Q}}\left[\int_0^T e^{-rt} dU_t\right] - FKn}{E^{\mathbf{Q}}\left[\sum_{t_m} e^{-rt_m} C_m \left(Kn - U_{t_m}\right)\right]} \, .$$

When fixing a market-observed CDS spread, the CDS-implied distance-to-default is indeed influenced by assumptions regarding the risk-free and recovery rates. On one hand, our simulation study demonstrates that variations in the risk-free rate assumptions have a negligible impact on the results.[8] On the other hand, our simulation study also reveals a negative association between the recovery rate and the model-implied senior tranche spreads, if all others remain equal. An increase in the loss rate assumption typically results in larger values for the CDS-implied distance-to-defaults, leading to a decrease in the number of simulated defaults in the portfolio. Despite the recovery-rate assumptions, the total expected losses remain unchanged; however, the distribution of portfolio losses shifts towards extreme values. Consequently, the expected loss for the equity tranche decreases, while the expected loss for the senior tranche increases, even when the index spread remains constant. To be precise, this assumption implies that the difference between the market-quoted and the model-implied tranche spreads captures the premium associated with default *loss* clustering risk.

We compare the CDX market tranche spread with the corresponding *reference* one as a benchmark, which is obtained by calculating the fair tranche swap spread using the same attachments and detachments as the original tranche and incorporating individual default risk premiums along with physical dependence structure implied by CDS spreads. Recall that the reference tranche spreads are derived solely from CDS spreads, which primarily capture the individual credit risk premium that we want to separate from the extraction of the SCRP. In contrast, market-quoted CDX tranche spreads incorporate both the individual default risk premium and the entirety of SCRP.

Given the model assumptions, the expected loss processes can be computed for a specific tranche position via simulation. This involves taking into account the joint distribution of default times, influenced by the distance-to-default derived from

[8] Further details are available upon request.

market-quoted CDS spreads and the estimated asset-return correlations implied by the model. Using these expected loss processes, we can calculate a *reference* tranche spread at each time, including individual default risk premiums but omits the critical components of SCRP. Therefore, we can determine the portfolio-wide premium for bearing systemic credit risk by comparing the reference tranche spread with the market-observed tranche spread after adjusting for the marginal default risk premium effect.

As empirically verified by Tarashev and Zhu (2008), we presume that the multi-name CDX and single-name CDS markets employ similar risk-neutral individual default risk premiums. Therefore, our definition of SCRP at each time t is given by

$$SCRP_t = (Market\ Tranche\ Spread)_t - (Reference\ Tranche\ Spread)_t\ ,$$

where the difference between the market tranche and reference tranche spreads reflects the systemic credit risk premium. If investors require compensation for taking the risk of excessively correlated defaults in the system, then the market tranche rate should exceed the reference tranche rate. Thus, the magnitude and time-series behavior of the discrepancy reflect the credit-market-implied market price of the systemic credit risk.

3.3. Implications of SCRP estimates

The estimated SCRP provides valuable information to policymakers and practitioners by serving as a crucial tool to assess and manage aggregate credit risk exposure at the system level. As a market-based measure, SCRP offers forward-looking signals in real time, capturing investor expectations and market sentiment instantly, while accounting-based indicators rely on historical data and are reported with delays IMF (2009); Borri et al. (2012). This distinction makes the SCRP a leading indicator for proactive systemic credit risk management, strengthening regulatory responses to market fluctuations. Unlike equity-based measures of systemic risk, which may not fully capture the required compensation to take aggregate credit risk, the estimated SCRP is derived from the prices of credit derivatives, directly reflecting market-wide default risk exposures as a whole Rodríguez-Moreno and Peña (2013); Suh et al. (2013). By more precisely capturing the market price of systemic credit risk, the SCRP provides critical insights for macroprudential authorities and central banks, enabling them to detect early signs of rising systemic credit risk and implement timely interventions to prevent broader financial instability.

From a practical standpoint, institutional investors and traders can leverage the estimated SCRP as a valuable market indicator to inform and refine their investment strategies and risk management decisions. By capturing market perceptions of systemic credit risk, the SCRP informs asset allocation decisions Kole et al. (2006); Meinerding (2012); Altinoglu (2023). For instance, a rising SCRP signals heightened systemic credit risk, prompting investors to hedge by shifting toward safe assets or employing credit derivatives to mitigate downside exposure. Conversely, if the SCRP remains low despite macroeconomic uncertainty, it may suggest that the market is underpricing systemic credit risk premia. In such cases, investors might apply leverage by increasing exposure to undervalued credit-sensitive assets, anticipating a market repricing. Furthermore, as empirically demonstrated in Section 4.3, the estimated SCRP, derived from credit derivatives market data, reveals significant insights into cross-market asset pricing dynamics. When treated as an external risk factor in the equity market, it allows investors to capture positive alpha through a long-short strategy based on the estimated SCRP beta, thereby improving the performance of equity portfolios.

4. Empirical Analysis

In this section, we provide information on our data and sample, analyze the time-series behavior of the extracted SCRP, and examine its cross-market asset-pricing implications, specifically in relation to the U.S. stock market. Given that the structured credit derivatives market, in contrast to the stock market, transforms latent credit risk premium into observable prices, our hypothesis is that the extracted SCRP may be priced in the equity market.

4.1. Data and sample

We obtain single-name CDS spreads and multi-name CDX index and tranche spreads from the Markit database. The CDX North American Investment Grade (CDX.NA.IG) index's senior tranche rates are of interest, as they do not incur any losses until substantial defaults occur, thereby providing critical information about how the market assesses systemic credit risk among high-quality firms; refer to Seo and Wachter (2018) for related discussions. The CDX.NA.IG index consists of 125 equally weighted CDS contracts on representative North American investment-grade firms. In general, on-the-run products with a 5-year maturity exhibit high liquidity in both the CDS and CDX tranche markets. Consequently, we have selected both CDS and CDX products with a 5-year maturity and on-the-run series to address liquidity concerns in our analysis.[9] Ultimately, we examine the 5-year super-senior tranche at the tranche-swap spread level, rather than the correlation level, to mitigate model risk across different tranches and maturities from a pricing perspective.

Furthermore, we limited our data selection to Wednesdays to remove any potential day-of-the-week effects. In cases where data were unavailable on a Wednesday, we calculated a weighted average of the adjacent trading days within the same week. If there were no trading days during a week, the data were considered incomplete. Our sample period for constructing the *reference* tranche spread ranges from Series 5 to Series 35, from September 2005 and March 2021, as the CDO market dataset is unavailable for the first four CDX indices, as stated by Koziol et al. (2015). Notably, our study period incorporates the 2007-9 financial crisis and the recent COVID-19 pandemic. We selected CDS contracts that align with the reference entities included in the CDX.NA.IG portfolio over time. We assumed a daily discretization interval by setting $\Delta t = 1/252$. To simulate default timing scenarios, we generated one million sample paths per day, with a time-to-maturity of five years, a risk-free rate of 2.5%, and a fixed loss rate of 60%. The

[9] Nevertheless, the estimated SCRP still accounts for the potential discrepancy in liquidity risk premiums between the multi-name CDX tranche and the single-name CDS markets. Therefore, from a broader perspective, it is desirable to interpret the fitted SCRP as inclusive of this cross-market liquidity premium differential, if any. More precisely, we treat the liquidity premium as one of the components contributing to the broader landscape of systemic credit risk premium. Any further decomposition is beyond the scope of our study and is left for future work.

statistical correlations among asset returns were numerically estimated through maximum likelihood estimation using the DCC-GARCH(1,1) model with a rolling-window approach, employing a window size of one year.

4.2. The time-series behavior of the fitted SCRP

As the CDX.NA.IG series evolved, changes occurred over time that affected the tranche attachment points, trading units, and fixed coupon rates. To facilitate a meaningful comparison of market prices between the CDX senior tranches and the reference tranches as benchmark, we calculated their *adjusted* fair spreads. Specifically, these adjusted spreads are based on the consistent tranche width, trading units over time, accompanied by the appropriate adjustments for fixed coupon rates. For the senior tranche, the tranche width is typically set in the range of 0.15 to 1.00, consistent with recent years. Trading units are aggregated into spreads. As for the reference tranche, the adjusted fair spreads are adjusted by setting the prepayment upfront rate set to zero. To calculate the adjusted fair spreads for the market tranches, we combine the market-quoted CDS spreads and the base correlations of the senior tranche.

[Figure 1 about here.]

Figure 1 shows the time series of the market and reference tranche spreads. As shown, the time-series behavior of market tranche spreads generally aligns with that of reference tranche spreads, with market tranche spreads typically higher. The dynamics of the SCRPs are derived by calculating the difference between the market price of the CDX senior tranches and the value of synthetic reference tranches, both based on the same CDS contracts on the reference entities that are constituents of CDX.NA.IG.

[Table 1 about here.]

Table 1 presents summary statistics for the estimated SCRPs. Over the entire period, market participants demanded an average compensation of 13 bps for systemic credit risk. Following the complete redesign of the CDX product with Series

15 (September 2010), we also report summary statistics for the periods before and after Series 15. The mean value decreased after Series 15, suggesting that market participants no longer demand higher compensation for systemic credit risk after the restructuring, indicating that the product changes contributed to market stabilization.

[Figure 2 about here.]

Figure 2 shows the time series of the estimated SCRPs. If investors require compensation for bearing systemic credit risk, the market-quoted senior tranche rate should exceed the reference tranche rate. For instance, the SCRP peaked in March 2008, coinciding with the Bear Stearns bailout, the first major intervention for an investment bank, which had a significant psychological impact on market participants. Notably, the SCRP steadily increased from mid-2007 until the Bear Stearns crisis, indicating growing compensation demands for systemic credit risk, even before the official onset of the recession. In September 2008, Lehman Brothers' bankruptcy caused the SCRP to reach its second-highest value, marking the largest financial shock of the global financial crisis. While CDX products were disrupted after Lehman's collapse, the Bear Stearns bailout was perceived as more traumatic. Following the reorganization of CDX tranche swap contracts in September 2010, the market resumed normal trading, though the trading volume continued to decline. By January 2016, the SCRP had begun to fall, likely due to the central clearing system's role in enhancing CDS market stability. The SCRP surged again in March 2020 due to the COVID-19 crisis, contrasting with the earlier steady rise, but then declined as financial markets stabilized.

Recall that we do not require the estimated SCRP to be strictly positive. As noted by Huang (2020), CDS contracts can serve as a risk-betting tool, enabling investors to speculate on the default risk of a reference entity without holding its reference liability. Although the estimated SCRP is generally positive, occasional dips below zero may signal overconfidence in the market's perception of systemic credit risk. Notably, the fitted SCRP dropped below zero prior to both the global financial crisis and the onset of the COVID-19 pandemic, indicating that such instances could serve as early warning signals of impending system-wide credit risk events, such as the collapse of a systemic bubble.

4.3. *Cross-market asset-pricing implications*

Our empirical analysis examines how U.S. equity market investors perceive systemic credit risk by analyzing the extracted SCRPs from structured credit market data. In contrast to stock prices, which reflect latent credit risks, credit derivatives make these risks observable, thereby providing a clearer measure of systemic credit risk. The goal is to assess whether stock market participants price the estimated SCRP as a significant risk factor. If the SCRP is found to significantly affect equity prices, it would suggest that both equity and credit market investors demand compensation for their exposure to systemic credit risk, with the CDS market serving as a transparent mechanism for incorporating these risks into equity pricing. Conducting this analysis during both crisis and normal periods offers a more comprehensive view, as the perceived importance of systemic risk may vary across market conditions. By comparing these two periods, we can better understand how market participants adjust their risk perceptions in response to evolving financial environments.

Our economic reasoning is that the SCRP is closely linked to the cross-section of stock returns, particularly during financial crises, when systemic risks rise as defaults cluster across firms through common macroeconomic channels. During these periods, stocks more exposed to systemic risk or with higher default correlation, such as those in highly leveraged sectors or industries sensitive to economic downturns, tend to underperform. This underperformance reflects the increased demand for compensation for bearing the risk of correlated defaults. During crises, investors typically engage in a flight to quality, reallocating capital toward safer assets, which further depresses the returns of riskier stocks. Furthermore, the widening of credit spreads and rising CDS premiums signal higher default correlation risk, which is priced into the market. As a result, we conjecture that there is greater cross-sectional variation in stock returns, with riskier, more correlated assets commanding higher risk premiums to compensate for the increased probability of joint defaults during crisis periods.

To test whether the estimated SCRP correlates with a premium in returns, we estimated the SCRP betas based on a rolling-window regression with a window size of one year for each stock by taking the fitted SCRP as a risk factor in the stock market. We then sorted the stocks into ten decile groups based on their SCRP beta levels to construct value-weighted portfolios. Subsequently, we created a long-short portfolio by combining the upper and lower decile portfolios to investigate whether the SCRP factor exhibits a significant premium even after controlling for the Fama and French (1993) three factors and the Carhart (1997) momentum factor. We further examined whether the estimated SCRP is a time-varying risk factor for equity returns, specifically during distressed periods when systemic credit risk is high. To achieve this, we employ various indices that differentiate between stable and distressed periods, such as the Chicago Fed National Activity Index (CFNAI) from the Federal Reserve Bank of Chicago, the St. Louis Fed Financial Stress Index (STLFSI) from the Federal Reserve Bank of St. Louis, and the Office of Financial Research Financial Stress Index (OFRFSI) from the Office of Financial Research. Stock returns are obtained from *CRSP*, factor data are from *Kenneth French's website*, and indices that distinguish between stable and distressed periods are from the websites of the organizations that produce them. Summary statistics for the variables used in the analysis are presented in Table 2.

[Table 2 about here.]

The CFNAI is a monthly economic indicator measuring the overall economic activity and inflationary pressure in the United States. It is produced by the Federal Reserve Bank of Chicago and is based on 85 different economic indicators, including production, employment, consumption, and sales indicators. It is designed to provide a comprehensive and timely snapshot of the U.S. economy and to analyze economic trends and potential changes in the economy's direction. A positive CFNAI reading indicates that economic activity is above the historical trend, while a negative reading suggests that economic activity is below it. As such, the CFNAI is used to distinguish between expansion and contraction periods.

The STLFSI is a weekly index measuring the stress level of the U.S. financial system based on a set of financial indicators. The index is calculated by the Federal Reserve Bank of St. Louis and is based on 18 financial market indicators, including seven interest rates, six yield spreads, and five other indicators. The

STLFSI is used to monitor the health of the financial system and identify potential risks to financial stability. An STLFSI below zero suggests below-average financial market stress, while above zero suggests above-average financial market stress. As such, the STLFSI is used to distinguish between stable and distressed periods.

The OFRFSI is another index measuring the stress level of the financial system. It is calculated by the Office of Financial Research (OFR), an independent bureau within the U.S. Department of the Treasury established in response to the 2008 financial crisis. The OFRFSI is based on 33 financial market indicators, including credit, equity valuation, funding, safe assets, and volatility. The OFRFSI's key features are that it covers the global scope and is updated daily to provide real-time insights into changes in financial market conditions. Like STLFSI, an OFRFSI below zero indicates that financial market stress is below average, while above zero indicates above average. As such, the OFRFSI is used to distinguish between stable and distressed periods.

[Figure 3 about here.]

Figure 3 presents the alphas for value-weighted portfolios constructed from the ten deciles of SCRP beta levels, which are calculated using a rolling-window approach with a one-year window. The portfolios are adjusted to account for Fama-French's three factors and a momentum factor. To assess the statistical significance of the factor risk premiums, the standard errors were adjusted using the method of Newey and West (1987) with a lag of $T^{1/4}$, where T is the number of observations. As shown, portfolios with higher SCRP betas tend to exhibit positive alphas, whereas portfolios with lower SCRP betas generally have negative alphas, indicating a positive correlation between SCRP betas and stock returns.

[Figure 4 about here.]

To further explore the implications of SCRP, we implement a long-short strategy by purchasing high-SCRP portfolios and selling low-SCRP portfolios. The univariate time-series regression is specified as

$$Y_t = \alpha_0 + \beta_1 MKTRF_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 MOM_t + \epsilon_t \ , \qquad (2)$$

where Y_t represents the difference in returns between high- and low-SCRP portfolios in week t. In the regression model of Equation (2), the statistical significance of the alpha indicates whether stock market participants require additional compensation for the SCRP factor.

Figure 4 presents the estimated alphas obtained from regressing the weekly returns of the long-short SCRP portfolio on the Fama-French three factor and momentum factor models, which are long in the top deciles and short in the bottom deciles of the SCRP beta levels. The box plot displays the estimated alpha values and their corresponding confidence intervals. The center line represents the alpha estimate, the outer perimeter of the box represents the 90% confidence interval, and the whiskers represent the 95% confidence interval. The dashed line represents zero, and if the confidence interval encompasses zero, it suggests that the estimated alpha is not statistically significant at the given significance level. The reported results indicate that the estimated alphas are not statistically significant during the expansion and stable periods as well as the entire period. However, the alphas are significantly positive during the contraction and distressed periods.

These results imply that additional compensation for the SCRP factor is required for distressed and contraction periods after controlling the Fama-French three factors and the momentum factor. The significance of the SCRP factor becomes more pronounced during distressed periods compared to contraction periods, indicating that the SCRP more strongly relates to financial stability than the economic business cycle. Given that the estimated SCRP entails a premium for systemic credit risk, it is reasonable that the significance of the SCRP factor is observed only during distressed periods when systemic credit risk is more salient. As such, the SCRP derived from the credit derivatives market can be considered a transient and pro-cyclical risk factor in the stock market, subject to variations over time.

4.4. Robustness checks

Our empirical results in the previous subsection show that equity market investors demand extra compensation for the SCRP factor obtained from the credit market when the financial system is vulnerable, even after adjusting for the Fama-French three factors and the momentum factor. To test the robustness of our findings, we conduct a Fama and MacBeth (1973) cross-sectional regression analysis to investigate whether equity market investors require an additional premium for the SCRP factor, controlling for common downside risk measures such as the Chicago Board Options Exchange Volatility Index (VIX), Moody's Seasoned Baa Corporate Bond minus Federal Funds Rate (BAAFF), and the Treasury-Eurodollar (TED) spread as additional control variables.

VIX represents the market's expectation of 30-day forward-looking volatility and is calculated using the implied volatility of a basket of S&P 500 index options. It is used to measure investor sentiment and risk aversion, with higher numbers indicating greater uncertainty and risk in the market. BAAFF measures the yield spread between corporate bonds rated Baa and the risk-free rate and is often used as a benchmark to measure the credit risk of corporate bonds. A high level of BAAFF means investors demand higher returns in exchange for investing in riskier corporate bonds. TED is calculated by the difference between the three-month London Interbank Offered Rate (LIBOR) and the interest rate on three-month U.S. Treasury bills and is a measure of perceived credit risk in the economy. LIBOR is the rate at which banks trade short-term funds between themselves, so a wider TED spread means that investors perceive a higher risk of default on interbank loans. The data on these risk measures come from the Federal Reserve Economic Data (FRED), and all other data come from the sources previously mentioned. Summary statistics are presented in Table 2. Note that the Fama-French factors are already expressed in terms of returns, thereby obviating the need to apply any changes or differentials. Moreover, control variables such as VIX, BAAFF, and TED are known to exhibit mean-reverting behavior, in contrast to asset prices, which tend to diverge.[10] By dividing the dataset into stable and distressed periods, we mitigate potential non-stationarity concerns, as non-stationary behavior is expected to be less pronounced within each subset of the mean-reverting data, reducing the risk of spurious regression results.

Panel A of Table 3 reports the estimated risk premium for each factor, indicated by the time-series averages of the beta estimates from cross-sectional regressions,

[10] Comparable specifications incorporating VIX and TED spread as control variables can be found in Kim et al. (2017) and Han and Kong (2022).

separately for stable and distressed periods as distinguished by the OFRFSI. These estimates are obtained from the Fama-MacBeth two-stage regressions Fama and MacBeth (1973): (i) regressing each stock's returns on the risk factors, along with additional factors such as SCRP, VIX, BAAFF, and TED, to estimate the cross-sectional betas for each stock, and (ii) regressing stock returns for each of T time periods on the estimated cross-sectional betas to determine the risk premiums for each factor. The t-statistics, shown in parentheses, are adjusted using Newey-West standard errors with a lag of $T^{1/4}$. The effects of SCRP are significant in the distressed period, regardless of the additional control variables such as VIX, BAAFF, and TED. These results suggest that equity market investors demand compensation for the SCRP factor during the distressed period, even with additional controls on common risk measures in financial markets. However, the effects of SCRP are generally not significant during stable periods. These results are the same as the previous results of time-series regressions. SCRP's negative coefficient when incorporating BAAFF and its statistical significance is intriguing.

[Table 3 about here.]

The results presented in Panel B of Table 3 provide further clarification that the impact of SCRP remains significantly negative during financially stable periods. This is consistent with the conclusions drawn by Danielsson et al. (2018) that low volatility prompts risk-taking, resulting in riskier investments. Moreover, it is noted that the negative impact of the SCRP is more pronounced in the STLFSI, which measures the stress level of the US financial system, than in the OFRFSI, which captures the stress level of the global financial system.

While Panel C of Table 3 shows similar results to previous analyses, the significance of SCRP's effectiveness is weakened for the contraction period than during the distress period, and the effect of SCRP is insignificant when TED is included. These results imply that SCRP is related to financial stability rather than the business cycle. Notably, the reduced explanatory power of SCRP when both SCRP and the TED spread are included suggests that SCRP serves a comparable function to the TED spread during the distressed periods.[11] This, in turn,

[11]Our analysis reveals that the estimated SCRPs and TED spreads exhibit a positive cor-

highlights the practical relevance of SCRP, particularly in light of concerns regarding the use of the TED spread as a proxy for aggregate counterparty credit risk, particularly its reliance on the LIBOR rate, which has a limited capacity to capture the nuanced credit risks within the banking system. Moreover, the TED spread is highly sensitive to short-term market fluctuations and primarily reflects short-term funding risks, making it potentially misleading during periods of market uncertainty and inadequate for capturing broader, longer-term systemic risks.

Although not reported in the table, the cross-sectional analysis for the entire period confirms that the SCRP factor's impact lacks statistical significance, consistent with the previous time series analysis. Our findings suggest that equity investors demand additional compensation for the SCRP factor in periods of financial fragility, accordant with the results of our previous time-series analysis using Fama-French's three factors and the momentum factor. Including additional control variables on common downside risk measures such as VIX, BAAFF, and TED does not change the results that market participants require compensation for the SCRP factor during distressed or contraction periods.

5. Conclusion

This paper investigates the *systemic credit risk premium* (SCRP), which quantifies the extra compensation demanded by investors exposed to the risk of experiencing a series of defaults that occur in a connected and systemic manner. To isolate the SCRP level more precisely and directly at the portfolio level, this study employs both CDS and CDX tranche rates by focusing on the CDX North American Investment Grade portfolio between September 2005 and March 2021. As such, we construct time series of *reference* tranche rates that have been adjusted to isolate the systemic credit risk premium incorporated in the multi-name CDX tranche market. When investors require additional compensation for correlated defaults within a portfolio, the senior tranche rate quoted by the market is anticipated to

relation during distressed periods (OFRFSI: 0.426, STLFSI: 0.432, CFNAI: 0.383), whereas the correlation turns negative during stable periods (OFRFSI: -0.194, STLFSI: -0.299, CFNAI: -0.115).

surpass the reference tranche rate, thereby capturing the premiums for bearing systemic credit risk. Furthermore, our empirical study shows that the estimated SCRP, as a risk factor, has considerable implications for asset pricing, notably impacting the investment opportunities available to U.S. stock investors when the financial system is vulnerable.

Our research contributes to the existing literature by presenting a novel approach to extracting the time-series dynamics of the SCRP, considering the portfolio default risk premium while controlling for the individual default risk premium, which has not been adequately addressed in the existing literature. In addition, our findings underscore the significance and pertinence of SCRP in various systemic events, such as the global financial crisis and the COVID-19 pandemic. This provides valuable insights into how market participants perceive systemic credit risk, and how the credit derivatives and equity markets are linked in terms of the systemic credit risk premium.

The evolution of the extracted SCRP provides insightful information to policymakers who use credit market signals to make decisions. The inter-market asset pricing implication of the fitted SCRP carries valuable insights for risk management and investment strategies, as it enables a deeper understanding of the market price of systemic credit risk and provides opportunities for achieving excess returns while managing systemic credit risk.

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Data Availability Statement

Data for CDX.NA.IG for the period September 2005 through March 2021, as well as CDS contracts corresponding to the reference entities in the CDX.NA.IG portfolio, are obtained from Markit. Equity returns are obtained from CRSP and factor data are obtained from Kenneth French's website. Indices that distinguish between stable and distressed periods, such as the Chicago Fed National Activity Index (CFNAI) from the Federal Reserve Bank of Chicago, the St. Louis Fed Financial Stress Index (STLFSI) from the Federal Reserve Bank of St. Louis, and the Office of Financial Research Financial Stress Index (OFRFSI) from the Office of Financial Research, are obtained from their respective websites. Common measures of downside risk, including the Chicago Board Options Exchange Volatility Index (VIX), Moody's Seasoned Baa Corporate Bond minus Federal Funds Rate (BAAFF), and the Treasury-Eurodollar (TED) spread, are obtained from the Federal Reserve Economic Data (FRED).

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Figure 1

The market and reference tranche spreads

This figure presents the time series of the market and reference tranche spreads for every Wednesday from September 20, 2006, to March 17, 2021. The reference tranche spreads are artificially generated tranche spreads via CDS. To compare the market prices of CDX senior tranches and reference tranches, we calculated adjusted fair spreads that incorporated tranche width and trading units and adjusted for fixed coupon rates. The tranche width of the senior tranche is set to an attachment point between 0.15 and 1.00, as with the recent year. The trading units are aggregated into spreads. For the reference tranche, the adjusted fair spreads are the fair spreads obtained with the prepayment rate set to zero.

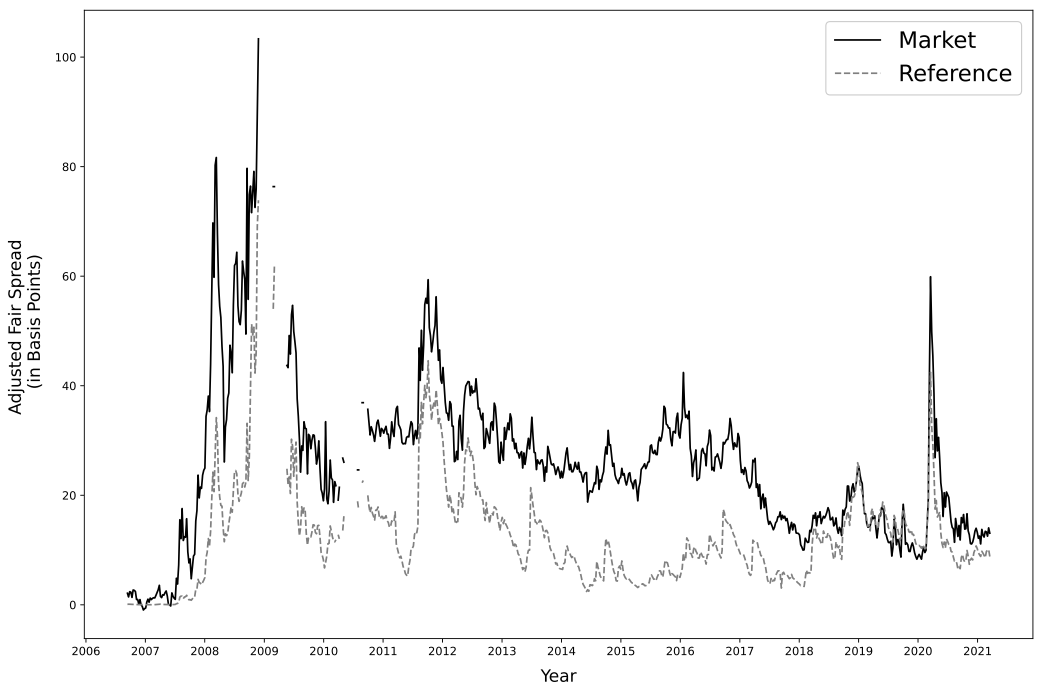

Figure 2

The estimated Systemic Credit Risk Premium

This figure presents the time series of the SCRPs for every Wednesday from September 20, 2006, to March 17, 2021. SCRPs are calculated through the difference between the market tranche spread and the artificially generated tranche spread via CDS. The SCRP units are the basis points, and the vertical lines represent important events.

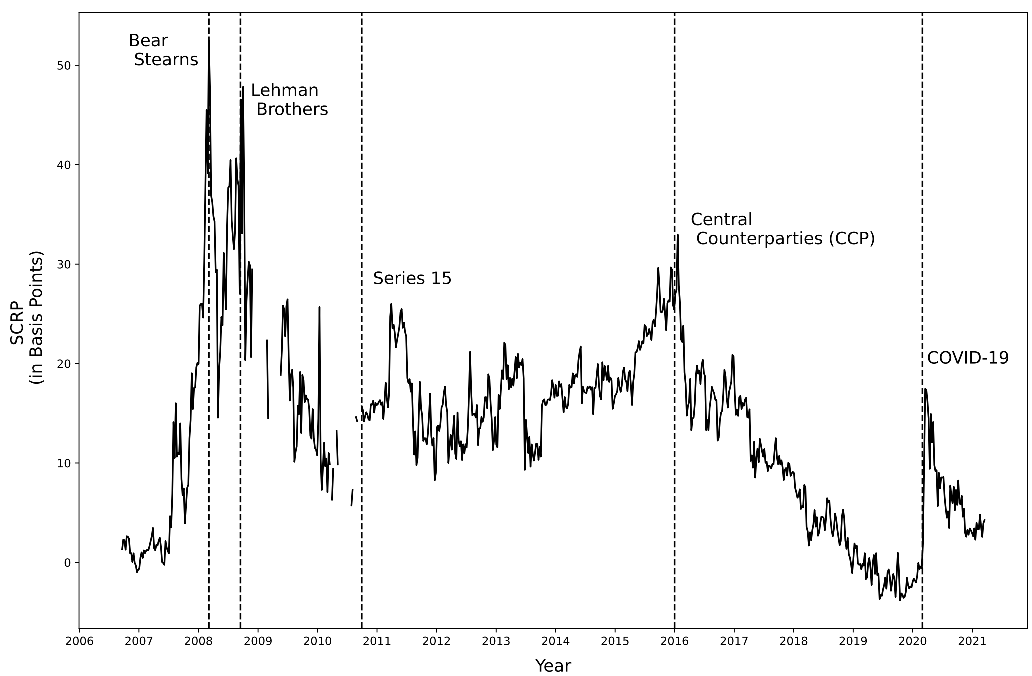

Figure 3

Alphas for portfolios based on SCRP beta levels

This figure presents the alphas obtained for the value-weighted portfolios constructed based on the ten deciles of the SCRP beta levels, controlling for Fama-French's three factors and a momentum factor. The sample period covers September 20, 2006, to March 17, 2021. The value-weighted portfolios are formed based on the ten deciles of the SCRP beta levels calculated using a rolling-window method with a window size of one year. The units on the y-axis are percentages (%), and the x-axis are portfolios organized by SCRP beta levels.

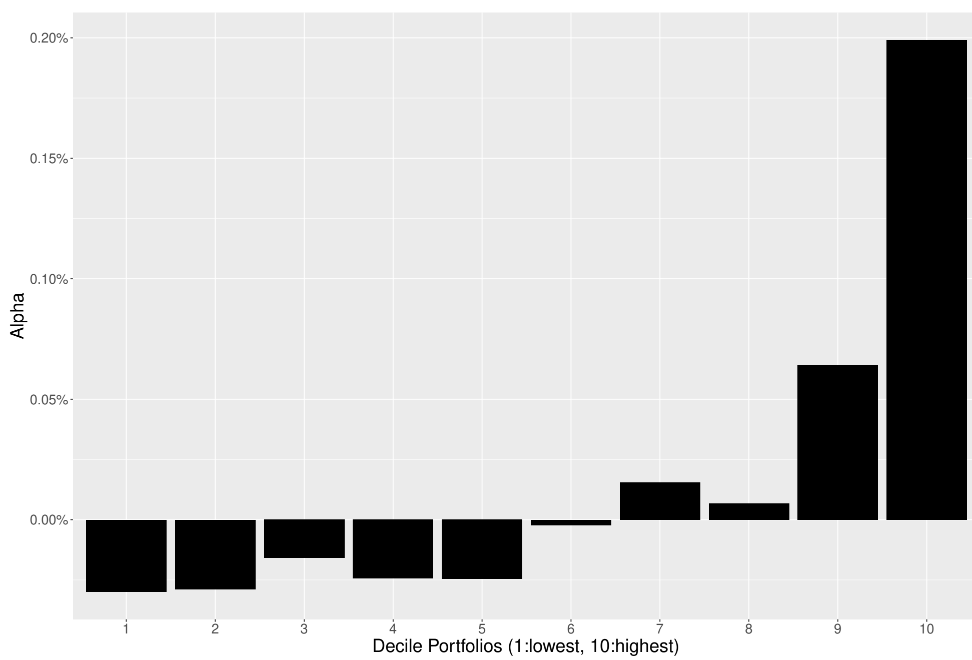

Figure 4

The estimated alphas for high-minus-low portfolio returns in relation to SCRP

This figure presents the estimated alpha values and their corresponding confidence intervals for the regression model (as illustrated in Equation (2)) applied to the long-short SCRP portfolio, including the Fama-French three factors and momentum factor models. The period sample is from September 20, 2006, to March 17, 2021. The value-weighted portfolios are formed based on the ten deciles of the SCRP beta levels calculated through a rolling-window approach with a window size of one year. The box plot displays the estimated alpha values and their corresponding confidence intervals. The center line represents the alpha estimate, the outer perimeter of the box represents the 90% confidence interval, and the whiskers represent the 95% confidence interval. The factor model includes Fama and French's three factors (MKTRF, HML, SMB) and the Carhart momentum (MOM) factor. Confidence intervals for alpha estimates are calculated using t-statistics based on the Newey-West standard error with lag $T^{1/4}$, where T is the number of observations. The Chicago Fed National Activity Index (CFNAI), the St. Louis Fed Financial Stress Index (STLFSI), and the Office of Financial Research Financial Stress Index (OFRFSI) are indices that distinguish between stable and distressed periods. A negative value of CFNAI indicates a contraction period, while a positive value indicates an expansion period. Similarly, a positive value of STLFSI and OFRFSI indicates a distressed period, while a negative value indicates a stable period.

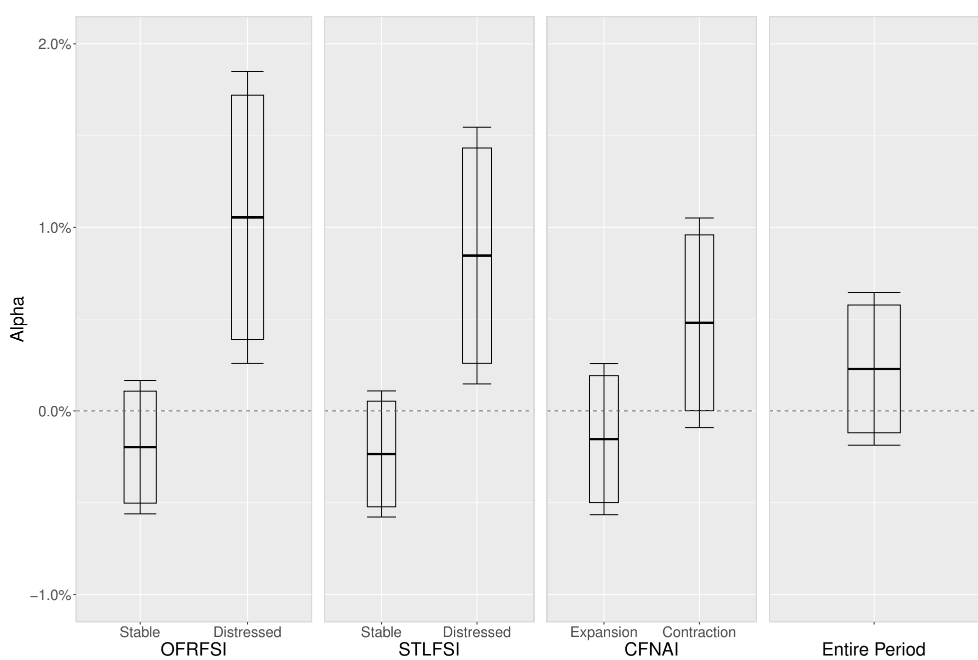

Table 1

Descriptive statistics of the estimated SCRP

This table reports the summary statistics for the estimated SCRPs for every Wednesday from September 20, 2006, to March 17, 2021. The estimated SCRPs are the difference between the market tranche and reference tranche spreads. Tranches with attachment points between 0.15 and 1.00 are defined as senior tranches, and we unified their trading units in basis points. The first column is based on time series of SCRPs throughout the entire sample period. The second and third columns are the SCRPs for the period before and after Series 15, respectively, where there was a significant change in CDX.NA.IG.

	Entire Period	**Before Series 15**	**After Series 15**
count	716	169	547
mean	13.30	15.87	12.50
stdev.	9.32	12.83	7.77
min	-3.82	-0.98	-3.82
25%	5.95	3.54	6.56
50%	14.46	14.21	14.56
75%	18.36	25.45	17.78
max	52.50	52.50	32.98

Table 2
Descriptive statistics of the variables

This table reports summary statistics of the variables we used for cross-market asset-pricing implications analysis. Stock returns are obtained from *CRSP* by referring to Scheuch et al. (2023), and Fama and French's three factors (MKTRF, HML, SMB) and the Carhart momentum (MOM) factor data are from *Kenneth French's website*. Daily data were converted to weekly data, and the sample period was every Wednesday from September 20, 2006, to March 17, 2021. The excess returns are winsorized at the 0.5th and 99.5th percentiles to control for extreme values, and the number of observations is 2,985,745. The risk factors, such as the Chicago Board Options Exchange Volatility Index (VIX), Moody's Seasoned Baa Corporate Bond minus Federal Funds Rate (BAAFF), and the Treasury-Eurodollar (TED) spread, are also used as an additional control. All units are the percent.

	Excess return	**MKTRF**	**HML**	**SMB**	**MOM**	**VIX**	**BAAFF**	**TED**
mean	0.04	0.20	-0.06	0.03	0.01	20.01	22.54	2.22
stdev.	3.44	2.47	1.70	1.27	2.50	9.78	9.95	2.39
min	-13.98	-15.64	-8.36	-6.09	-14.27	9.15	3.56	0.33
25%	-1.33	-0.71	-0.82	-0.80	-0.79	13.42	15.51	0.99
50%	0.00	0.40	-0.15	0.02	0.17	17.29	23.38	1.40
75%	1.33	1.44	0.64	0.79	1.18	23.14	28.51	2.17
max	16.38	11.05	9.52	6.08	11.37	76.45	55.24	19.95

Table 3
Fama and MacBeth cross-sectional regression

The table reports the estimated risk premiums from the Fama and MacBeth cross-sectional regressions of weekly stock excess returns, with the sample period covering September 20, 2006, to March 17, 2021. In addition to Fama and French's three factors (MKTRF, HML, SMB) and the Carhart momentum (MOM) factor, risk factors, such as Chicago Board Options Exchange Volatility Index (VIX), Moody's Seasoned Baa Corporate Bond minus Federal Funds Rate (BAAFF), and the Treasury-Eurodollar (TED) spread, are also used as additional control factors. The t-statistics, presented in parentheses, are adjusted based on the Newey-West standard error with lag $T^{1/4}$, where T is the number of observations. $***$, $**$, and $*$ indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The Chicago Fed National Activity Index (CFNAI), St. Louis Fed Financial Stress Index (STLFSI), and Office of Financial Research Financial Stress Index (OFRFSI) are indices that distinguish between stable and distressed periods. It is a contraction period if CFNAI is negative; otherwise, it is an expansion period. In contrast, it is a distressed period when STLFSI and OFRFSI are positive and otherwise a stable period. Panels A and B show the results of the analysis distinguished between stable and distressed periods according to OFRFSI and STLFSI, respectively. Panel C shows the results of the analysis distinguished between expansion and contraction periods according to the CFNAI. The intercept is included in the regression model but not in the table.

Panel A. OFRFSI

	Stable				**Distressed**			
SCRP	-0.0073	-0.0067	**-0.0078***	-0.0062	**0.0509****	**0.0499****	**0.0529****	**0.0502****
	(-1.6165)	(-1.4728)	(-1.6990)	(-1.2894)	(2.1727)	(2.2696)	(2.2346)	(2.2041)
MKTRF	0.0081	0.0160	0.0405	0.0125	-0.5266	-0.4169	-0.3504	-0.4356
	(0.1051)	(0.2097)	(0.5270)	(0.1637)	(-1.6206)	(-1.4973)	(-1.1681)	(-1.4582)
SMB	-0.0103	-0.0014	-0.0081	-0.0110	-0.1543	-0.0705	-0.0812	-0.1095
	(-0.1894)	(-0.0260)	(-0.1459)	(-0.1997)	(-1.1942)	(-0.6288)	(-0.6960)	(-0.9446)
HML	-0.0292	-0.0326	-0.0138	-0.0434	0.0162	-0.0425	0.0232	-0.0705
	(-0.4080)	(-0.4560)	(-0.1852)	(-0.6153)	(0.1265)	(-0.3103)	(0.1781)	(-0.5553)
MOM	0.0127	0.0037	-0.0253	0.0382	0.1092	0.0885	-0.0464	0.2196
	(0.1677)	(0.0482)	(-0.3138)	(0.5089)	(0.4807)	(0.4091)	(-0.2191)	(1.0194)
VIX		-0.3001				6.7064**		
		(-0.7353)				(2.5511)		
BAAFF			-0.7495***				4.1733**	
			(-2.9487)				(2.2584)	
TED				-0.0804				1.4694*
				(-1.4064)				(1.8101)

Table 3
Fama and MacBeth cross-sectional regression (Cont.)

Panel B. STLFSI

	Stable				Distressed			
SCRP	**-0.0077***	**-0.0072***	**-0.0081****	**-0.0071***	**0.0364***	**0.0358****	**0.0376****	**0.0368****
	(-1.9442)	(-1.7913)	(-2.0270)	(-1.7710)	(1.9625)	(2.0510)	(1.9985)	(2.0294)
MKTRF	-0.2219***	-0.2204***	-0.1980*	-0.2069***	-0.0537	0.0390	0.0975	-0.0004
	(-2.8044)	(-2.7332)	(-2.5293)	(-2.6067)	(-0.2166)	(0.1867)	(0.4301)	(-0.0020)
SMB	-0.0593	-0.0534	-0.0579	-0.0625	-0.0457	0.0230	0.0102	-0.0091
	(-1.0457)	(-0.9464)	(-1.0041)	(-1.0904)	(-0.4425)	(0.2568)	(0.1099)	(-0.0972)
HML	-0.0292	-0.0365	-0.0147	-0.0385	0.0043	-0.0343	0.0149	-0.0706
	(-0.3978)	(-0.4959)	(-0.1921)	(-0.5346)	(0.0359)	(-0.2825)	(0.1236)	(-0.6200)
MOM	0.1351*	0.1263*	0.1060	0.1474**	-0.0935	-0.1115	-0.2315	0.0138
	(1.8808)	(1.7481)	(1.3864)	(2.0174)	(-0.5038)	(-0.6303)	(-1.3209)	(0.0803)
VIX		-0.6745*				5.4283***		
		(-1.7483)				(2.6669)		
BAAFF			-0.7727***				2.927**	
			(-3.2401)				(2.0645)	
TED				-0.1396***				1.1524*
				(-2.6364)				(1.8479)

Panel C. CFNAI

	Expansion				Contraction			
SCRP	-0.0078	-0.0063	-0.0085	-0.0048	**0.0228***	**0.0219***	**0.0237***	0.0217
	(-1.3175)	(-1.0350)	(-1.4463)	(-0.7386)	(1.6852)	(1.7182)	(1.7215)	(1.6335)
MKTRF	-0.2057*	-0.2170*	-0.1668	-0.1789	-0.1169	-0.0436	-0.0156	-0.0837
	(-1.7794)	(-1.8465)	(-1.4847)	(-1.4662)	(-0.6600)	(-0.2858)	(-0.0948)	(-0.5169)
SMB	-0.0292	-0.0253	-0.0264	-0.0144	-0.0708	-0.0202	-0.0327	-0.0590
	(-0.3938)	(-0.3389)	(-0.3507)	(-0.1978)	(-0.9152)	(-0.2927)	(-0.4594)	(-0.8154)
HML	-0.0351	-0.0590	-0.0117	-0.0775	-0.0020	-0.0194	0.0036	-0.0336
	(-0.3064)	(-0.5066)	(-0.0997)	(-0.6736)	(-0.0213)	(-0.2069)	(0.0392)	(-0.3779)
MOM	0.0681	0.0802	0.0121	0.1318	0.0236	-0.0060	-0.0620	0.0660
	(0.5034)	(0.5941)	(0.0879)	(0.9816)	(0.1829)	(-0.0477)	(-0.5016)	(0.5338)
VIX		0.5634				2.6818		
		(0.9272)				(1.6090)		
BAAFF			-0.8061**				1.8055*	
			(-2.5870)				(1.7671)	
TED				-0.1016				0.7264
				(-1.2443)				(1.5874)