Finance and Economics Discussion Series

Federal Reserve Board, Washington, D.C.
ISSN 1936-2854 (Print)
ISSN 2767-3898 (Online)

Default Clustering Risk Premium and its Cross-Market Asset Pricing Implications

Kiwoong Byun, Baeho Kim, and Dong Hwan Oh

2023-055

Please cite this paper as:
Byun, Kiwoong, Baeho Kim, and Dong Hwan Oh (2023). "Default Clustering Risk Premium and its Cross-Market Asset Pricing Implications," Finance and Economics Discussion Series 2023-055. Washington: Board of Governors of the Federal Reserve System, https://doi.org/10.17016/FEDS.2023.055.

Default Clustering Risk Premium and its Cross-Market Asset Pricing Implications *

Kiwoong Byun†, Baeho Kim‡ and Dong Hwan Oh§

August 11, 2023

Abstract

This study examines the market-implied premiums for bearing default clustering risk by analyzing credit derivatives contracts on the CDX North American Investment Grade (CDX.NA.IG) portfolio between September 2005 and March 2021. Our approach involves constructing a time series of *reference* tranche rates exclusively derived by single-name CDS spreads. The *default clustering risk premium* (DCRP) is captured by comparing the original and reference tranche spreads, with the former exceeding the latter when investors require greater compensation for correlated defaults at the portfolio level. The fitted DCRP level significantly increased in response to the 2007-9 global financial crisis and remained relatively stable for a period, followed by a gradual decline beginning in 2016. Notably, the COVID-19 shock caused another sharp rise in the DCRP level. Our empirical analysis finds that the estimated DCRP has significant implications for asset pricing, particularly in affecting the investment opportunities available to U.S. stock investors during times of instability in the financial system.

Keywords: Credit Default Swap (CDS); CDS Index (CDX); Reference Tranche Rate; Default Clustering Risk Premium

---

*We thank Jihyeok Jeong, Heebum Lee, Bumjean Sohn, Marko Hans Weber, seminar participants at Korea University Business School, and conference participants at AsianFA 2023 Annual Conference for helpful discussions and comments. This work was supported by the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea (NRF-2021S1A5A2A01063707).

†Korea University Business School, Seoul, South Korea, Email: `bkw1120@korea.ac.kr`.

‡Corresponding Author, Korea University Business School, Seoul, 02841, South Korea, Phone: +82-2-3290-2626, Fax: +82-2-922-7220, Email: `baehokim@korea.ac.kr`.

§Federal Reserve Board, Washington, D.C. 20551, USA, Email: `donghwan.oh@frb.gov`.

1 Introduction

Credit derivative market participants face the risk of encountering correlated defaults. Given the potential impact of a significant cluster of correlated defaults on the entire system, market participants generally require significant premiums to account for the dynamic risk of default time correlation. The 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.

In this paper, we investigate the *default clustering risk premium* (DCRP), 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. DCRP 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, DCRP 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.

DCRP's implication has considerable academic significance in finance. It is also pertinent for policymakers who utilize credit market signals to make decisions, as the systemic credit risk premium is a critical aspect of DCRP. 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. 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 COVID-19 pandemic caused a downturn in financial markets and a subsequent banking system crunch due to increasing interest rates. This highlights the possibility of future similar scenarios, even with the potential resolution of the pandemic-related adverse feedback loop.

This research aims to extract the time-series dynamics of DCRP based on the portfolio 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 default clustering 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. 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, 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 only CDS data to estimate it.

Indeed, it is evident that participants in the single-name CDS market also demand a non-trivial level of premiums for taking default clustering risks. The relevant literature on CDS networks, such as Markose et al. (2012) and Paddrik et al. (2016), provides valuable insights into this phenomenon. However, as shown in Amato and Gyntelberg (2005), different CDX tranches exhibit different price sensitivities to the time-varying default correlations. Consequently, the DCRP captured by CDS spreads (or, equivalently, CDX index spreads) alone differs from the spreads across CDX tranches with different attachment and detachment points. In our study, we focus specifically on the (super-) senior tranche spreads of the CDX North American Investment Grade, which serve as a proxy for the systemic credit risk premium. In this context, the DCRP is positively associated with the senior tranche spread. This positive relationship arises because the occurrence of (super-) senior tranche losses is limited to extreme scenarios, making the corresponding DCRP specific to the senior tranche a meaningful measure of the market's perception of the prevailing portfolio default clustering risk.

The DCRP presented in this paper is inferred from 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 DCRP provides the benefit of being more directly related to the systemic 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. 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 DCRP. However, the DCRP, estimated from credit derivatives directly related to corporate default, can be seen as a conceptually more relevant measure of the 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. They suggest that measures based on CDS spreads outperform measures based on interbank rates or stock market prices.

Furthermore, this paper empirically analyzes how U.S. equity market participants perceive DCRP information extracted from the credit derivatives market. Our analysis shows that, after controlling for Fama and French's three factors and a momentum factor in both time-series and cross-sectional regression analyses, stock market participants demand additional compensation for taking on default clustering risk, primarily when the financial system is vulnerable. These findings demonstrate that the estimated DCRP is an important cross-market pricing factor affecting stock investors' decisions during periods of financial instability.

This paper makes an original and important contribution compared to related studies in that it directly estimates the DCRP, an estimate of the systemic credit risk premium, and investigates market participants' perceptions of recent major crises, including the global financial crisis and COVID-19 periods. Similar to our study, 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 DCRP. The DCRP units are the same as market-traded instrument units, allowing for a more direct interpretation of DCRP. In addition, our empirical analysis sheds light on the cross-market implications for asset pricing, revealing that the estimated DCRP 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

DCRP on the equity market, thereby establishing a link between this market and the credit derivatives market.

This article proceeds as follows. Section 2 presents the motivation and main objectives of this research. Section 3 explains the methodology for estimating the DCRP. Section 4 presents the results of our empirical analysis, and finally, Section 5 concludes.

2 Motivation

This section outlines our research objectives, introduces the concept of market-implied DCRP in credit derivatives, and explains how to apply the fitted DCRP 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 DCRP 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 DCRP 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 DCRPs 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 DCRPs, estimated from credit market data, by exploring how equity market investors perceive the risk of default clustering associated with 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 DCRP, regarding it as a risk factor that affects changes in portfolio returns in the equity market. If the DCRP factor is significantly priced in the equity market, we can conjecture that the cross-market asset pricing implications of the estimated DCRP are significant, particularly with respect to the investment opportunities accessible to stock investors.

2.2 Identifying the default clustering risk premium

We extract the dynamics of DCRPs 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 default clustering 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 DCRPs 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 default clustering 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 default clustering 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 default clustering risk premiums, as it is composed of multiple reference entities.

Therefore, DCRPs 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 a 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 DCRP. 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

Our inter-market empirical analysis employs the fitted DCRPs sourced from credit market information to investigate how equity market investors view the default clustering risk. In other words, our asset-pricing study presumes that the credit-market-implied DCRP 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. 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.

The nature of DCRP 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 DCRPs signify the compensation level for taking on default clustering 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 DCRPs have divergent impacts on equity returns during these different periods. 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 DCRPs 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

Q, which is equivalent to **P** and is associated with a constant risk-free rate $r > 0$.[1]

3.1 CDS-implied dependence structure

Our model specification aims to capture the time-series patterns of DCRP 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 Merton (1974) and Kitwiwattanachai and Pearson (2015), 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 name'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 $\mathbf{Q}$. In our framework, the default time density under $\mathbf{Q}$ is expressed as a function of the distance-to-default, represented by m, at each point in time. This default time density is utilized to calculate the present value of the cash flow stream associated with CDS contracts. Specifically, the risk-neutral distribution of the default time is derived from the first passage time distribution of a Brownian motion to zero. The risk-neutral default time density is given by[2]

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

A CDS contract involves 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.

[1]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.

[2]Refer to Theorem 3.7.1 from Shreve (2004) for details.

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.[3] 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 $g(t) = \frac{1}{4}\sum_{j:0<u_j\le t} e^{-ru_j}$ 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 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

[3]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.

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

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

Then, we introduce the **P**-correlation $\rho_{ij}(t)$ between the physically observed statistical behaviors of the CDS-implied returns of the underlying assets of any two firms i and j estimated at time t is given by

$$\rho_{ij}(t) = Corr^{\mathbf{P}} \left(dW_i(t), dW_j(t) \right) = Corr^{\mathbf{P}} \left(dm_i(t), dm_j(t) \right) \ .$$

To estimate pairwise asset correlations, we incorporate the CDS market's dynamic information flow on the co-movement of asset returns by employing the DCC-GARCH(1,1) model proposed by Tse and Tsui (2002) and Engle (2002). Accordingly, the conditional correlation matrix

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

indicates the statistically estimated correlation between the time-t innovations of the distance-to-defaults.[4] 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.

[4]To estimate a one-step-ahead forecast conditional correlation matrix based on the DCC-GARCH(1,1) model, we employed the *dccfit* function in the R package *rmgarch*; see Ghalanos (2022) for details.

3.2 Extracting the DCRP estimates

Notice that the statistically estimated asset-correlation structure inferred from the time-series evolution of the CDS spreads alone cannot fully address the default clustering risk premium implied by the market-observed CDX tranche spreads. In this vein, we wish to assess credit market participants' perception of default clustering 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 value following a geometric Brownian motion, we extend this framework to the multi-name level when calculating the reference tranche spreads. This involves incorporating the statistically estimated asset-return correlation structure, enabling us to infer a multivariate geometric Brownian motion.

In turn, we evaluate the reference tranche spreads using the statistically estimated correlation matrix as input. Monte Carlo simulation is a versatile tool for numerically calculating the first passage time of a multivariate geometric Brownian motion by jointly simulating the distance-to-default process for a portfolio consisting of $n = 125$ assets. A constituent defaults when its distance-to-default process hits zero, and we count the number of defaults in the portfolio for a given horizon. That is, at each time t, we simulate the correlated default times by using the statistically estimated correlation matrix Σ_t, which is assumed to be constant throughout the simulation horizon. This approach imposes a hypothetical interdependence structure among the *risk-neutral* default times of different entities for generating the reference tranche spreads. Our goal 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 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. 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. 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.[5] 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

[5] Further details are available upon request.

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 DCRP. In contrast, market-quoted CDX tranche spreads incorporate both the individual default risk premium and the entirety of DCRP.

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 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 DCRP. Therefore, we can determine the portfolio-wide premium for bearing default clustering 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 DCRP at each time t is given by

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

where the difference between the market tranche and reference tranche spreads reflects the default clustering risk premium.

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 default cluster risk among high-quality firms; see Seo and Wachter (2018) for related discussions. 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.

4 Empirical Analysis

In this section, we provide information on our data and sample, analyze the time-series behavior of the extracted DCRP, and examine its cross-market asset-pricing implications, specifically in relation to the U.S. stock market.

4.1 Data and sample

We obtain single-name CDS spreads and multi-name CDX index and tranche spreads from the Markit database, Markit (2023). Our study focuses on Investment Grade (IG) firms from the constituents of CDX North America (CDX.NA.IG). This index consists of 125 equally weighted CDS contracts on representative North American investment-grade firms. In general, on-the-run products (the most recent series) and products with a 5-year maturity have high liquidity. To mitigate the liquidity premium effect, CDX products with a 5-year maturity and on-the-run series have been chosen. 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 asset-return correlations were estimated using the rolling-window approach, employing a window size of one year as the baseline parameter specifications. As a result, DCRPs are extracted starting from September 13, 2006.

4.2 The time-series behavior of the fitted DCRP

In the case of CDX.NA.IG, as the series changed, the definition of the senior tranche, trading unit, and fixed-coupon rates continued to change. To construct the reference tranche spread, we use the same coupon rates as CDX for each period and tranche. In addition, the tranche width of the senior tranche is unified using the base correlation, as in recent years, and the trading unit is unified into the spread. The summary statistics for the DCRP are shown in Table 1.

[Table 1 about here.]

The results for the entire period show that market participants demand an average compensation of 13 basis points for default clustering risk and sometimes require negative premiums. Since the CDX product was completely reorganized, starting with Series 15 (September 2010), we have also broken out the summary statistics. Comparing before and after Series 15, we see that the mean value decreased after Series 15, indicating that market participants are not demanding higher compensation after Series 15 compared to before. This suggests that the post-Series 15 product restructuring effectively stabilizes the market.

[Figure 1 about here.]

Figure 1 shows the time series of the estimated DCRPs. If investors require compensation for taking the risk of excessively clustering defaults in the system, then the market-quoted senior tranche rate should exceed that of the reference tranche rate. The first line was in March 2008 and had the highest value. At that time, Bear Stearns went bankrupt, the first time this happened to a large investment bank, resulting in a substantial psychological impact on market participants during our sample period. The second line was in September 2008, when Lehman Brothers went bankrupt. The DCRP hit the second-highest value as this was the biggest financial shock during the global financial crisis. CDX products had not been traded normally since Lehman Brothers went bankrupt. However, the first incident, the bankruptcy of Bear Stearns, is perceived as more traumatic by market participants. The third line is September 2010, the beginning of Series 15, when CDX products were completely reorganized. The CDX tranche swap contracts have been traded normally since that date, but the CDX market size has continued to decline, according to Aldasoro and Ehlers (2018). The fourth line was in January 2016, and importantly, the DCRP has been falling since then, which can be attributed to the continuous development of central clearing system contributing significantly to the financial stability of the CDS market (Coughlan et al. 2019, Ivanov et al. 2021). The systemic risk premium may have decreased due to the introduction of central clearing which aims for improving financial stability. The last line was in March 2020, when the DCRP surged again due to the impact of COVID-19. The subsequent decline in DCRP suggests that the government's rapid intervention effectively stabilized financial markets.

4.3 Cross-market asset-pricing implications

Our empirical analysis examines how U.S. equity market investors perceive the risk of default clustering associated with systemic credit risk compensation by investigating the extracted DCRPs from credit market data. The aim is to analyze whether stock market participants require compensation for the estimated DCRP, considering it as a significantly priced risk factor in the stock market. If the DCRP factor is found to have significant pricing implications in the stock market, it would suggest that both equity and credit market investors require substantial compensation for their exposure to systemic credit risk.

To test whether the estimated DCRP correlates with a premium in returns, we estimated the DCRP betas based on a rolling-window regression with a window size of one year for each stock by taking the fitted DCRP as a risk factor in the stock market. We then sorted the stocks into ten decile groups based on their DCRP 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 DCRP 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 DCRP is a time-varying risk factor for equity returns, specifically during distressed periods when default clustering 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,[6] the St. Louis Fed Financial Stress Index (STLFSI) from the Federal Reserve Bank of St.

[6]https://www.chicagofed.org/research/data/cfnai/current-data

Louis,[7] and the Office of Financial Research Financial Stress Index (OFRFSI) from the Office of Financial Research.[8] Stock returns are obtained from *CRSP*, factor data are from *Kenneth French's website*,[9] and indices that distinguish between stable and distressed periods are from the websites of the organizations that produce them.

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 U.S. 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.

To evaluate the significance of each factor risk premium, we use Newey and West (1987)

[7]https://www.stlouisfed.org/

[8]https://www.financialresearch.gov/financial-stress-index/

[9]https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/

standard errors with lag $T^{1/4}$, where T is the number of observations. Figure 2 shows the alphas obtained for value-weighted portfolios constructed based on the ten deciles of the DCRP beta levels calculated through the rolling-window approach with a window size of one year, controlling for Fama-French's three factors and a momentum factor.

[Figure 2 about here.]

Figure 2 demonstrates that portfolios with high DCRP betas tend to have positive alphas, whereas portfolios with low DCRP betas tend to have negative alphas. This finding indicates a positive correlation between DCRP betas and stock returns. To further discuss the DCRP, we implement a long-short strategy involving purchasing high-DCRP portfolios and selling low-DCRP portfolios. The time-series regression of the long-short portfolios for the DCRP proceeds as

$$Y_t = \alpha_{0,t} + \beta_{1,t} MKTRF + \beta_{2,t} SMB + \beta_{3,t} HML + \beta_{4,t} MOM \ , \qquad (1)$$

where Y_t represents the difference in returns between high- and low-DCRP portfolios in week t.

[Figure 3 about here.]

In the regression model 1, the statistical significance of the alpha indicates whether stock market participants require additional compensation for the DCRP factor. Figure 3 presents the estimated alphas obtained from regressing the weekly returns of the long-short DCRP 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 DCRP 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 statistically insignificant 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 DCRP is required for distressed and contraction periods after controlling the Fama-French triad and the momentum factor. The significance of the DCRP factor becomes more pronounced during distressed periods compared to contraction periods, indicating that the DCRP more strongly relates to financial stability than the economic business cycle. Given that the estimated DCRP entails a premium for default clustering risk, it is reasonable that the significance of the DCRP factor is observed only during distressed periods when default clustering risk is more salient. As such, the DCRP derived from the credit derivatives market can be considered a transient and procyclical 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 DCRP 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 DCRP factor while accounting for other common downside risk measures in financial markets. Specifically, we include 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.

The 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. The 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 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 risk measure data are from the Federal Reserve Economic Data (FRED), and all other data are from the sources previously mentioned.

[Table 2 about here.]

Panel A of Table 2 reports the estimates from the Fama and MacBeth (1973) cross-sectional regressions for stable and distressed periods distinguished by OFRFSI. The effects of DCRP 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 DCRP during the distressed period, even with additional controls on common risk measures in financial markets. However, the effects of DCRP are generally not significant during stable periods. These results are the same as the previous results of time-series regressions. DCRP's negative coefficient when incorporating BAAFF and its statistical significance is intriguing. The results presented in Panel B of Table 2 provide further clarification that the impact of DCRP remains significantly negative during financially stable periods. While Panel C of Table 2 shows similar results to previous analyses, the significance of DCRP's effectiveness is weakened for the contraction period than during the distress period, and the effect of DCRP is insignificant when TED is included. These results imply that DCRP is related to financial stability rather than the business cycle. Although not reported in the table, the cross-sectional analysis for the entire period confirms that the DCRP factor's impact lacks statistical significance, consistent with the previous time series analysis. Our findings suggest that equity investors demand additional compensation for DCRP 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 risk measures in financial markets such as VIX, BAAFF, and TED does not change the results that market participants require compensation for DCRP during distressed or contraction periods.

5 Conclusion

This paper investigates the *default clustering risk premium* (DCRP), 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 DCRP 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 a time series of *reference* tranche rates that have been adjusted to isolate the default clustering 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 surpass the reference tranche rate, thereby capturing the premiums for bearing default clustering risk. Furthermore, our empirical study shows that the estimated DCRP, 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 DCRP, 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 DCRP 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 DCRP provides insightful information to policymakers who use credit market signals to make decisions, as the systemic credit risk premium is a crucial aspect of the DCRP. The inter-market asset pricing implication of the fitted DCRP carries valuable insights for risk management and investment strategies, as it enables a deeper understanding of the market price of default clustering risk and provides opportunities for achieving excess returns while managing systemic credit risk.

References

Adrian, Tobias and Markus K. Brunnermeier (2016), 'CoVaR', *American Economic Review* **106**(7), 1705–1741.

Aldasoro, Inaki and Torsten Ehlers (2018), 'The credit default swap market: what a difference a decade makes', *BIS quarterly review, June* .

Amato, Jeffery D and Jacob Gyntelberg (2005), 'CDS index tranches and the pricing of credit risk correlations', *BIS Quarterly Review, March* .

Azizpour, Shahriar, Kay Giesecke and Baeho Kim (2011), 'Premia for correlated default risk', *Journal of Economic Dynamics and Control* **35**(8), 1340–1357.

Brownlees, Christian and Robert F Engle (2017), 'SRISK: A conditional capital shortfall measure of systemic risk', *The Review of Financial Studies* **30**(1), 48–79.

Carhart, Mark M (1997), 'On persistence in mutual fund performance', *The Journal of Finance* **52**(1), 57–82.

Carr, Peter and Liuren Wu (2011), 'A simple robust link between american puts and credit protection', *The Review of Financial Studies* **24**(2), 473–505.

Celık, Sibel (2012), 'The more contagion effect on emerging markets: The evidence of DCC-GARCH model', *Economic Modelling* **29**(5), 1946–1959.

Chen, Nai-Fu, Richard Roll and Stephen A Ross (1986), 'Economic forces and the stock market', *The Journal of Business* **59**(3), 383–403.

Chen, Ren-Raw, Xiaolin Cheng, Frank J Fabozzi and Bo Liu (2008), 'An explicit, multi-factor credit default swap pricing model with correlated factors', *The Journal of Financial and Quantitative Analysis* **43**(1), 123–160.

Chen, Ren-Raw, Xiaolin Cheng and Liuren Wu (2013), 'Dynamic interactions between interest-rate and credit risk: Theory and evidence on the credit default swap term structure', *Review of Finance* **17**(1), 403–441.

Cho, Jang Hyung and Ali M Parhizgari (2009), 'East Asian financial contagion under DCC-GARCH', *International Journal of Banking and Finance* **6**(1), 17–30.

Coughlan, John, Richard Haynes, Madison Lau and Bruce Tuckman (2019), 'Recent trends in CDS markets', *OCE Staff Papers and Reports* .

Driessen, Joost (2005), 'Is default event risk priced in corporate bonds?', *The Review of Financial Studies* **18**(1), 165–195.

Driessen, Joost, Pascal J Maenhout and Grigory Vilkov (2009), 'The price of correlation risk: Evidence from equity options', *The Journal of Finance* **64**(3), 1377–1406.

Engle, Robert (2002), 'Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models', *Journal of Business & Economic Statistics* **20**(3), 339–350.

Fama, Eugene F and James D MacBeth (1973), 'Risk, return, and equilibrium: Empirical tests', *Journal of Political Economy* **81**(3), 607–636.

Fama, Eugene F and Kenneth R French (1993), ‘Common risk factors in the returns on stocks and bonds’, *Journal of Financial Economics* **33**(1), 3–56.

Friewald, Nils, Christian Wagner and Josef Zechner (2014), ‘The cross-section of credit risk premia and equity returns’, *The Journal of Finance* **69**(6), 2419–2469.

Ghalanos, Alexios (2022), ‘The rmgarch models: Background and properties’, *Vignette for R package ‘rmgarch’, version 1.3-0* pp. 1–23.

Girardi, Giulio and A Tolga Ergün (2013), ‘Systemic risk measurement: Multivariate GARCH estimation of CoVaR’, *Journal of Banking & Finance* **37**(8), 3169–3180.

Ivanov, Stanislav, Richard Jordan and Ian Springle (2021), ‘Credit default swap market retrospective: Observations from the 2008–9 financial crisis and the onset of the COVID-19 pandemic’, *Journal of Financial Market Infrastructures* **9**(3), 53–72.

Kitwiwattanachai, Chanatip and Neil D Pearson (2015), ‘Inferring correlations of asset values and Distances-to-Default from CDS spreads: A structural model approach’, *The Review of Asset Pricing Studies* **5**(1), 112–154.

Koziol, Christian, Philipp Koziol and Thomas Schön (2015), ‘Do correlated defaults matter for CDS premia? An empirical analysis’, *Review of Derivatives Research* **18**(3), 191–224.

Li, Junye and Gabriele Zinna (2014), ‘On bank credit risk: Systemic or bank specific? Evidence for the United States and United Kingdom’, *Journal of Financial and Quantitative Analysis* **49**(5-6), 1403–1442.

Longstaff, Francis A, Sanjay Mithal and Eric Neis (2005), ‘Corporate yield spreads: Default risk or liquidity? New evidence from the credit default swap market’, *The journal of finance* **60**(5), 2213–2253.

Markit (2023), ‘IHS Markit Ltd., Credit Default Swaps (CDS)’.

Markose, Sheri, Simone Giansante and Ali Rais Shaghaghi (2012), ‘ ‘Too interconnected to fail’ financial network of US CDS market: Topological fragility and systemic risk’, *Journal of Economic Behavior & Organization* **83**(3), 627–646.

Merton, Robert C (1974), ‘On the pricing of corporate debt: The risk structure of interest rates’, *The Journal of Finance* **29**(2), 449–470.

Newey, Whitney K and Kenneth D West (1987), 'Hypothesis testing with efficient method of moments estimation', *International Economic Review* **28**(3), 777–787.

Oh, Dong Hwan and Andrew J Patton (2018), 'Time-varying systemic risk: Evidence from a dynamic copula model of CDS spreads', *Journal of Business & Economic Statistics* **36**(2), 181–195.

Paddrik, Mark, Sriram Rajan and H Peyton Young (2016), 'Contagion in the CDS market', *Office of Financial Research Working Paper* (16-12).

Pan, Jun and Kenneth J Singleton (2008), 'Default and recovery implicit in the term structure of sovereign CDS spreads', *The Journal of Finance* **63**(5), 2345–2384.

Rodríguez-Moreno, María and Juan Ignacio Peña (2013), 'Systemic risk measures: The simpler the better?', *Journal of Banking & Finance* **37**(6), 1817–1831.

Seo, Sang Byung and Jessica A Wachter (2018), 'Do rare events explain CDX tranche spreads?', *The Journal of Finance* **73**(5), 2343–2383.

Shreve, Steven E (2004), *Stochastic calculus for finance II: Continuous-time models*, Springer Science & Business Media.

Tarashev, Nikola and Haibin Zhu (2008), 'The pricing of correlated default risk: Evidence from the credit derivatives market', *The Journal of Fixed Income* **18**(1), 5–24.

Tse, Yiu Kuen and Albert K C Tsui (2002), 'A multivariate generalized autoregressive conditional heteroscedasticity model with time-varying correlations', *Journal of Business & Economic Statistics* **20**(3), 351–362.

Figure 1

The estimated Default Correlation Risk Premium

This figure presents the time series of the DCRPs for every Wednesday from September 13, 2006, to March 17, 2021. DCRPs are calculated through the difference between the market tranche spread and the artificially generated tranche spread via CDS. The DCRP units are the basis points, and the vertical lines represent important events.

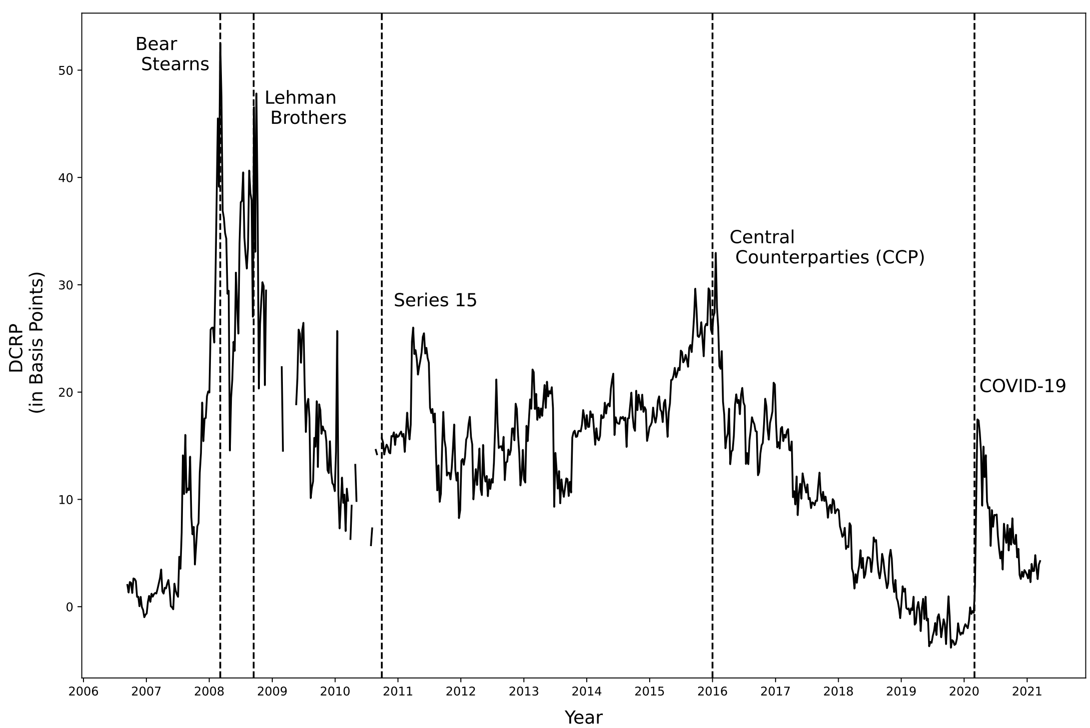

Figure 2

Alphas for portfolios based on DCRP beta levels

This figure presents the alphas obtained for the value-weighted portfolios constructed based on the ten deciles of the DCRP beta levels, controlling for Fama-French's three factors and a momentum factor. The sample period covers September 13, 2006, to March 17, 2021. The value-weighted portfolios are formed based on the ten deciles of the DCRP 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 DCRP beta levels.

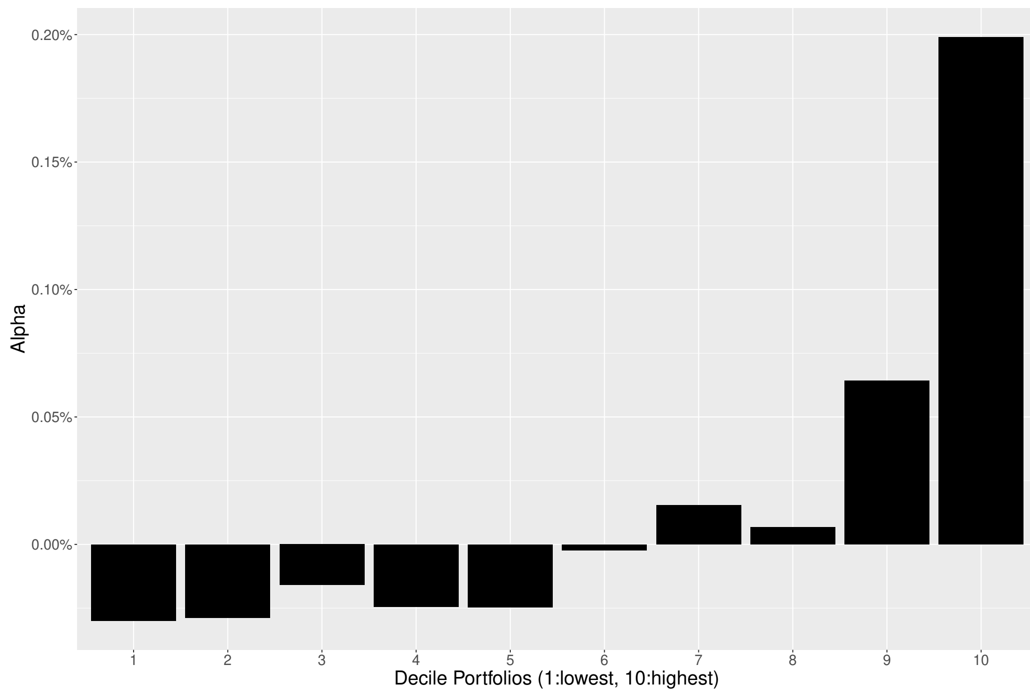

Figure 3

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

This figure presents the estimated alpha values and their corresponding confidence intervals for the regression model (as illustrated in formula 1) applied to the long-short DCRP portfolio, including the Fama-French three factors and momentum factor models. The period sample is from September 13, 2006, to March 17, 2021. The value-weighted portfolios are formed based on the ten deciles of the DCRP 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 the alpha are estimated 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.

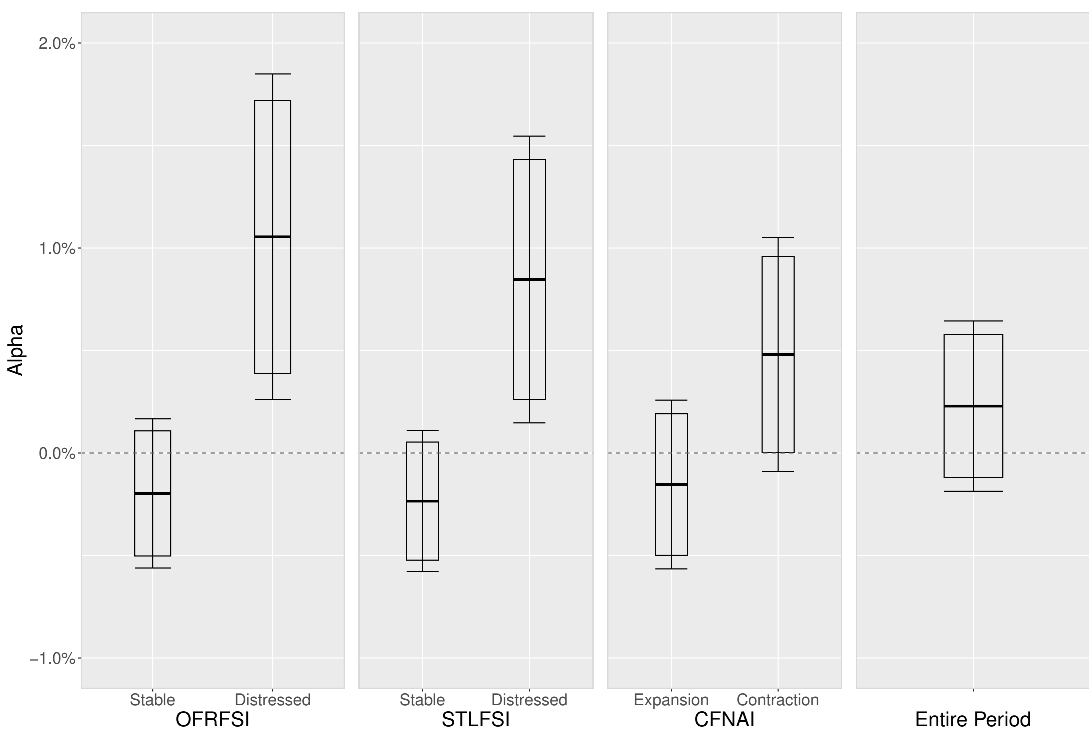

Table 1

Descriptive statistics of the estimated DCRP

This table reports the summary statistics for the estimated DCRPs. The CDX.NA.IG.5Y on-the-run senior tranche swaps and CDS for all reference entities in the tranche swaps are sourced from Markit, with a sample period from September 21, 2005, to March 19, 2021. 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 DCRP is estimated using data from the past year, using the DCRP from each Wednesday. The first column is based on a time series of DCRPs throughout the entire sample period. The second and third columns are the DCRPs 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	717	170	547
mean	13.28	15.79	12.50
stdev.	9.32	12.84	7.77
min	-3.82	-0.98	-3.82
25%	5.95	3.48	6.56
50%	14.45	14.16	14.56
75%	18.36	25.45	17.78
max	52.50	52.50	32.98

Table 2
Fama and MacBeth cross-sectional regression

The table reports the estimates from the Fama and MacBeth cross-sectional regressions of weekly stock excess returns, with the sample period covering September 13, 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. t-statistics are presented in parentheses and are 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**			
DCRP	-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 2
Fama & MacBeth cross-sectional regression (Cont.)

Panel B. STLFSI

	Stable				**Distressed**			
DCRP	**-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**			
DCRP	-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)