How to (Properly) Compute Credit Default Swap Returns

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Abstract

This paper studies alternative empirical methods to measure Credit Default Swap (CDS) return and explores its factor structure. Our analysis shows that conventional, approximated returns differ significantly from actual CDS returns due to two factors: upfront fees and protection sellers' required margins, both of which vary by maturity and credit risk. The market return, individual volatility and skewness positively predict actual CDS returns, but pricing factors constructed with bond characteristics do not have explanatory power. Stock market factors also help explain the cross-section, and the intermediary capital risk factor (ICRF) is priced, highlighting the role of financial institutions in CDS market-making.

Keywords: Credit Default Swap, Upfront Fee, Volatility, Intermediary Capital

JEL Classification: G12, G14, G24

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1 Introduction

The credit default swap (CDS) market has been expanding significantly over the last two decades and experienced turbulent periods during the financial crisis of 2007-2009. Despite its growing importance as a vehicle for investing and risk management, few studies exist regarding the dynamic factor structure of CDS returns. Alas, prior studies use approximated returns or changes in CDS spreads instead. This poses difficulties in adequately comparing CDS to other asset returns, and the approximated returns can lead to pricing errors. To better understand the profit and loss statement (P&L) and its factor structure, we define a relevant measure of CDS returns, which incorporates a key metric in the current CDS trading mechanism that the previous literature has not considered. We find that approximated CDS returns deviate significantly from actual returns calculated in line with market conventions especially during times of high volatility, highlighting the need for this study. Our realistic CDS return measure facilitates studying the cross-section of CDS returns with conventional methods in the empirical asset pricing literature, finding common factors unidentifiable when using approximated returns, and evaluating pricing models properly.

Computing actual CDS returns necessitates a detailed understanding of the trading institutions. In 2009, the International Swaps and Derivatives Association (ISDA) introduced a set of standardization measures that altered the notion and related trading rules to a fixed CDS spread system, referred to as the "CDS Big Bang". Under the new system, the CDS spread is preset and invariant[1], with standardized coupon and maturity dates. These measures aim to enhance the fungibility and liquidity of the CDS market and facilitate settlement. How does this work? The CDS seller receives fixed amounts of cash flow until the contract matures or a pre-specified credit event occurs to terminate the contract. Because the periodic spread does not vary and the uniform pricing makes the value of CDS non-zero at trade initiation for both the buyer and the seller, an initial payment called the *upfront fee*

[1]It is either 100 basis points or 500 basis points, usually depending on the rating of the CDS.

is exchanged to ensure that the contract is consistent with the no-arbitrage condition. Prior to the standardization, setting periodic coupons equal to the running CDS spread reveals the fair price to make the premium and protection values equal, whereas the new rule states a uniform periodic payment and computes the correct initial fee at the front end. The market convention is to calculate the upfront fee from the perspective of the seller, so if the upfront fee is positive (negative), the CDS seller (buyer) receives this amount from the buyer (seller) since the fixed CDS coupon is lower (higher) than the fair market value of the protection.

Under the new ISDA convention, the CDS seller resembles a corporate bondholder in that she receives a fixed coupon-like payment each period and prefers no credit event until maturity. This intuition paves the path for our definition of CDS return. Because the CDS seller insures against a credit event of the reference corporate debt, a positive (negative) upfront fee (or points up-front, PUF) operates as a discount (premium) in entering into a CDS contract. Thus, it makes sense to quote the price as (1− points up-front), where 1 refers to the \$1 of notional amount to be insured.[2] Then, the holding period return for a single entry CDS from a protection seller's perspective is

$$\frac{(1 - PUF_t) - (1 - PUF_{t-1})}{(1 - PUF_{t-1})}.$$

This simple definition aligns with the new ISDA rule and is compatible with other financial assets' holding period returns. Intuitive as it may be, one caveat of this return measure is that unlike bonds, the initial investment for CDS is not always close to the notional – in addition to exchanging the upfront fee, CDS market participants must post margins that vary with the credit risk (quoted spread) and maturity of the contract.[3] Thus, we calculate our main measure of CDS return by incorporating the margin requirements set by the Financial

[2]This is how CDS prices are actually shown in the Bloomberg terminal.

[3]The margin requirements of CDS buyers are set at half those of the sellers. Data regarding margin requirements is available from June 2009, which limits the construction of actual returns based on variable margin.

Industry Regulatory Authority (FINRA). The resultant return equation is slightly modified to

$$\frac{(m_{t-1} - PUF_t) - (m_{t-1} - PUF_{t-1})}{(m_{t-1} - PUF_{t-1})},$$

where m_{t-1} is the margin requirement at trade initiation. Different types of investors can view either of these returns (based on full or variable margin) as their benchmark, and cross-checking the results with both versions will add robustness to our study.

In addition to variable margins, a regular coupon payment from buyers to sellers, denoted as C, is included. Finally, we also incorporate another crucial component in fixed income pricing. The PUF is a clean price - that is, it does not take into account the riskless days from the first accrual start date to the trade date. Therefore, the seller needs to *pay* the accrued coupon to the buyer (since she did not provide protection for the relevant period) and the cash settlement amount becomes $PUF - AI$ where AI stands for accrued interest. Subtracting this dirty price from the margin completes the seller's cashflows, and the price of the CDS at $t-1$ (trade initiation) becomes $m_{t-1} - (PUF_{t-1} - AI_{t-1})$, or $m_{t-1} - PUF_{t-1} + AI_{t-1}$.[4] The all-inclusive seller's return then becomes:

$$\frac{-(PUF_t - PUF_{t-1}) + (AI_t - AI_{t-1}) + C_t}{m_{t-1} - PUF_{t-1} + AI_{t-1}}.$$

The similarity to a bond buyer's return highlights the need to quote CDS prices and calculate returns from the protection seller's perspective. The buyer's return does *not* simply mirror the seller's, due to different margin requirements.

Existing studies use the running spread of CDS mostly for simplicity, and the approximated return formulas measure the differences in current and lagged running CDS spreads. There exist two major issues in this approach. First, as noted, this approximated return

[4] A detailed description is available in cdsmodel.com/assets/cds-model/docs/Standard CDS Examples Updated Oct 2012.

assumes that CDS sellers receive payments each period based on the running CDS spread (i.e., a floating rate). However, if the current ISDA standard of fixed spreads applies, the approximated return represents a conflicting position which causes confusion. Second, even with the right adjustment, approximation results in inaccuracies depending on the cross-sectional distribution of CDS returns. If higher statistical moments such as return volatility and skewness affect the CDS return distributions, the quality of approximated returns formula is likely to deteriorate. Incomplete markets with heterogeneous agents can produce stochastic discount factors that depend on the cross-sectional distribution of asset returns, and time-varying covariations with the higher-order return moments can explain the cross-section of expected returns, as suggested by Kraus and Litzenberger (1976), Harvey and Siddique (2000), Dittmar (2002), and Chabi-Yo (2012). According to our constructed data, approximated returns indeed contain significant mispricing.

In this light, we pay attention to statistical moments such as volatility, skewness, and kurtosis of asset returns. Specifically, we perform bivariate sorts on single-name credit default swaps into two groups by size and three groups based on various underlying bond characteristics or the statistical moments of CDS and bond returns, independently. Factors constructed in the conventional way with CDS returns sorted on the above characteristics reveal the following. First, the overall performance of the market and the individual volatility and skewness of CDS significantly and positively predict future CDS returns. Second, bond-related factors have weak explanatory power in the CDS return cross-section. We suspect that this is because the variable margin requirements already reflect the variation in underlying bond credit risk and maturity, and CDS prices contain default-related information in excess of that provided by credit rating agencies for bonds. Our formal tests include conventional factor pricing models such as the Fama-French models, and the relevant factors can price CDS if the stock market reasonably represents overall financial markets. Our test results using the Fama and MacBeth (1973) method show that there is indeed a spillover effect from the stock market to the CDS market. In addition to the various asset markets, we test the intermediary capital risk factor (ICRF) of He and Krishnamurthy (2013) to find that it is significantly priced. This result suggests the importance of financial institutions' risk-taking capacity in providing credit protection and market-making in CDS.

Additional analyses reveal that approximate returns can be problematic in accurately representing the market or providing insight into the structure of CDS returns. During our sample period, the mean CDS seller's return, in its approximated form, is *negative* 4 basis points, suggesting CDS protection providers (i.e., sellers) are incurring losses. Since the data cover a nontrivial period of time, the representative statistic itself is very unconvincing, as there is no incentive (nor rationale) for financial institutions to remain in the market according to the result with approximate returns. On the other hand, our actual return measures are significant and positive for both the full and variable margin versions. Finally, cross-sectional regressions with approximate returns as the dependent variable find no meaningful results for any of the variables we test. Consequently, analyses employing this measure are likely to yield insignificant and misleading results.

The rest of the paper proceeds as follows. Section 2 reviews the related literature, and Section 3 explains the CDS market and its institutions, followed by the construction of actual CDS returns in Section 4. Section 5 describes the data and presents main empirical results, and Section 6 concludes the paper.

2 Related Literature

The main contribution of this paper is to directly tackle the metric of CDS returns. The first line of related literature approximates CDS returns using changes in the running CDS spread. For example, Ericsson et al. (2009) use the daily quoted CDS spread difference to study the determinants of CDS spreads, and Berndt and Obreja (2010) and Bongaerts et al.

(2011) compute CDS returns as changes in CDS spreads multiplied by an annuity factor. Hilscher et al. (2015) approximate the CDS buyer's return using the percentage change in CDS spreads. The second common method accounts for the first order impact of CDS spread changes on CDS value. Palhares (2013) and He et al. (2017) define the CDS return on a short CDS strategy as a sum of the return due to premium payments and the capital gain return. Approximated CDS returns in these studies, however, do not incorporate the current ISDA standard and hence ignore the upfront payment paid for the contract, which could lead to substantial mispricing. To mitigate this problem, Augustin et al. (2020) approximate cash flow-based CDS returns from the protection buyer's side using contract prices as inputs.

Our definition of CDS returns also incorporates the price or the upfront payment of a CDS contract but differs from Augustin et al. (2020) in several important ways. First, we propose an actual return from the seller's perspective, in line with the market convention to quote CDS prices. More importantly, our measure incorporates the fact that the upfront payment could be either *positive* or *negative* depending on the value of the contract at trade initiation, hence more realistic and plausible than the simple return calculation of Augustin et al. (2020). Our return calculation also enables us to easily incorporate the varying margin requirements set by FINRA, unlike the approximate measures. Lastly, we account for accrued interest and coupons when calculating CDS returns, which the prior literature has not yet considered, but are real cash flows for CDS contracts.

Another contribution of this study is that we investigate the common factor structure of the cross-section of CDS returns in the U.S. Few papers have studied the source of commonality in CDS returns. Berndt and Obreja (2010) use a sample of corporate CDSs in the European market and show that the first principal component of CDS returns, which proxies the economic catastrophe risk, can explain almost half of the cross-sectional variation in CDS returns. Palhares (2013) shows that a conditional CAPM can explain the cross-sectional variation in CDS returns by maturity in the U.S. corporate CDS market. He et al. (2017) find that assets' exposure to financial intermediary capital shocks can explain cross-sectional variation in expected returns of many asset classes, including CDS. To the best of our knowledge, no existing research has yet explored a comprehensive set of various return and bond characteristics as in this paper to find the common factors and tested how these factors are priced in the cross-section.

This paper also connects to a literature that examines the empirical determinants of corporate CDS risk premiums[5] – for example, Collin-Dufresne et al. (2001), Fabozzi et al. (2007), Ericsson et al. (2009), Zhang et al. (2009), Berndt and Obreja (2010), Bongaerts et al. (2011), Pu et al. (2011), Qiu and Yu (2012), Bao and Pan (2013), Doshi et al. (2013), and Gamba and Saretto (2013). We find that the CDS market, individual volatility and skewness can significantly price the CDS return cross-section, and the stock market factor is also important.

3 Credit Default Swaps

This section delves into the institutional aspects of CDS contracts that are pertinent to calculating holding period returns.

3.1 The CDS Contract

In a CDS contract, the credit protection buyer pays a periodic coupon to the protection seller until contract maturity or a pre-defined credit event, in return for compensation of losses in the case of default. The asset being protected is usually a bond issued by a third party, called the reference obligation. There may be one or more reference obligations covered by a CDS contract, and the issuer of the reference obligation(s) is referred to as the reference entity. In the case of a credit event, the counterparties can agree to make a physical or

[5] See Culp et al. (2016) for a detailed literature review.

cash settlement - as the outstanding amount of CDS can be well in excess of its underlying reference obligation(s), physical delivery of the bond for payment of the notional can lead to liquidity squeezes and is impractical. Auction settlement - determining the payoff of the CDS following an auction of the defaulting entity's reference obligations - is the prevalent method.[6]

3.1.1 Standard CDS Contract Specification

The ISDA defines rules and conventions regarding CDS markets, among other derivatives. For the North American Corporate Standardized Contract, CDS dates are specified as the 20th of March, June, September, or December. The first coupon payment date is the earliest of the mentioned dates after $t+1$ (where t equals the trade date) - for instance, a CDS with quarterly fee payments traded on 18th March 2009 will pay the first coupon on 20th March 2009, but a trade done on 19th March 2009 will pay the first coupon on 22nd June 2009 (20th June 2009 is a Saturday). CDS maturities (last day of protection) are calculated from the first coupon date, and the protection dates are unadjusted - i.e., a one-year CDS contract traded in February 2009 protects the buyer until Saturday, 20 March 2010. The coupon payment date convention is adjusted following, and the final payment will happen on Monday, 22 March 2010 for the mentioned contract. Coupon payments are fixed at 100 or 500 basis points depending on how trading counterparties agree, and the coupon payment frequency can also be set as either quarterly or semi-annual.[7] The legal protection is effective from $t-60$ days for credit events and $t-90$ days for succession events, and the payoff from protection seller to the protection buyer in the case of default is par value of the reference obligation minus its recovery value.

[6] Auction settlement converts physical-settled CDSs into cash-settled CDSs, following an auction of the bonds of the defaulting reference entity to determine the recovery rate. This differs from simple cash settlement which depends on the assessment of expected recovery value.

[7] Examples in this paragraph are from Standard North American Corporate CDS Contract Specification (ISDA, 2009), and Standard CDS Examples (ISDA, 2012)

3.1.2 Credit Events

Since the CDS contract is a contingent claim on pre-specified credit events, the definition of such events is important. With the burgeoning of the product, the 1999 ISDA Credit Derivatives Definitions identified six types of credit events - bankruptcy, obligation acceleration, obligation default, failure to pay, repudiation/moratorium, and restructuring. The 2003 definitions refine some of these definitions.[8] The 2014 definitions add governmental intervention as a credit event. Before the Standardization initiative in 2009 (often referred to as the "CDS Big Bang"), the protection buyer notified the seller in the occurrence of a credit event. If the seller did not agree, the dispute was referred to court rulings. The "Big Bang Protocol" created Determination Committees for each region to decide on specific cases of CDS contract application, and introduced auction settlement as the default method for the settlement of single-name CDSs.

Not all CDS are equal - that is, there exist contracts that differ in which credit events they do or do not cover. CDS can trade under various "document clause" depending on how the contract accounts for restructuring events. The four types of restructuring clauses are Full Restructuring (the protection buyer can deliver bonds of any maturity following restructuring of any form), Modified Restructuring (deliverable obligations are limited to those with maturities of less than 30 months), Modified-Modified Restructuring (deliverable obligations are limited to those with maturities of less than 60 months), and No Restructuring (excludes restructuring events altogether from coverage of the CDS contract). The quoted CDS spread for a given reference entity can vary according to document clause, and the No Restructuring clause mainly trades in North America.

[8] For more detail on the definition of credit events and its history, refer to Culp et al. (2016).

3.1.3 Credit Derivatives Determination Committees

The basic concept of the CDS contract is simple, but the legalities and procedures involved can be quite complex. This is why the Credit Derivatives Determination Committees are needed - consisting of up to 10 sell-side and 5 buy-side voting firms, their role is to make decisions on the application of CDS contracts to specific cases.[9] Examples of questions submitted to the committee are "Has a Bankruptcy Credit Event occurred with respect to The Hertz Corporation?", "Is there a Successor to Goodrich Corporation?", and "Has a Restructuring Credit Event occurred with respect to Novo Banco S.A.?", to list a few. The committee also decides whether a CDS auction should be held in the case of a credit event, and facilitates the process together with the DC Administration Services.

3.1.4 Margin Requirements

The Financial Industry Regulatory Authority (FINRA) adopted a pilot program regarding margin requirements for CDS contracts in 2009. The essence of the rule is that short CDS positions (selling protection) are more risky than long positions, thus initial margins required of sellers are double those of buyers. In its earliest version (June to September 2009), FINRA required all CDS not cleared through the Chicago Mercantile Exchange (CME) to post a margin that varied according to the contract maturity and the quoted spread. There were five groups based on the basis point spread, and four on maturity. CDS cleared through CME followed the exchange's set of rules.

In the following years, margin requirements were updated annually (except during 2012 and 2013 in which there were multiple updates) and became more granular. As of July 2020, relevant to the latest portion of our sample period, margin requirements were defined for six groups based on the quoted spread and nine groups according to contract maturity.

[9] More information on Credit Derivatives Determination Committees can be found at https://www.cdsdeterminationscommittees.org/.

The minimum required margin remained at 1% of the notional amount, but the maximum increased to 50% of the notional for CDS contracts with quoted spreads greater than 700 bps and maturities longer than 10 years. These rules applied to all CDS not cleared through a central counterparty with an approved margin methodology by the FINRA, and over-the-counter trades.[10]

We calculate CDS margin requirements during our sample period for sellers and buyers separately, taking into account the time variations in FINRA rules. Since these are cash flows demanded of CDS market participants at trade initiation, we also compute returns utilizing the initial margins instead of the notional amount. This approach leads to differences in seller's and buyer's returns not only in direction but also in size, providing additional insight into market structure and trading motivation.

3.1.5 The CDS "Big Bang", or Standardization

Prior to April 2009, each CDS was traded with a coupon rate equal to the prevailing quoted spread (making the value of the CDS zero at the time of inception). Each day, the CDS also traded with a different maturity date. Intuitive as this was, the explosive growth in the CDS market, which peaked in 2007, brought about needs to facilitate trading and settlement. The result was a set of standardization measures, often referred to as the CDS "Big Bang". Two key features affected by the standardization are maturity dates and coupons. The maturity date, which had been reset daily, was standardized to the 20th of every March, June, September, and December. Together with the maturity date, coupon payment dates were standardized also, and are now not staggered throughout the year. The recommended "fixed" coupon for CDS rated BBB or better is 100 basis points, and for BB or below 500

[10]For more information on CDS margin requirements, refer to https://www.finra.org/rules-guidance/rulebooks/finra-rules/4240. Since April 6, 2022, the pilot program has ended and FINRA has adopted a more comprehensive margin requirement system, defining CDS to be a type of Security-Based Swap (SBS). The new rules define a variation margin based on current exposure in addition to the initial margin. The variation and initial margins may be netted.

bps.

The standardization of maturity dates and coupon rates not only increases fungibility of CDS contracts, but also provides immense benefits in regard to settlement, especially in the mentioned environment of rising trade volume. On the other hand, it creates a wedge between zero (the value of the CDS at inception when traded at rolling maturity dates and coupons set equal to quoted spreads) and the value of the standardized CDS. This difference, or the present value of the CDS contract, is exchanged between counterparties as an $upfront$ fee at trade initiation, the calculation of which is detailed in the following sections.

4 Construction of CDS returns

This section constructs holding period returns of credit default swaps. We begin by describing how to handle time variations of the yield curve to discount future cash flows appropriately. CDS data are from MarkIt, which identifies CDS reference entities by Reference Entity Data (RED) code. Our analysis focuses on U.S. dollar-denominated CDS with senior unsecured debt as reference obligations, requiring the reference entity to be based in the United States. The most liquid tenor in the CDS market is five years, which is our sample space. Any observation with a quoted spread of greater than 100% is deleted.[11] Computing CDS prices uses the term structure of interest rates – following ISDA's curve construction documentation, we gather interest rate swaps data from the Intercontinental Exchange Benchmark Administration (IBA) for various maturities from Bloomberg, and interpolate the rates with a cubic function to fill in missing values for each quarter.[12] We match $t-1$ business day curve data to t day CDS data, following the market convention.

[11]Intuitively, it does not make sense to pay more than the notional value of the asset for protection against default. Strictly speaking, this only holds for horizons of one year or more, but we choose to exclude these extreme cases.

[12]The raw curve data consists of 1-,2-,3-, and 6-month, and 1-,2-,3-,4-,5-,6-,7-,8-,9-,10-,12-,15-,20-,25-, and 30-year maturities. See https://www.ice.com/iba/ice-swap-rate for more information.

4.1 Actual CDS Returns

This section details the method to compute actual returns for standardized CDS contracts. We introduce $Points\ Up - Front$ (PUF) and fixed periodic payments, but the daycount convention is not elaborated here for the sake of brevity (For more details, refer to White (2013)). A reduced-form model is used to value both the protection and premium legs of a CDS contract, where the premium leg is the value of the CDS buyer's contingent payments and the protection leg is the value of the CDS seller's potential liability. Both functions share the same default probability, which equalizes the value of the short and long positions' claims.[13]

Using market-quoted CDS spread data, we numerically find the implied default probability, then construct the new CDS contract that pays a fixed premium payment with an upfront fee. The upfront fee accounts for the difference between the value of the old CDS contract and that of the new CDS contract (the standardized ISDA contract). The standardized CDS contract pays periodic standardized coupons (100 bps or 500 bps) plus an initial upfront fee, whereas the old CDS contract pays non-standardized coupons (set equal to the quoted CDS spread at the time of trade) with zero initial payment.

Start with valuation of CDS contracts before the standardization. The present value of the protection leg (per 1 unit of notional amount) is

$$PV_{ProtectionLeg} = \mathbb{E}^{\mathbb{Q}}\left[Z\left(\tau\right)\left(1 - RR(\tau)\right)\mathbb{I}_{\tau<T}\right] \tag{1}$$

where $Z(\tau) = e^{-\int_0^{\tau} r(s)ds}$, which is the present value of one-unit of cash flow at stopping (default) time (τ) discounted by the current zero curve, $r(s)$, RR is recovery rate, and $\mathbb{I}_{\tau<T}$ is an indicator function that gives 1 if the underlying firm defaults before the maturity date T and zero otherwise. We convert the binary indicator function to a survival curve, $Q(\tau)$,

[13] An online appendix provides an explanation and illustration of the economic mechanism of the model in a binomial framework.

assuming that recovery rates are independent of interest rates, default probability (λ), and are constant. Further assuming that interest rates and hazard rates are independent,

$$PV_{ProtectionLeg} = -(1 - RR)\int_0^T Z(s)dQ(s) \tag{2}$$

where $Q(\tau)$ represents survival probability ($= e^{-\lambda_t(T-t)}$), of which the term structure is assumed to be flat for now (later, its term structure is bootstrapped using multiple CDS), and λ_t is default probability (implied). Our goal is to numerically find the implied default probability that equalizes values of the short and long positions for each CDS contract. The numerical counterpart of Eq. (2) is:

$$PV_{ProtectionLeg} \approx (1 - RR)\sum_{i=1}^{T} Z(t_i)[Q(t_{i-1}) - Q(t_i)] \tag{3}$$

The premium leg is a product of the CDS spread and risky present value of one basis point (RPV01) which consists of two parts: periodic coupons and accrued interest paid upon default.[14]

$$PV_{PremiumLeg} = s_t \cdot RPV01 \tag{4}$$

where s_t is the CDS spread which is fixed for the entire life of the contract for those who trade at t, and

$$RPV01 = \underbrace{\mathbb{E}^{\mathbb{Q}}\left[\sum_{j=1}^{T} Z(t_j)\,\mathbb{I}_{t_j<\tau}\right]}_{\text{periodic coupons}} + \underbrace{\mathbb{E}^{\mathbb{Q}}\left[\sum_{j=1}^{T} \Delta(t_{j-1},\tau)Z(\tau)\,\mathbb{I}_{t_{j-1}<\tau<t_j}\right]}_{\text{accrued interest}} \tag{5}$$

where Δ is a fraction that accounts for accrued days following the daycount convention.

[14]The coupon payment is accrued from the most recent coupon date and reaches to full coupon amount on the next payment date.

We assume that the credit event occurs in the middle of coupon payment dates on average, $\Delta = 0.5$. Hence,

$$RPV01 \approx \sum_{i=1}^{T} Z(t_i) \left[Q(t_i) - \frac{Q(t_i) - Q(t_{i-1})}{2} \right] \tag{6}$$

Finally, CDS sellers and buyers agree on the following equation.

$$PV_{ProtectionLeg}(\lambda_t;\ r, T, RR) = PV_{PremiumLeg}(\lambda_t;\ s_t, r, T, \Delta) \tag{7}$$

Similar to the method to numerically compute implied volatility using option price and an option pricing equation, we use the CDS spread data and Eq.(7) to find implied default probability (λ_t) that equalizes the CDS valuation for long and short positions. However, this method implicitly assumes that the term structure of implied default probabilities is flat. Bootstrapping the implied default probabilities addresses this problem. Suppose we have n number of CDS contracts with different maturities at time t for a single reference entity. Using the aforementioned method, we can numerically find the implied default probability for the contract with shortest maturity ($\lambda_t^{(1)}$) using $s_t^{(1)}$. Then, we bootstrap an implied default probability from the one with a slightly longer maturity to get $\lambda_t^{(2)}$ using $\lambda_t^{(1)}$ and $s_t^{(2)}$, and so on to get $\lambda_t^{(1)}, \cdots, \lambda_t^{(n)}$ following Eq.(8).

$$\begin{aligned}
Q(t, T^{(1)}) &= e^{-\lambda_t^{(1)}(T^{(1)}-t)} \\
Q(t, T^{(2)}) &= e^{-\lambda_t^{(1)}(T^{(1)}-t)-\lambda_t^{(2)}(T^{(2)}-T^{(1)})} \\
&\ \ \vdots \\
Q(t, T^{(n)}) &= e^{-\lambda_t^{(1)}(T^{(1)}-t)-\lambda_t^{(2)}(T^{(2)}-T^{(1)})-\ \cdots\ -\lambda_t^{(n)}(T^{(n)}-T^{(n-1)})}
\end{aligned} \tag{8}$$

Thus, bootstrapping as shown above produces a term structure of implied default probabilities with which we finally value CDS, accounting for the curve information.

So far, we have shown how legacy CDS contracts are valued, and now introduce standardized CDS contracts. Since the CDS Big Bang, CDS buyers pay or receive the initial upfront fee at trade inception and pay standardized coupons rather than the quoted spread as premiums.[15] The valuation equation, Eq.(7) becomes as follows

$$PUF_t = PV_{ProtectionLeg}(\lambda_t;\ r, T, RR) - PV_{PremiumLeg}(\lambda_t;\ s_t^*, r, T, \Delta) \tag{9}$$

where s_t^* is the 'standardized' coupon which is usually 100 basis points for contracts rated BBB or better and 500 bps for others. Thus, for standardized CDS contracts, we first estimate implied default probabilities from the legacy CDS valuation (Eq.(7)), then second, change the quoted credit spread (s_t) to a standardized coupon (s_t^*), and finally, calculate the points upfront that makes the inequality equal. Positive (negative) PUF implies that the seller (buyer) receives the amount from the buyer (seller).

4.1.1 Actual Returns Based on Notional Amount (Full Margin)

The points up-front, or the upfront fee as a fraction of the notional, has so far been calculated based on a notional of 1. The market convention is to quote CDS prices as a percentage of the notional, that is, as 100 - $PUF(\%)$. More generally, to calculate CDS returns from time $t-1$ to t for any notional N, we use the following return equation.

$$r_t^{Act} = \frac{N \cdot (1 - PUF_t)}{N \cdot (1 - PUF_{t-1})} - 1 \quad = \frac{-PUF_t + PUF_{t-1}}{1 - PUF_{t-1}}$$

The equations differ from a simple return calculation, $(P_t/P_{t-1}) - 1$ (Augustin et al. (2020)), in two senses, yet they are similar to the price quoting convention of swap contracts.[16] First,

[15] The buyer or seller pays the upfront fee depending on the sign of the contract's present value.

[16] Augustin et al. (2020) focus on the correlations between different return metrics. In our case, we place a strong emphasis on adhering to market conventions and providing a flexible and realistic approach to managing traders' positions. We appreciate the anonymous referee for bringing this point to our attention.

the actual return is the seller's return, in line with the market's convention of quoting CDS prices. Second, the sign of PUF can be negative or positive, thus negative PUF implies that a seller pays the upfront fee to a buyer. Since the sign of PUF can be flipped when the seller closes her position, conventional return calculation is not applicable to the case of CDS. Also, when the denominator (P_{t-1}) equals zero, return calculation is simply infeasible using existing methods. Lastly, we compute actual returns for each document clause of single name CDS: Full restructuring, Modified restructuring, Modified-modified restructuring, and No restructuring, averaging them at each time t to get consistent time-series data.

Taking into account accrued interest (AI) and coupons (C), the equation becomes:

$$
\begin{aligned}
r_t^{Sell} &= \frac{N \cdot (1 - PUF_t + AI_t + C_t)}{N \cdot (1 - PUF_{t-1} + AI_{t-1})} - 1 \\
&= \frac{-(PUF_t - PUF_{t-1}) + (AI_t - AI_{t-1}) + C_t}{1 - PUF_{t-1} + AI_{t-1}}.
\end{aligned}
\tag{10}
$$

where C is the 100 or 500 bps fixed rate that the protection buyer pays the protection seller at quarterly intervals. It is also worthwhile to note that for a CDS contract, each coupon payment is equal to (annual coupon rate/360) $\times$ (number of days in accrual period), and thus can differ between coupon dates. AI is simply (annual coupon rate/360) $\times$ (number of days since last coupon date). This method of calculation implies that the cost of protection for each day in the contract period is equivalent.[17]

Contrary to other assets, the CDS buyer's return is not simply the opposite of the seller's. Margin requirements and fees at trade initiation create different sets of cash flows for involved parties, which creates a fundamental asymmetry between their returns. From the market convention to quote CDS prices (or equivalently, assuming full margins), the buyer's return

[17]In contrast, bonds usually pay equal amounts for each coupon, and thus the accrued interest per day can differ according to how many days are in the accrual period and the daycount convention.

becomes

$$r_t^{Buy} = \frac{N \cdot (1 + PUF_t - AI_t - C_t)}{N \cdot (1 + PUF_{t-1} - AI_{t-1})} - 1$$
$$= \frac{(PUF_t - PUF_{t-1}) - (AI_t - AI_{t-1}) - C_t}{1 + PUF_{t-1} - AI_{t-1}}. \tag{11}$$

Comparing equations (10) and (11), we can see that the numerators are simply of the opposite sign, but the difference in the denominators renders the absolute size of the two returns unequal.

4.1.2 Actual Returns with Margin Requirements

As intuitive and appealing as the above return calculation based on market conventions may be, possible concerns remain regarding the notional not being part of real cash flows for CDS trades. Apart from the points-up-front (PUF), CDS traders are required to post margins, which we incorporate into an alternate definition of CDS returns. Different margin requirements for CDS sellers and buyers necessitate separate calculation of seller's and buyer's returns based on the varying initial margin amounts, which can be expressed as:

$$r_t^{Sell} = \frac{N \cdot (m_{t-1}^{Sell} - PUF_t)}{N \cdot (m_{t-1}^{Sell} - PUF_{t-1})} - 1 \quad = \frac{-PUF_t + PUF_{t-1}}{m_{t-1}^{Sell} - PUF_{t-1}},$$

$$r_t^{Buy} = \frac{N \cdot (m_{t-1}^{Buy} + PUF_t)}{N \cdot (m_{t-1}^{Buy} + PUF_{t-1})} - 1 \qquad = \frac{PUF_t - PUF_{t-1}}{m_{t-1}^{Buy} + PUF_{t-1}}$$

where m_{t-1} is the margin requirement at CDS initiation, and the superscript indicates the side of the trade. The requirement differs according to credit risk and tenor, and the trade direction. Buyers are to post half the margin required of sellers. In calculating these returns, we incorporate the time-varying margin requirements during the sample period according to

FINRA rules.[18] Figure 1 shows seller's required margins for the 5-year CDS contract for the sample period.

[Insert Figure 1 around here.]

Taking into account accrued interest and coupons, the equations become:

$$
\begin{aligned}
r_t^{Sell} &= \frac{N \cdot (m_{t-1}^{Sell} - PUF_t + AI_t + C_t)}{N \cdot (m_{t-1}^{Sell} - PUF_{t-1} + AI_{t-1})} - 1 \\
&= \frac{-(PUF_t - PUF_{t-1}) + (AI_t - AI_{t-1}) + C_t}{m_{t-1}^{Sell} - PUF_{t-1} + AI_{t-1}},
\end{aligned} \tag{12}
$$

and

$$
\begin{aligned}
r_t^{Buy} &= \frac{N \cdot (m_{t-1}^{Buy} + PUF_t - AI_t - C_t)}{N \cdot (m_{t-1}^{Buy} + PUF_{t-1} - AI_{t-1})} - 1 \\
&= \frac{(PUF_t - PUF_{t-1}) - (AI_t - AI_{t-1}) - C_t}{m_{t-1}^{Buy} + PUF_{t-1} - AI_{t-1}}.
\end{aligned} \tag{13}
$$

for the protection seller and buyer, respectively.

The formulas show that the asymmetry between CDS seller's and buyer's returns can be amplified when the margin requirements differ, the implications of which we explore in the empirical analyses and discussions. However, only approximately 2.7% of the samples have negative denominators when seller's actual returns are calculated using time-varying margins in the post-GFC period. To the best of our knowledge, this study is the first to incorporate variable margins, together with accrued interest and coupons, in CDS return calculation.

[18] The central counterparty retains a portion of the interest earned on collateral (margin). For simplicity, accrued interest on margin and fees associated with central clearing are omitted in the return equation. For more details on the fee structure, see https://www.ice.com/publicdocs/clear_credit/ICE_Clear_Credit_Collateral_Management.pdf.

4.2 Approximated CDS returns

Existing studies approximate CDS returns using changes in the CDS spread: $s_t - s_{t-1}$ (Ericsson et al., 2009), and $s_t/s_{t-1} - 1$ (Hilscher et al., 2015). However, the approximated returns do not incorporate a first order impact of spread changes on future cash flows. In order to mitigate this problem, Palhares (2013) and He et al. (2017) use a new CDS return equation that accounts for the first order impact.[19] Following He et al. (2017), the approximated CDS return on a short position ($r_t^{Aprx.}$: per dollar monthly holding period return) is

$$r_{t,RS}^{Aprx.} = \underbrace{s_{t-1}/12}_{\text{Premium (Coupon)}} + \underbrace{(s_t - s_{t-1}) \times RD_{t-1}}_{\text{Capital changes}} \tag{14}$$

where s_t is the running CDS spread and RD_{t-1} is lagged risky duration of the CDS. If we assume that the market quotes fixed CDS spread[20], the approximated return should be

$$r_{t,FS}^{Aprx.} = \underbrace{s_{t-1}/12}_{\text{Premium (Coupon)}} - \underbrace{(s_t - s_{t-1}) \times RD_{t-1}}_{\text{Capital changes}} \tag{15}$$

The approximated return consists of two components: periodic premium received today and present value of changes in future premiums. The latter is approximated using the interest rate swap curve and the default rate.[21] To be specific, the risky duration for CDS with quarterly premium payments is approximated as follows:

$$RD_t = \frac{1}{4}\sum_{j=1}^{4M} exp\left(-\frac{j}{4}(\nu_t + r_{j/4,t})\right) \tag{16}$$

[19] Augustin et al. (2020) also propose a highly nonlinear, approximate return formula to address the same issue. However, their method works when the term structure of interest rates is flat, and can be sensitive to small changes in the CDS spread. Plus, their measure accounts for risky duration, similar to Palhares (2013).

[20] He et al. (2017) show the approximated returns assuming that the market quotes running CDS spread. In this case, when the market suffers a negative credit shock, CDS sellers get increased returns from discounted cash flows (capital gain). If the market quotes fixed CDS spread, the sellers realize capital loss.

[21] The interest rate swap curve is the same as the one used to calculate actual CDS returns - the IBA curve as designated by ISDA documentation.

where M is maturity (in years) of the CDS contract, j stands for the jth quarter, and $r_{j/4,t}$ is jth quarter's discount rate. Assuming a flat term structure of credit risk and a constant recovery rate (RR) of 40%, we follow He et al. (2017) and Palhares (2013) to approximate returns as

$$\nu_t = 4log\left(1 + \frac{s_t}{4(1 - RR)}\right) \tag{17}$$

The approximation has an advantage of bypassing the computational burden by assuming a flat default probability curve, which does not require CDS with many different maturities. However, the approximated returns do not reflect the standardized ISDA CDS contract features such as $Points\ Up - Front(PUF)$, hence empirical studies with the measure may be misleading. Neither can it reflect the variability in returns due to differing margin requirements nor the asymmetry between CDS sellers and buyers. Furthermore, this approximation abstracts from higher-order terms and thus does not properly capture the actual CDS return variation in turbulent times when sudden changes in credit risk arise.

4.3 Visual Comparison of Actual and Approximated CDS Returns

Before describing other variables used in empirical analyses, we offer a quick visual probing of how actual CDS returns differ from the approximated measures. For actual returns, we employ the version based on the notional, because variable margins cannot be incorporated into approximated returns and also shorten the sample period. Figure 2 scatterplots the actual and approximated returns, showing the need for this study. Panel A plots daily and monthly versions of actual and approximated seller's returns for single-name CDS, showing a convex relation for both measurement horizons. The deviation of approximated from actual return increases as returns move further away from zero – that is, approximated returns mismeasure the size of CDS returns especially in times of substantial changes in the price of credit risk. When actual returns are highly positive, approximated returns underestimate, and when actual returns are significantly negative, approximated returns overestimate the CDS returns. Given the nature of the CDS contract – a contingent claim designed for (extreme) credit events – this poses serious questions about using approximated returns in CDS studies. Panel B shows the relation between actual buyer's return and approximated return, also showing considerable deviations. Since the approximated return is the seller's, we plot its negative value against the buyer's return for a comparable visual representation. The figure illustrates clearly how seller's and buyer's returns are not simply of the opposite sign but also differ in absolute size. Approximated returns, in addition to other limitations, do not incorporate this fundamental asymmetry.

[Insert Figure 2 around here.]

The convex relation mentioned between seller's returns indicates that actual returns will, on average, be higher than approximated returns, and this pattern will be most pronounced in times of high volatility. We graph in more detail the difference between actual and approximated single-name CDS returns in Figure 3, and confirm this case. The sample period covers the end of the dot-com crash, the subprime mortgage crisis, the global financial crisis, Brexit, and the COVID-19 outbreak. The mentioned episodes are periods of heightened market turbulence, and we observe significant increases in return differences when the price of credit moves significantly.

[Insert Figure 3 around here.]

5 Empirical Analysis

This section presents the main empirical results. We measure various sorting characteristics, using daily returns to estimate higher moments of bond or CDS returns. Then, monthly CDS return factors are constructed using size and one of the characteristics. Fama-MacBeth regression analyses of monthly CDS returns follow to find meaningful factors in the cross-section.

5.1 Data

In addition to CDS data from MarkIt, we supplement our CDS return measures with data from numerous other sources. Mergent's Fixed Income Securities Database (FISD) provides bond characteristics, while the Enhanced Trade Reporting and Compliance Engine (TRACE) offers bond returns. To link CDS to bonds, we connect the Reference Entity Data code (REDcode) to the issuer-level CUSIP using information provided by MarkIt through Wharton Research Data Services (WRDS).

Single-name credit default swaps are referenced on debt obligations of a specific entity. Thus, it is natural to control for various properties of the firm's bonds when studying corporate CDS. We match CDS to bonds using the MarkIt-WRDS link, and monthly returns for corporate bonds are calculated from Enhanced TRACE data. First, intraday trades are cleaned for cancellations, corrections, and reversals, and very small trades (reported trade volume of less than \$10,000) are removed. Transactions that are labeled as when-issued, locked-in, special sales conditions, or have settlement dates more than 2 business days from the trade date are also deleted. Price outliers – trades with a reported price of less than 5 or more than 1,000 – are also excluded, and the remaining intraday trades are volume-weighted to calculate the daily weighted-average price. The 'month-end' price is the latest available price in the last 5 trading days of a month, and monthly returns are calculated from these prices accounting for coupon payments, should there be any. In the case that month-end to month-end price pairs do not exist, the month-start to month-end price pairs are considered, where the 'month-start' price is the first available price in the beginning 5 trading days. On issue level, floating rate, convertible, asset-backed, foreign-currency denominated, mortgage-backed, and preferred securities are eliminated. The data cleaning process follows Dick-Nielsen (2014). When calculating daily returns, we let the interval between a pair of prices to be at most 7 calendar days in case the bond does not trade every day.

Our empirical analysis controls for other bond characteristics. $MEAN^{Bond}$, VOL^{Bond}, $SKEW^{Bond}$, and $KURT^{Bond}$ are measured from daily bond returns over 1-, 3-, 6-, and 12-month estimation windows. The variables are mean, volatility, skewness, and kurtosis of bond returns, respectively. $Beta^{Bond}$ is measured from regressions of bond excess return on bond market excess return. $ILLIQ^{Bond}$ is a proxy for bond illiquidity after Bao et al. (2011), measuring the covariance of daily changes in bond prices in the observation month. In addition, we include the average bond credit rating score ($Rating^{Bond}$), the time left until maturity at the observation date ($Maturity^{Bond}$), and the amount outstanding ($Outstanding^{Bond}$) from Mergent's FISD. We gather the aforementioned bond characteristics at issue level first, then average each characteristic to calculate issuer level characteristics, except for bond amount outstanding which is aggregated to issuer level (6-digit CUSIP).

5.2 Descriptive Statistics

We begin our empirical analysis by tabulating descriptive statistics for the actual and approximated returns. Points-up-front can be calculated using either a 100 or 500 basis point fixed spread, depending on the credit rating. Specifically, we use 100 basis points for ratings BBB or above, and 500 basis points for contracts rated BB and below. Based on the points up-front, we calculate two versions of the actual return, one with the notional amount (full margin) and the other with the margin requirements that vary across maturity and quoted spread (variable margin). Actual returns differ for the seller and the buyer not only in direction but also in size, from the PUF working as a discount for one investor and a premium for the counterparty. In the case of variable margin versions, the differences become even more accentuated. Since margin requirements are available from June 2009, the variable margin versions are only presented for the post-GFC period. Table 1 shows various versions of individual and market CDS returns, and confirms the need for this study.[22] The return distributions vary considerably across measurement methods, and it is essential that the "correct" version is used in any cross-sectional study of CDS returns.

[Insert Table 1 around here.]

As visualized in the scatterplots and time-series graphs, approximated returns substantially underestimate CDS sellers' returns. Panel A of Table 1 shows that over the full sample period, approximated returns for the seller are *negative* 4 basis points per month, which casts doubts about protection sellers being able to remain in the market for meaningful periods, and for the continued existence of the CDS market if true. On the other hand, our methodology leads to a more acceptable result that CDS sellers earn, on average, decent positive returns.

Panel B presents return statistics post the global financial crisis, and in this period we expand the type of returns calculated to account for margin requirements set by the Financial Industry Regulatory Authority (FINRA). Both approximated and actual seller's returns based on the notional (full margin) are slightly higher for the post-GFC period than in Panel A, suggesting that the cost of credit protection has increased after the global shock. The mean actual seller's return with variable margin is 5.26% per month, considerably higher than those based on full margin (0.25%), as the 5-year margin requirement ranges from a

[22] Market returns are calculated from individual CDS returns with bond amounts outstanding as weights.

minimum of 4% of the notional to a maximum of 25%. In the face of funding costs and significant credit risks, such returns can justify the business model for protection sellers. Buyers' margin requirements are half those of their counterparts; therefore, their returns are of the opposite sign and larger in magnitude. We note that such returns are related to speculative positions – for those buying CDS to protect an underlying asset, returns based on the notional (around -24.5 bps on average, which is less than one-thirtieth of calculations based on variable margins) may be more relevant.

It follows that CDS market returns, constructed from weighted averages of individual returns, cannot but differ substantially among the various versions. Panel C shows that average market returns (weighted by bond amounts outstanding) are somewhat smaller than their individual counterparts, but the general patterns observed in Panel B carry over. The approximated aggregate returns for sellers are nearly zero, suggesting that credit protection, as a whole, is essentially costless. This observation is counterfactual, again supporting the argument for an accurate measurement of CDS returns. Significant differences between actual and approximated returns suggest that using approximated returns can produce biased effects of the cross-sectional moments of CDS and the fundamental assets in explaining CDS returns. In particular, higher-order moments such as volatility and skewness are natural candidates in this regard. We proceed to construct variables and conduct various analyses with actual seller's returns based on variable margin (Eq.(12)), our primary return specification. This is the return that most accurately reflects the actual cash flows to CDS sellers.[23]

Table 2 shows summary statistics of CDS seller's returns with variable margin requirements, bond returns, and important bond characteristics. Superscripts related to the higher moments indicate from which asset the returns are measured. Where relevant, the horizon in parentheses after the various moments indicate the measurement window. For example,

[23]For brevity, we only present statistics for the seller's returns. However, we do construct factors from buyers' returns and test the cross-section of CDS buyers' returns as well. The results are available in the Online Appendix.

$SKEW^{CDS}(6M)$ is skewness measured from daily actual CDS returns over a 6-month period. Variables without horizon specifications are as of month-end. $Rating^{Bond}$ is the bond's average credit rating score, $Maturity^{Bond}$ the time left until maturity date in years, and $Outstanding^{Bond}$ the bond notional outstanding in millions of dollars. $Beta^{Bond}$ is sensitivity of bond excess return on the respective market excess return,[24] and $ILLIQ^{Bond}$ is measured from daily bond returns within a month, following Bao et al. (2011). A pertinent next step is to check if these characteristics determine the cross-section of future CDS returns.

[Insert Table 2 around here.]

5.3 Properties of Factors

With the representative characteristics of CDS and bonds in the previous table, we proceed to construct monthly return factors from bivariate sorts. To construct the factors, independent sorts are done to classify individual CDS into Small and Big (based on the reference entity's bond amount outstanding), and into terciles (High, Medium, Low) on one of the statistical moments of returns.[25] Characteristics used for sorting are as of time $t-1$. Portfolios are then formed monthly and factors calculated as 1/2(Small High + Big High) - 1/2(Small Low + Big Low) of CDS returns, as is standard in the finance literature. We report figures for portfolio returns weighted by bond amounts outstanding. Factors based on bond characteristics are constructed in the same method.

UMD are Up-minus-Down factors formed from sorts on size and mean return ($MEAN$), VMT are Volatile-minus-Tranquil factors from size and volatility (VOL), PMN are Positive-

[24] Following common methods in the literature, we measure bond beta with 36 monthly returns, with a minimum requirement of 24 return observations.

[25] MarkIt does not provide metrics regarding the size (for example, amount outstanding or trading volume) of individual CDS contracts. Thus, we use the size of underlying assets instead.

minus-Negative factors from size and skewness ($SKEW$), and FML are Fat-minus-Lean factors from sorts on size and kurtosis ($KURT$). The superscripts of variable names indicate the characteristic used in portfolio formation – for example, $UMD^{B \to C}$ denotes that size and bond return $MEAN$ were used to construct CDS portfolio returns (size is always a default characteristic, so it is omitted in the notation). The horizon in the parentheses indicates the measurement window of the sorting characteristic.[26]

Table 3 reports representative facets of the zero-cost portfolios. $VMT^{C \to C}$ and $PMN^{C \to C}$ are factors with statistically significant and positive means for CDS-characteristic sorted portfolios, and the volatility factor sorted on bond characteristics ($VMT^{B \to C}$) is also significant. Return volatility is a measure of risk, and in CDS is also related to higher returns. A positively skewed return distribution for the seller indicates that the most likely outcome is more negative than the average return compared to a distribution with negative skew, which she dislikes. Or, the preference for negative skew may suggest overconfidence in estimation of outcomes in the case of extreme credit events. In any case, the higher the skewness, the less the seller likes the CDS, and accordingly requires higher returns. Higher volatility in the underlying asset value indicates higher probability of a credit event, for which the seller also requires appropriate premiums. Underlying bond return volatility thus naturally spills over to the related CDS. Higher bond market beta also indicates higher risk, and thus the related factor ($Beta^{B \to C}$) has positive and significant monthly mean returns. Longer bond maturity can be related to better issuer quality and lower rollover risk, and is negatively related to CDS returns.

[Insert Table 3 around here.]

[26] We present our baseline results using 6-month measurement windows. The Online Appendix shows factors based on alternative measurement windows for the sorting variables (1, 3, and 12 months) to show that the significance of the factors are similar for all specifications.

We investigate whether the results simply depend on size, which can proxy for various dimensions of firm quality. Table 4 shows the details of bivariate sorts where size is a fixed variable,[27] and for the sake of brevity, we only report the factors based on the return moments. Panel A shows portfolio returns for factors constructed from CDS return characteristics. Sorted independently on one of the return moments and size, the analysis shows that the differences between High and Low volatility portfolios are all statistically and economically significant. For skewness and kurtosis, the differences between Small High and Small Low portfolios are meaningful. On the other hand, Small minus Big portfolio returns are indistinguishable from zero in the majority of cases. Panel B repeats the process for portfolios sorted on underlying bond characteristics, and results for volatility-sorted portfolios are significant. Again, the breakdown confirms that the significance of CDS return factors is not generated by size.

[Insert Table 4 around here.]

5.4 Pricing the Cross-Section of CDS

The bivariate, independent-sort portfolio analysis results suggest that the second cross-sectional moment (volatility) of CDS or bond returns strongly predicts CDS returns. The third moment (skewness) of CDS returns should also have predictive power, and we move on to explore the factor structure of CDS returns in a regression setup. Since a CDS relates its payoff to a major credit event regarding its fundamental asset (reference obligation), a natural starting point of this analysis is to adopt the capital asset pricing model (CAPM) with our potential factors sorted by the past cross-sectional moments of CDS and bond returns. To determine which factors are priced in the market, we apply Fama and MacBeth

[27]In unreported tables, all of the double sorted factors in Table 3 are tested, but we focus here on the meaningful results.

(1973) regressions using individual CDS returns as test assets. This approach provides a more rigorous test than studies focused on the cross-section of portfolio returns (e.g., decile portfolios or double-sorted 5×5 portfolios). Many existing empirical stock return factors fail to account for the cross-section of individual returns, largely due to the greater idiosyncratic noise and measurement errors associated with individual assets. However, it turns out that our model can span the cross-section of individual actual returns, despite the stringency.

Table 5 shows results of contemporaneous Fama-MacBeth regressions, where we explain the cross-section of CDS returns with the loadings (i.e., betas) on aggregate CDS market return, and the return-based factors. The dependent variable is the actual seller's return, calculated using a variable margin and either a 100 or 500 basis point fixed spread,[28] our primary return specification. This is the return that reflects actual cash flows involved in CDS transactions most accurately. For consistency, the factors are also constructed from the same definition of returns. Betas are measured over 6-month rolling windows (from daily data), and to be included in the regression analyses, a single-name CDS must have at least four monthly return observations in each year. When this filtering rule is not met for a given year, all observations for that year will be eliminated, while data for years that conform to the filtering criteria are retained. Standard errors are adjusted after Newey and West (1987) with 12 lags.

Column (1) tests the explanatory power of the CDS market beta, and column (2) adds sensitivities to factors based on the CDS return moments. Results show that the CDS market return is relevant for explaining the CDS cross-section, and volatility and skewness are significant pricing factors in line with the bivariate sorting results. Contrary to lottery-type preferences documented in the stock market (Kumar, 2009), CDS sellers require additional compensation for positive skewness. Columns (3) and (4) test the bond market and other bond characteristic-based factors, and apart from the market, sensitivity to bond return

[28]We use a 100 basis point spread for ratings AAA, AA, A, and BBB, and a 500 basis point spread for BB and below.

skewness, maturity, and beta are weakly priced. Columns (5) and (6) test the stock market factors of Fama and French (2015), and only the market return is priced. Thus, all three, the CDS, bond, and stock market factors significantly and positively price the cross-section of CDS returns when tested individually.

To better align the pricing factors to the stochastic discount factors of key marginal investors, column (7) tests the intermediary capital risk factor (ICRF) by He and Krishnamurthy (2013). We find that the ICRF factor is positively and significantly priced in the cross-section of CDS returns. Finally, the specification of column (8) performs a kitchen-sink regression with all of the mentioned variables included.

The comprehensive setup shows that, first of all, the CDS factors that were significantly different from zero (VMT and PMN), plus the CDS market, are priced. While factors related to the overall market return and volatility require little explanation, skewness deserves more attention. To reiterate the argument made in Table 3, the mode of a positively skewed distribution is lower than the mean, which the investor dislikes in this case. The phenomenon can also be attributed to the type of investor – the lottery-type preference in the stock market is documented for individual investors (Kumar, 2009), whereas CDS sellers are institutional. Factors related to bond returns, save for beta, are all statistically insignificant. Since single-name CDS are products that purely focus on the default probability of individual underlying entities, CDS prices can contain additional default-related information over and above the alphanumeric indicators of credit risk assigned by rating agencies. Such results can also be interpreted in line with prior literature that finds CDS markets lead bonds (for example, Lee et al., 2018). A bond's market beta, being a strong indicator of systematic risk, contains other information than the return moments or credit ratings, and survives the extensive setup. Contrary to the bond market, there is evidence that documents the flow of information from equity to CDS (Hilscher et al., 2015). Of the stock return factors of Fama and French (2015), the market, book-to-market, and investment factors help explain individual CDS returns.

Echoing the results of bivariate sorts, firm size seems irrelevant. The ICRF beta also retains its explanatory power in the all-inclusive specification, corroborating the conjecture that risks related to financial intermediaries' capital are distinct from those related to returns of various asset markets.[29]

[Insert Table 5 around here.]

Next, Table 6 tests if CDS returns calculated with PUF and full margin (the market convention to quote CDS price) are consistent with our set of factors. The factors used in this table are reconstructed with returns that match the dependent variable definition. Regressions with the notional-based seller's return as the regressand show that the CDS market return and volatility factors are consistently priced. However, there also exist numerous differences. Sensitivity to the return factor related to bond ratings that was not priced in Table 5 now appears as significant, because full margins do not include the information contained in variable margins that account for the differences across ratings (credit risk). For similar reasons, underlying bond maturity is now negatively related to CDS returns, because longer time to debt repayment likely indicates lower rollover risk and substitutes the information incorporated in variable margins. The stock market is again relevant to explain the CDS return cross-section, in line with results from the previous table. However, the effects of other stock-market factors differ.[30]

Price quotes with full margin is a natural benchmark for all CDS market players, and

[29] Due to the varying and asymmetric margin requirements between sellers and buyers, the profits and losses of buyers do not mirror those of sellers. Table A.2 of the Online Appendix presents the buyer's return regressions. For buyers, factors related to CDS market return, CDS return volatility and skewness, and bond return volatility have significant explanatory power. The coefficients on betas to CDS market return and the volatility factor are negative, opposite to those of the seller's. Interestingly, the sign of the coefficient in relation to CDS return skewness is also positive (same as the seller's), indicating that buyers also dislike the most likely outcome being less than the mean return.

[30] Analyses with buyer's returns based on full margin are presented in Table A.3 of the Online Appendix. Similar to results with sellers' returns, the significance of the skewness related factor disappears.

can serve as a useful metric to express CDS risk and return proportional to the size of the asset being protected (covered positions). However, full margins can introduce considerable distortions to CDS return calculation, especially for players who trade naked CDS positions. First and foremost, they understate the real returns to protection sellers, who are likely to be large financial institutions. Misunderstanding of market structure and incentives to trade are likely consequences, especially if the focus is on major players or the marginal investor. Second, the understatement is likely to be greatest for protection written on safe names, as the variable margin requirements are smallest for them. Ironically, contracts for safe names have the least upside for the seller, while the potential losses (perceived or real) from deterioration in the reference entity's credit quality can be substantial (the most extreme case being outright default). Thus, another way of interpreting the positive loading on the CDS skewness factor in Table 5 is that CDS sellers require higher returns for more positive skewness because it is related to reference entities with higher risk. Return calculations with full margins do not account for this asymmetry; therefore, we do not see such significance in Table 6. In a similar vein, the loss of statistical significance of the ICRF factor in column (8) of Table 6 can be attributed to the fact that the assumption of full margins do not reflect real pressures on intermediaries' capital.

[Insert Table 6 around here.]

To further document the need for proper return measurement, we repeat the regression analyses with approximated CDS returns as test assets. Factors are again reconstructed with approximated returns to match the dependent variable. Table 7 presents the results to show the stark contrast – with approximated returns, we cannot gain any insight into the determinants of CDS returns. In Column (8), nothing - out of all the various CDS, bond, stock and intermediary capital related factors - has statistical significance.

The results justify our method of constructing 'actual' CDS returns. While it can be considered as complex and laborious, the problems of bypassing the process are evident. When variable margin requirements are not incorporated into the return calculation, we lose information regarding CDS return skewness, are misled about the significance of both bond- and stock-related factors, and also about the importance of intermediary capital. Further omitting crucial components such as the points-up-front leaves us with zero information regarding the determinants of CDS returns. Without accounting for the various market conventions and actual cash flows involved in CDS trading, any attempt to understand the CDS cross-section with the approximated return measure is most likely to be misleading.

[Insert Table 7 around here.]

6 Conclusion

This paper explains CDS pricing, consistent with the market convention set by the ISDA and the margin requirements of FINRA. This facilitates the computation of CDS' holding period returns based on the upfront fee, which can be either paid or received by the CDS sellers. Our method provides a realistic way to study the CDS returns, comparable to those of other assets. Data show that gaps between actual and approximated returns are often substantial, highlighting the need for actual return measurement especially in times of heightened credit risks.

We explore common factors determining the cross-section of CDS returns to find systematic CDS pricing factors. Given the economic nexus of CDS to corporate bonds, it is surprising that the conventional bond factors have weak explanatory power. Instead, the CDS market, return volatility and skewness are significant pricing characteristics to explain actual CDS returns in the cross-section. There is evidence of information spillover from the stock market to the CDS market, and risks related to financial intermediaries' capital requirements also affect CDS returns significantly. We relate this to the capacity of financial institutions to provide credit protection and to market-make CDS.

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Figure 1: Margin Requirement

This figure presents historical margin requirements (in %) for 5-year CDS sellers according to FINRA (from June 2009 to April 2022). The margin requirement varies by the quoted CDS spread, and the buyer's margin is half that of the seller's. There are no changes in margin requirements for 5-year CDS contracts except in 2012, when an additional category was introduced.

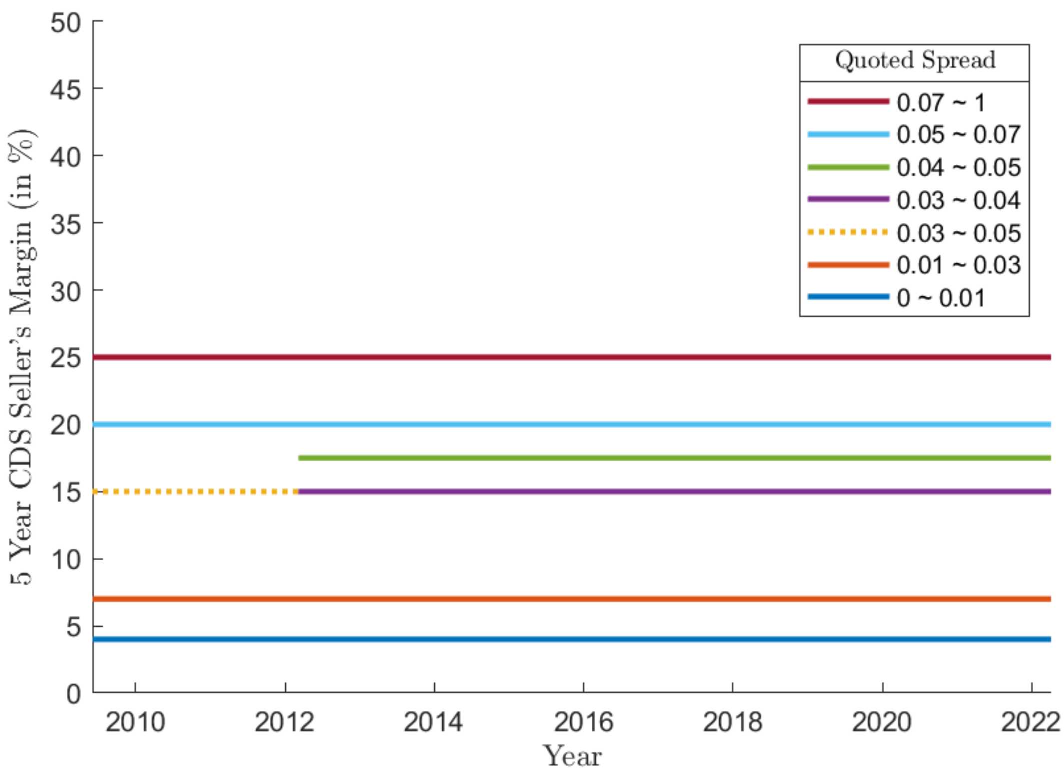
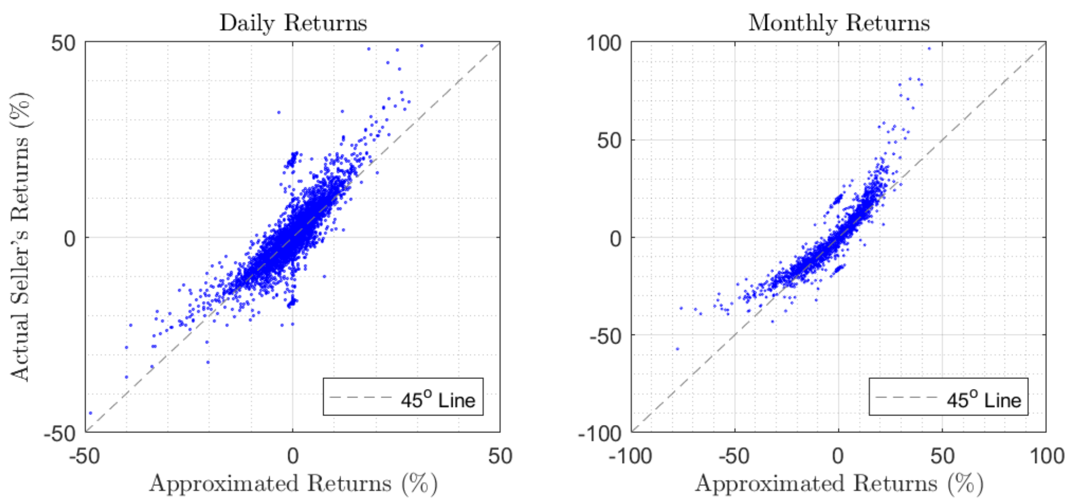


Figure 2: Actual vs. Approximated CDS Returns

Panel A (B) compares the actual seller's (buyer's) CDS return of Eq.(10) (Eq.(11)), with the approximated CDS return (Eq.(15)) for two different measuring frequencies: daily (left) and monthly (right). To match the properties of approximated CDS returns, the actual returns are computed assuming that no coupon and accrued interest are paid and that full margin is required. The sample period covers from January 2002 to March 2020.

Panel A: Daily and Monthly Seller's CDS Returns



Panel B: Daily and Monthly Buyer's CDS Returns

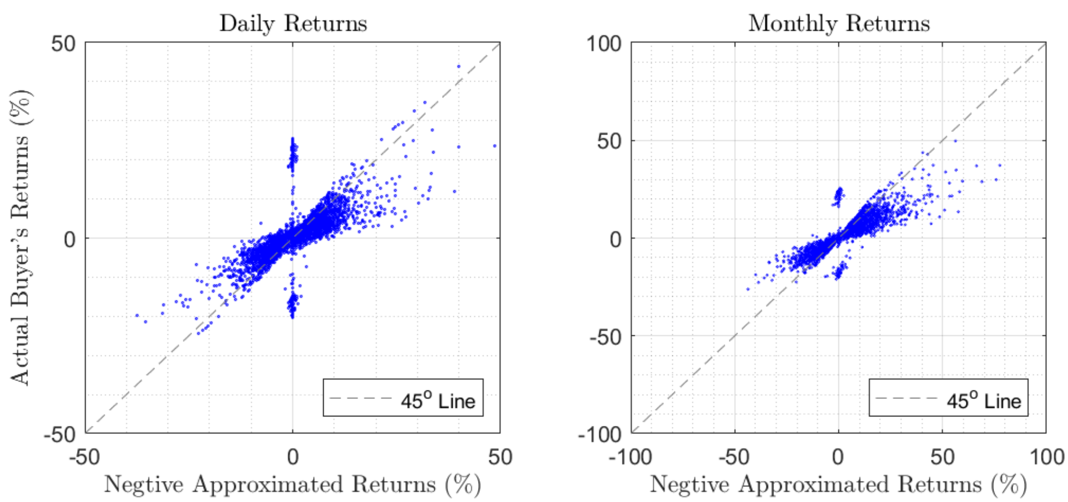


Figure 3: Time-Series Illustration of Approximation Errors

This figure shows time-series of monthly return (single name) differences from January 2002 to March 2020. The return differences are computed by subtracting approximated monthly return (Eq. (15)) from actual monthly return (Eq. (10)). To match the properties of approximated CDS returns, the actual returns are computed assuming that no coupon and accrued interest are paid and that full margin is required. Equal-weighted cross-sectional average differences and their 99% confidence intervals are plotted for each year group.

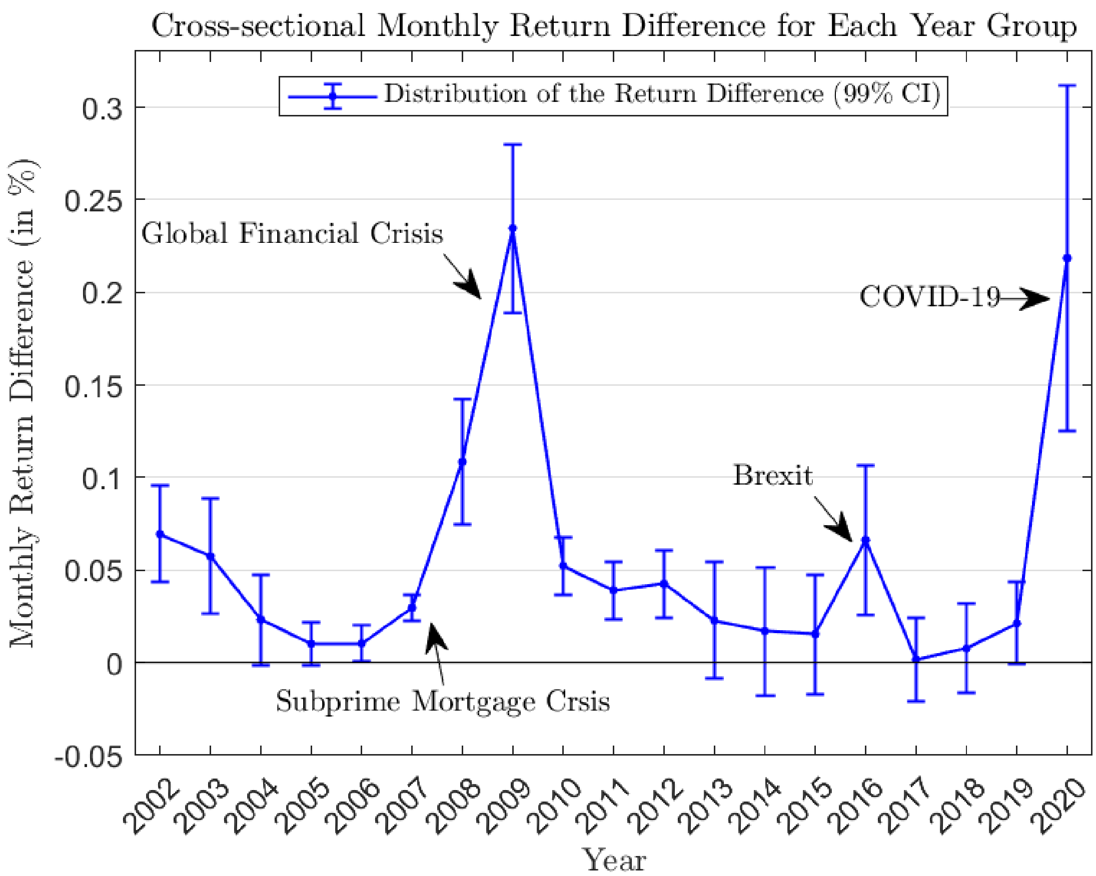


Table 1: Descriptive Statistics (Returns)

Panels A and B show monthly CDS single-name returns (in percentage points). *Aprx. Return* is approximated return in Eq.(15), *Act. Return* is one of the returns from Eq.(10)∼Eq.(13), calculated using a fixed spread. Specifically, we apply a 100 basis point spread for ratings AAA, AA, A, and BBB, and a 500 basis point spread for BB and below. Position and margin requirement assumptions are indicated in each panel. Full margin means $m = 1$ for both sides of the trade, and variable margin requirements follow Figure 1. CDS buyer's variable margin is half that of the seller's. Panel A reports returns using data from February 2002 to March 2020. Panels B and C present data after June 2009 (post-global financial crisis period) when FINRA's margin requirements are available. Panel C reports market returns weighted by bond amounts outstanding. All returns are winsorized at the top and bottom 1% for each month.

Panel A: Individual Returns

Variable	Position	Margin Requirement	Mean	t-stat	SD	N	Percentiles						
							1st	5th	25th	Median	75th%	95th%	99th
Aprx. Return	Seller	Full	-0.040	-6.49	2.31	140,031	-7.71	-2.21	-0.19	0.01	0.27	2.08	6.02
Act. Return	Seller	Full	0.181	34.07	1.99	140,031	-6.41	-1.94	-0.07	0.12	0.45	2.44	6.37
Act. Return	Buyer	Full	-0.176	-41.02	1.61	140,031	-5.09	-2.41	-0.51	-0.13	0.07	1.93	5.63

Panel B: Individual Returns (Post GFC period)

Variable	Position	Margin Requirement	Mean	t-stat	SD	N	Percentiles						
							1st	5th	25th	Median	75th%	95th%	99th
Aprx. Return	Seller	Full	0.042	6.53	1.88	85,466	-5.83	-1.68	-0.16	0.01	0.27	1.95	5.51
Act. Return	Seller	Full	0.253	44.37	1.67	85,466	-4.97	-1.45	-0.04	0.13	0.45	2.33	6.04
Act. Return	Buyer	Full	-0.245	-52.26	1.37	85,466	-4.90	-2.32	-0.50	-0.14	0.05	1.46	4.33
Act. Return	Seller	Variable	5.263	26.81	56.92	84,034	-68.20	-17.65	-0.59	1.67	5.19	26.99	140.57
Act. Return	Buyer	Variable	-7.718	-31.88	70.77	85,465	-261.25	-61.46	-7.42	-0.84	0.30	29.68	143.93

Panel C: Market Returns (Post GFC period)

Variable	Position	Margin Requirement	Mean	t-stat	SD	N	Percentiles						
							1st	5th	25th	Median	75th%	95th%	99th
Aprx. Mkt. Ret.	Seller	Full	0.007	0.12	0.66	129	-2.04	-0.88	-0.25	0.07	0.27	0.82	1.73
Act. Mkt. Ret	Seller	Full	0.150	2.60	0.66	129	-1.79	-0.66	-0.17	0.17	0.38	1.09	2.03
Act. Mkt. Ret	Buyer	Full	-0.137	-2.55	0.61	129	-1.86	-1.03	-0.41	-0.19	0.16	0.67	1.64
Act. Mkt. Ret.	Seller	Variable	4.874	2.63	21.06	129	-50.67	-18.26	-2.46	2.65	6.97	39.90	75.46
Act. Mkt. Ret.	Buyer	Variable	-5.945	-2.41	28.06	129	-65.15	-37.54	-21.81	-12.17	6.04	34.66	97.37

Table 2: Descriptive Statistics (Characteristics)

This table shows characteristics of monthly CDS seller's returns in Eq.(12) and bonds that are used to form zero-cost CDS portfolios. The sample period covers from July 2009 to Feburary 2020. *MEAN*, *VOL*, *SKEW*, and *KURT* are mean, volatility, skewness, and kurtosis, respectively, estimated using various windows. The horizon in parentheses after the various moments of returns indicates the measurement window. For example, $SKEW^{CDS}(6M)$ is skewness estimated from daily CDS returns over a 6-month period. *Rating* is the bond credit rating score (the lower the better, investment grade cut off is 10), *Maturity* is the time (year) left until bond maturity, and *Outstanding* is log of bond amount outstanding in millions of dollars. *Beta* is loading on the respective market excess return, and *ILLIQ* is an illiquidity measure after Bao et al. (2011). Significance levels are 1% (***), 5% (**), and 10% (*).

Variable	Mean	t-stat	SD	N	Percentiles						
					1st	5th	25th	Median	75th%	95th%	99th
MEAN^{CDS} (6M)	0.11	16.15	2.16	96,989	-2.90	-0.37	-0.03	0.02	0.12	0.98	5.20
VOL^{CDS} (6M)	3.89	120.34	10.05	96,715	0.07	0.42	0.73	1.22	2.39	17.68	54.69
SKEW^{CDS} (6M)	-1.49	-162.64	2.84	96,492	-7.90	-6.88	-3.00	-1.06	0.07	2.66	6.39
KURT^{CDS} (6M)	17.81	304.20	18.16	96,308	0.00	1.34	4.64	10.89	25.54	55.88	77.87
MEAN^{Bond} (6M)	0.04	84.42	0.07	30,707	-0.10	-0.03	0.01	0.03	0.06	0.12	0.25
VOL^{Bond} (6M)	0.64	221.49	0.50	30,707	0.15	0.22	0.36	0.51	0.75	1.40	2.42
SKEW^{Bond} (6M)	-0.06	-18.69	0.53	30,707	-1.47	-0.69	-0.24	-0.05	0.12	0.53	1.21
KURT^{Bond} (6M)	2.46	108.90	3.96	30,707	-0.26	0.11	0.82	1.56	2.78	7.18	17.37
Rating^{Bond}	9.30	688.93	3.31	60,189	2.50	5.00	7.07	9.00	10.59	16.00	18.33
Maturity^{Bond}	9.11	400.15	5.58	60,189	1.50	2.79	5.28	7.60	12.15	18.73	24.93
Outstanding^{Bond}	3.68	142.92	6.32	60,189	0.12	0.25	0.70	1.70	4.05	13.15	28.55
Beta^{Bond}	0.99	295.85	0.73	48,389	0.07	0.29	0.58	0.84	1.20	2.14	3.70
ILLIQ^{Bond}	-0.04	24.73	2.80	48,770	-0.18	-0.01	0.04	0.10	0.27	1.10	3.25

Table 3: Properties of Zero-Cost Portfolios (Bivariate Sort)

This table shows bivariate independent-sort CDS portfolio returns (in percentage) formed on $t-1$ bond amount outstanding with various CDS and bond characteristics (rebalanced monthly). Actual CDS seller's returns in Eq.(12) are sorted into terciles based on their corresponding $t-1$ characteristics (High, Medium, Low) and on $t-1$ bond amount outstanding into Small, and Big, independently. Portfolios are formed monthly and factor returns calculated as 1/2(Small High + Big High) - 1/2(Small Low + Big Low), weighted by bond amounts outstanding. UMD are Up-minus-Down portfolios formed on MEAN, VMT are Volatile-minus-Tranquil portfolios on return VOL, PMN are Positive-minus-Negative portfolios on SKEW, and FML are Fat-minus-Lean portfolios on KURT. The arrowed letters are indicative of the variables used in portfolio formation - for example, UMD$^{B\to C}(6M)$ is the CDS return factor formed on size and mean bond return estimated from daily bond returns over a 6-month period. Other characteristics are as described in Table 2. All statistics are computed using data from the period of August 2009 to March 2020.

Factors	Mean	t-stat	SD	Percentiles						
				1st	5th	25th	Median	75th%	95th%	99th
UMD$^{C\to C}$(6M)	1.46	0.79	20.82	-85.48	-18.71	-3.00	1.30	5.56	22.61	88.47
VMT$^{C\to C}$(6M)	9.1**	2.49	41.36	-124.48	-31.75	-5.12	3.76	15.15	76.82	157.83
PMN$^{C\to C}$(6M)	2.606*	1.74	16.92	-30.74	-19.72	-3.80	2.24	5.82	27.19	66.02
FML$^{C\to C}$(6M)	2.819	1.55	20.60	-52.57	-15.17	-4.78	0.51	5.89	37.26	76.34
UMD$^{B\to C}$(6M)	4.4	1.50	33.29	-113.33	-32.36	-1.32	1.05	7.54	64.30	122.92
VMT$^{B\to C}$(6M)	5.041**	2.36	24.20	-59.31	-17.48	-2.91	1.66	7.90	46.74	96.46
PMN$^{B\to C}$(6M)	-1.369	-0.73	21.34	-78.85	-28.51	-4.70	-0.84	1.88	23.35	91.18
FML$^{B\to C}$(6M)	1.191	0.59	22.78	-82.90	-23.30	-2.65	0.33	4.41	33.33	68.74
Rating$^{B\to C}$	2.086	1.52	15.52	-34.87	-13.37	-4.02	1.29	5.55	22.98	65.10
Maturity$^{B\to C}$	-2.365*	-1.94	13.79	-72.31	-20.19	-3.45	-0.32	1.94	6.20	17.19
Beta$^{B\to C}$	4.971**	2.26	24.87	-35.56	-19.28	-1.99	1.21	4.93	37.63	107.83
ILLIQ^{Bond}	0.541	0.54	11.24	-39.67	-20.62	-1.39	0.85	3.64	16.21	37.13

Table 4: Bivariate Independent-Sort Portfolio Analysis

Panels A and B show time series averages of bond amount outstanding-weighted zero-cost CDS portfolio returns (in %), double-sorted independently on size and a CDS characteristic from the previous month. The CDS returns are the seller's returns in Eq.(12) with the margin requirement in Figure 1. Portfolios are rebalanced monthly. H-L (S-B) means High minus Low (Small minus Big) portfolio. UMD are Up-minus-Down portfolios formed on MEAN and PMN are Positive-minus-Negative portfolios on SKEW. The arrowed letters are indicative of the variables used in portfolio formation. For example, $\text{UMD}^{B\to C}$(6M) are zero-cost CDS portfolios formed on bond MEAN estimated using daily returns over a 6-month measurement window. All statistics are computed using data from the period of August 2009 to March 2020. Significance levels are 1% (***), 5% (**), and 10% (*).

Panel A: CDS Characteristics

Soring Var. 1 (H,M,L): $\text{UMD}^{C\to C}$(6M) Sorting Var. 2 (S,B): Bond Outstanding				Soring Var. 1 (H,M,L): $\text{VMT}^{C\to C}$(6M) Sorting Var. 2 (S,B): Bond Outstanding			
	Small	Big	S-B		Small	Big	S-B
High	7.3620***	6.0702**	1.2918 (0.666)	High	12.0819***	8.4901**	3.5918* (1.741)
Medium	2.0830***	1.2658***	0.8172** (2.257)	Medium	1.4370***	1.2138**	0.2232 (0.789)
Low	5.4527***	5.0602*	0.3925 (0.247)	Low	1.3099***	1.0626***	0.2473** (2.155)
H-L	1.9093 (0.96)	1.01 (0.392)		H-L	10.7721*** (2.969)	7.4275* (1.878)	

Soring Var. 1 (H,M,L): $\text{PMN}^{C\to C}$(6M) Sorting Var. 2 (S,B): Bond Outstanding				Soring Var. 1 (H,M,L): $\text{FML}^{C\to C}$(6M) Sorting Var. 2 (S,B): Bond Outstanding			
	Small	Big	S-B		Small	Big	S-B
High	7.0192***	6.0484**	0.9708 (0.577)	High	6.3355***	4.7449	1.5906 (0.729)
Medium	3.4678***	2.4780**	0.9898 (1.125)	Medium	5.3544***	5.2515***	0.103 (0.089)
Low	4.2274***	3.6283*	0.5992 (0.403)	Low	3.0560**	2.3854**	0.6706 (0.763)
H-L	2.7918* (1.857)	2.4201 (1.118)		H-L	3.2795** (2.296)	2.3595 (0.849)	

(*Continued*)

Table 4—*Continued*

Panel B: Bond Characteristics

Soring Var. 1 (H,M,L): UMD$^{B\to C}$(6M) Sorting Var. 2 (S,B): Bond Outstanding				Soring Var. 1 (H,M,L): VMT$^{B\to C}$(6M) Sorting Var. 2 (S,B): Bond Outstanding			
	Small	Big	S-B		Small	Big	S-B
High	7.4201***	6.4837***	0.9364 (0.668)	High	7.9243**	8.1341**	-0.2098 (-0.094)
Medium	3.9833***	4.5728**	-0.5895 (-0.406)	Medium	3.8593***	3.4875	0.3718 (0.228)
Low	3.309	1.7941	1.515 (0.528)	Low	2.8047**	3.1714**	-0.3667 (-0.28)
H-L	4.111 (1.581)	4.6896 (1.19)		H-L	5.1196** (2.237)	4.9627** (2.043)	

Soring Var. 1 (H,M,L): PMN$^{B\to C}$(6M) Sorting Var. 2 (S,B): Bond Outstanding				Soring Var. 1 (H,M,L): FML$^{B\to C}$(6M) Sorting Var. 2 (S,B): Bond Outstanding			
	Small	Big	S-B		Small	Big	S-B
High	5.8775***	2.9069**	2.9705** (2.223)	High	5.8982**	3.041	2.8572 (1.359)
Medium	3.4519**	3.1828**	0.2691 (0.265)	Medium	5.5076**	4.8917**	0.6159 (0.307)
Low	5.4739**	6.0477*	-0.5738 (-0.212)	Low	4.1967***	2.3605**	1.8362* (1.863)
H-L	0.4036 (0.199)	-3.1408 (-1.085)		H-L	1.7015 (0.974)	0.6805 (0.251)	

Table 5: Fama-MacBeth Regression - Actual CDS Seller's Return

Columns (1) to (8) show Fama-MacBeth regression results. The dependent variable is the actual CDS seller's return (Eq.(12)) with the seller's margin requirement in Figure 1. The first-stage independent variables include conventional stock market research factors: Mkt^{Stock}-Rf, SMB, HML, CMA, and RMW (Fama and French, 2015), Intermediary Capital Risk Factor (ICRF) by He et al. (2017), and the moment factors reported in Table 3 which are estimated with 6-month window daily return characteristics. The second-stage independent variables are risk exposures estimated in the first stage regression. We report the estimates from the second stage (price of risk). All statistics are computed using data from August 2009 to March 2020. Standard errors are estimated after Newey and West (1987) with 12 lags, and significance levels are 1% (***), 5% (**), and 10% (*).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β(Mkt^{CDS}-Rf)	4.044**	3.865**						3.838**
	(2.15)	(2.13)						(2.28)
β(UMD$^{C\to C}(6M)$)		0.683						1.243
		(0.37)						(0.92)
β(VMT$^{C\to C}(6M)$)		9.466**						9.467**
		(2.28)						(2.43)
β(PMN$^{C\to C}(6M)$)		2.512*						3.349***
		(1.82)						(2.62)
β(FML$^{C\to C}(6M)$)		1.706						1.268
		(1.1)						(0.82)
β(Mkt^{Bond}-Rf)			0.393**	0.272**				0.145
			(2.23)	(2.01)				(1.36)
β(UMD$^{B\to C}(6M)$)				1.288				2.283
				(0.58)				(1.12)
β(VMT$^{B\to C}(6M)$)				4.327				3.619
				(1.61)				(1.53)
β(PMN$^{B\to C}(6M)$)				-2.280*				-1.771
				(-1.7)				(-1.4)
β(FML$^{B\to C}(6M)$)				1.916				1.266
				(0.75)				(0.47)
β(Rating$^{B\to C}$)				1.806				1.763
				(1.35)				(1.34)
β(Maturity$^{B\to C}$)				-2.503*				-2.371
				(-1.68)				(-1.58)
β(Beta$^{B\to C}$)				4.989*				4.604*
				(1.85)				(1.75)
β(IlliQ$^{B\to C}$)				-0.541				-0.675
				(-0.74)				(-0.98)
β(Mkt^{Stock}-Rf)					1.235**	1.086***		0.712***
					(2.59)	(2.91)		(3.29)
β(SMB)						0.568		0.208
						(1.29)		(1.04)
β(HML)						0.554		0.385*
						(1.37)		(1.67)
β(RMW)						-0.023		-0.174
						(-0.08)		(-1.17)
β(CMA)						0.207		0.392**
						(1.4)		(2.28)
β(ICRF)							1.731**	1.044**
							(2.27)	(2.5)
Intercept	1.551***	1.433***	2.125***	1.469***	1.506***	1.538***	2.148***	1.239***
	(3.53)	(4.96)	(2.88)	(4.3)	(3.69)	(4.67)	(6.74)	(4.98)
Rsq	0.082***	0.184***	0.054***	0.240***	0.081***	0.152***	0.081***	0.388***
	(3.76)	(5.88)	(4.17)	(6.06)	(4.12)	(5.77)	(4.08)	(8.46)
Adj. Rsq	0.080***	0.177***	0.053***	0.229***	0.080***	0.145***	0.080***	0.368***
	(3.68)	(5.62)	(4.04)	(5.69)	(4.04)	(5.46)	(4)	(7.75)

Table 6: Fama-MacBeth Regression - Actual CDS Seller's Return (Full Margin)

Columns (1) to (8) show Fama-MacBeth regression results. The dependent variable is the actual CDS seller's return (Eq.(10)) with full margin requirement. The first-stage independent variables include conventional stock market research factors: Mkt^{Stock}-Rf, SMB, HML, CMA, and RMW (Fama and French, 2015), Intermediary Capital Risk Factor (ICRF) by He et al. (2017). The moment factors are constructed using the actual CDS seller's return (with full margin), following a procedure similar to that described in Table 3, and are estimated based on six-month rolling windows of daily return characteristics. The second-stage independent variables are risk exposures estimated in the first stage regression. We report the estimates from the second stage (price of risk). All statistics are computed using data from August 2009 to March 2020. Standard errors are estimated after Newey and West (1987) with 12 lags, and significance levels are 1% (***), 5% (**), and 10% (*).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\beta(\text{Mkt}^{CDS}\text{-Rf})$	0.100**	0.096**						0.099**
	(1.98)	(2.27)						(2.2)
$\beta(\text{UMD}^{C\to C}(6M))$		0.103						0.067
		(1.45)						(1.18)
$\beta(\text{VMT}^{C\to C}(6M))$		0.217**						0.218**
		(2.16)						(2.16)
$\beta(\text{PMN}^{C\to C}(6M))$		0.058						0.068
		(0.96)						(1.32)
$\beta(\text{FML}^{C\to C}(6M))$		-0.111*						-0.115**
		(-1.78)						(-2)
$\beta(\text{Mkt}^{Bond}\text{-Rf})$			0.295*	0.211				0.172
			(1.96)	(1.58)				(1.57)
$\beta(\text{UMD}^{B\to C}(6M))$				0.114				0.096
				(1.59)				(1.42)
$\beta(\text{VMT}^{B\to C}(6M))$				0.116				0.115
				(1.28)				(1.23)
$\beta(\text{PMN}^{B\to C}(6M))$				0.032				0.036
				(0.73)				(0.97)
$\beta(\text{FML}^{B\to C}(6M))$				0.047				0.06
				(0.95)				(1.22)
$\beta(\text{Rating}^{B\to C})$				0.184**				0.187**
				(2.04)				(2.1)
$\beta(\text{Maturity}^{B\to C})$				-0.082*				-0.086*
				(-1.73)				(-1.95)
$\beta(\text{Beta}^{B\to C})$				0.136**				0.136**
				(2.26)				(2.2)
$\beta(\text{IlliQ}^{B\to C})$				0.043				0.041
				(0.95)				(1.12)
$\beta(\text{Mkt}^{Stock}\text{-Rf})$					0.751**	0.725**		0.627**
					(2.17)	(2.49)		(2.61)
$\beta(\text{SMB})$						0.365		0.330**
						(1.54)		(2.05)
$\beta(\text{HML})$						0.118		-0.104
						(0.29)		(-0.4)
$\beta(\text{RMW})$						-0.183		-0.230*
						(-1.11)		(-1.72)
$\beta(\text{CMA})$						0.076		0.033
						(0.37)		(0.25)
$\beta(\text{ICRF})$							1.276**	0.599
							(2.1)	(1.25)
Intercept	0.083***	0.077***	0.108***	0.078***	0.091***	0.088***	0.095***	0.075***
	(3.68)	(4.05)	(3.74)	(3.73)	(3.65)	(3.75)	(3.59)	(3.93)
Rsq	0.186***	0.272***	0.162***	0.345***	0.186***	0.256***	0.173***	0.476***
	(6.63)	(9.01)	(7.82)	(11.48)	(7.21)	(10.04)	(7.2)	(15.36)
Adj. Rsq	0.185***	0.267***	0.160***	0.336***	0.185***	0.250***	0.172***	0.460***
	(6.57)	(8.74)	(7.73)	(10.99)	(7.14)	(9.71)	(7.13)	(14.31)

Table 7: Fama-MacBeth Regression - Approximated CDS Seller's Return

Columns (1) to (8) show Fama-MacBeth regression results. The dependent variable is the approximated CDS seller's return (Eq.(15)). The first-stage independent variables include conventional stock market research factors: Mkt^{Stock}-Rf, SMB, HML, CMA, and RMW (Fama and French, 2015), Intermediary Capital Risk Factor (ICRF) by He et al. (2017). The moment factors are constructed using the approximated CDS seller's return, following a procedure similar to that described in Table 3, and are estimated based on six-month rolling windows of daily return characteristics. The second-stage independent variables are risk exposures estimated in the first stage regression. We report the estimates from the second stage (price of risk). All statistics are computed using data from August 2009 to March 2020. Standard errors are estimated after Newey and West (1987) with 12 lags, and significance levels are 1% (***), 5% (**), and 10% (*).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\beta(\text{Mkt}^{CDS}\text{-Rf})$	-0.007	0.001						-0.001
	(-0.13)	(0.02)						(-0.01)
$\beta(\text{UMD}^{C\to C}(6M))$		0.142**						0.064
		(2.15)						(1.04)
$\beta(\text{VMT}^{C\to C}(6M))$		-0.008						-0.017
		(-0.07)						(-0.16)
$\beta(\text{PMN}^{C\to C}(6M))$		0.017						0.034
		(0.47)						(0.96)
$\beta(\text{FML}^{C\to C}(6M))$		-0.016						-0.033
		(-0.47)						(-1.18)
$\beta(\text{Mkt}^{Bond}\text{-Rf})$			0.01	0.224				0.101
			(0.06)	(1.61)				(0.77)
$\beta(\text{UMD}^{B\to C}(6M))$				0.111				0.073
				(1.48)				(0.91)
$\beta(\text{VMT}^{B\to C}(6M))$				-0.039				-0.041
				(-0.37)				(-0.4)
$\beta(\text{PMN}^{B\to C}(6M))$				0.064*				0.03
				(1.77)				(0.83)
$\beta(\text{FML}^{B\to C}(6M))$				0.01				0.01
				(0.2)				(0.18)
$\beta(\text{Rating}^{B\to C})$				-0.025				-0.049
				(-0.28)				(-0.54)
$\beta(\text{Maturity}^{B\to C})$				0.037				0.049
				(0.74)				(0.94)
$\beta(\text{Beta}^{B\to C})$				0.05				0.039
				(0.9)				(0.71)
$\beta(\text{IlliQ}^{B\to C})$				0.049				0.038
				(1.25)				(0.96)
$\beta(\text{Mkt}^{Stock}\text{-Rf})$					-0.076	-0.062		-0.073
					(-0.2)	(-0.18)		(-0.24)
$\beta(\text{SMB})$						0.06		0.061
						(0.22)		(0.3)
$\beta(\text{HML})$						-0.125		-0.162
						(-0.25)		(-0.38)
$\beta(\text{RMW})$						-0.195		0.039
						(-1.14)		(0.3)
$\beta(\text{CMA})$						-0.247		-0.161
						(-0.9)		(-0.73)
$\beta(\text{ICRF})$							-0.04	0.45
							(-0.06)	(0.77)
Intercept	-0.005	-0.016	-0.016	-0.018	-0.005	-0.011	-0.011	-0.005
	(-0.24)	(-1.17)	(-0.48)	(-0.81)	(-0.22)	(-0.45)	(-0.51)	(-0.29)
Rsq	0.153***	0.254***	0.121***	0.350***	0.151***	0.263***	0.135***	0.508***
	(6.1)	(8.73)	(6.36)	(11.82)	(6.47)	(11.37)	(6.2)	(19.09)
Adj. Rsq	0.151***	0.248***	0.120***	0.341***	0.149***	0.258***	0.134***	0.492***
	(6.03)	(8.44)	(6.27)	(11.33)	(6.4)	(11.02)	(6.12)	(17.9)

Appendix

A CDS return

Assuming that the past CDS spread, s_{t-1}, was higher than 100 basis points (the seller receives the upfront cost) and is still higher than 100, the actual return of CDS on an investment grade bond is calculated as follows:

Initial Position	$t-1$	t	Return
Short	Receive upfront fee $N \cdot PUF_{t-1}$	Pay upfront fee $-N \cdot PUF_t$	$\frac{-PUF_t+PUF_{t-1}}{m_{t-1}^{Sell}-PUF_{t-1}}$
	Post collateral $-N \cdot m_{t-1}^{Sell}$	Receive collateral $N \cdot m_{t-1}^{Sell}$	
Long	Pay upfront fee $-N \cdot PUF_{t-1}$	Receive upfront fee $N \cdot PUF_t$	$\frac{PUF_t-PUF_{t-1}}{m_{t-1}^{Buy}+PUF_{t-1}}$
	Post collateral $-N \cdot m_{t-1}^{Buy}$	Receive collateral $N \cdot m_{t-1}^{Buy}$	

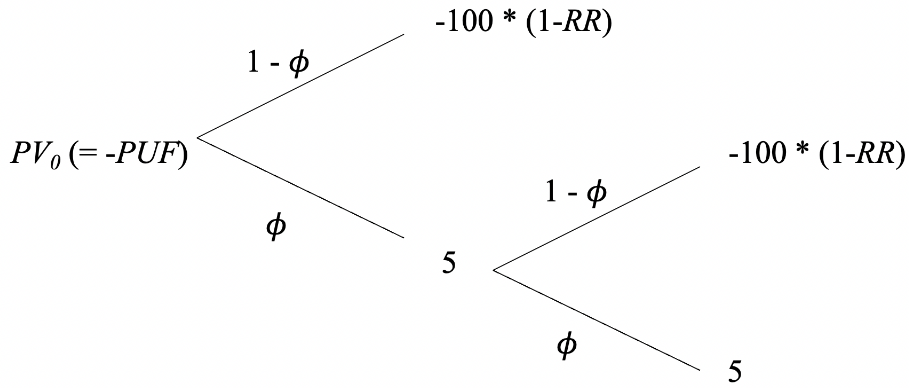
B A Binomial Model Illustration of CDS Returns

This appendix provides a two-period binomial model of CDS returns.

B.1 The Seller's Cash Flow Tree

Consider the following example in which the CDS seller (seller of protection) receives fixed coupons of 500 basis points (or 5%) per each period, on a notional amount of $100 for two periods.[31] Maturity is at period 2, and the risk-free interest rate r and risk-neutral survival rate ϕ ($0<\phi<1$) are assumed to be constant across time for simplicity in this illustration. RR denotes the recovery rate in the case of default of the underlying asset. Figure B.1 depicts the cash flow tree.

[31] The fixed coupon can be set at 100 bps or 500 bps, in line with the North American Standardized Convention for CDS.



We solve the model recursively. If the underlying asset defaults in period 1, the CDS seller compensates the CDS buyer for the loss in value, equal to 100×(1-RR). In the case of no default, we can write down the price of the CDS at period 1 as a function of outcomes in period 2 and their associated probabilities. The underlying asset will default with probability $1-\phi$, in which case the CDS seller's cash flow is -100×(1-RR). Otherwise, with probability ϕ, the contract simply concludes with the premium payment by the protection buyer to the protection seller. The present values of the CDS contract for the protection seller in each case can be expressed as:

$$PV_{1,1-\phi} = -100(1-RR)$$

$$PV_{1,\phi} = 5 + \frac{(1-\phi)(RR-1)100 + 5\phi}{1+r}.$$

Having worked out the present values in period 1, we move now to period 0. Applying the relevant probabilities for each state, the value of the CDS contract becomes

$$PV_0 = \frac{(1-\phi)(RR-1)100 + \phi\left(5 + \frac{(1-\phi)(RR-1)100+5\phi}{1+r}\right)}{1+r}.$$

One can see that PV_0 refers to the net present value of the CDS seller's payoffs. Thus, a negative (positive) value of PV_0 implies that the CDS seller receives (pays) this amount from (to) the CDS buyer at trade initiation. According to the ISDA convention, the initial upfront fee (points-up-front, or PUF) is, therefore, $-PV_0$ to make the sum zero in this model (i.e., $PUF = -PV_0$). Depending on the survival probability and the recovery rate, PV_0 can be either positive or negative.

B.1.1 CDS Return Calculation

Based on the example above, we explain the intuition of our method to compute the CDS returns. For a bond, the promised payment of principal at maturity means that the current price will usually be something comparable to the notional amount, and the price of a bond cannot become negative, because all future cash flows happen in the same direction. However, this is not the case for CDS contracts - although the seller receives periodic premium payments resembling those of fixed coupon bonds, there is no receipt of notional at maturity. Rather, depending on the occurrence of a credit event, the CDS seller has to *pay* a large amount rather than receive it. This means that the present value (PV_0) of the CDS can be positive or negative, depending on the relation between the quoted spread and the fixed coupon.

Suppose that the PV of a CDS contract is positive \$10, meaning that the CDS seller *pays* the amount to enter into a CDS contract. Next period, the PV of the CDS appreciates to \$15, meaning that the implied default risk has decreased. One way of computing the return from this trade is (15-10)/10, or 50%. In this situation, return calculation seems to be straightforward enough, focusing on capital gains only. However, imagine that the initial CDS value is -\$10 which then depreciates further to -\$15 in the next period, because the implied default probability goes up and insuring against credit events has become costlier. To unwind a position that she initially *received* \$10 dollars for, the CDS seller now needs to *pay* \$15 dollars in addition to the fixed coupon payment. However, there is no way to calculate this loss with the previous calculation method, as (-15-(-10))/-10 again equals 50%. Problems also arise when CDS contract prices alternate between positive and negative values.

The complexities set out above clarify why the initial present value of a CDS contract cannot be used as the denominator in calculating its return. An alternative is to treat the CDS like a bond, and utilize the notional amount. The negative (positive) present value is a discount (premium) to be added to the notional - thus, the -\$10 initial PV can be translated into a price of 90 dollars, and the +\$10 becomes a price of 110 dollars. With these new prices, we can easily compute returns - in the first case, the return is (115-110)/110, or 4.55%. For the second case, in which return calculation was previously erroneous, the return can now be calculated as (85-90)/90, or -5.56%. This scheme, in addition to being plausible and consistent, reflects how the CDS price is actually quoted in the market (for example, Bloomberg shows CDS prices following this scheme).

However, there may be concerns regarding the notional not being a part of actual cash flows for CDS players at trade initiation. Thus, we also construct actual returns with the

PUF and variable margins according to quoted spread. For example, if the above upfront fees were calculated against a margin of 20% of the notional, the returns in the two cases will now become (35-30)/(30) and (5-10)/10, or 16.67% and -50%, respectively. The returns, in line with smaller initial investment, are more inflated, and may induce protection sellers to remain in the market and for volatility to be priced.

Online Appendix to "How to (Properly) Compute Credit Default Swap Returns"

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Table A.1: Properties of Zero-Cost Portfolios (Bivariate Sort)

This table shows bivariate independent-sort CDS portfolio returns (in percentage) formed on $t-1$ bond amount outstanding with various CDS characteristics (rebalanced monthly). Actual CDS seller's returns in Eq.(12) are sorted into terciles based on their corresponding $t-1$ characteristics (High, Medium, Low) and on $t-1$ bond amount outstanding into Small, and Big, independently. Portfolios are formed monthly and factor returns calculated as 1/2(Small High + Big High) - 1/2(Small Low + Big Low), weighted by bond amounts outstanding. UMD are Up-minus-Down portfolios formed on MEAN, VMT are Volatile-minus-Tranquil portfolios on return VOL, PMN are Positive-minus-Negative portfolios on SKEW, and FML are Fat-minus-Lean portfolios on KURT. The arrowed letters are indicative of the variables used in portfolio formation - for example, $\text{UMD}^{B\to C}(6M)$ is the CDS return factor formed on size and mean bond return estimated from daily bond returns over a 6-month period. Other characteristics are as described in Table 2. All statistics are computed using data from the period of August 2009 to March 2020. Significance levels are 1% (***), 5% (**), and 10% (*).

Factors	Mean	t-stat	SD	Percentiles						
				1st	5th	25th	Median	75th%	95th%	99th
$\text{UMD}^{C\to C}$(1M)	2.511	1.22	23.30	-57.10	-21.12	-4.04	1.58	6.83	35.08	98.39
$\text{UMD}^{C\to C}$(3M)	2.614	1.19	24.86	-83.45	-20.85	-2.80	1.65	6.38	33.59	102.53
$\text{UMD}^{C\to C}$(6M)	1.46	0.79	20.82	-85.48	-18.71	-3.00	1.30	5.56	22.61	88.47
$\text{UMD}^{C\to C}$(12M)	1.179	0.70	19.17	-94.88	-17.98	-3.39	1.79	5.04	21.14	67.10
$\text{VMT}^{C\to C}$(1M)	8.17**	2.36	39.23	-120.30	-38.34	-5.34	4.19	13.95	67.43	133.59
$\text{VMT}^{C\to C}$(3M)	8.871**	2.43	41.24	-122.10	-41.78	-4.88	3.61	15.40	76.17	155.68
$\text{VMT}^{C\to C}$(6M)	9.1**	2.49	41.36	-124.48	-31.75	-5.12	3.76	15.15	76.82	157.83
$\text{VMT}^{C\to C}$(12M)	9.077**	2.49	41.28	-122.38	-32.16	-5.79	3.93	14.90	77.13	157.31
$\text{PMN}^{C\to C}$(1M)	2.987**	2.15	15.70	-26.76	-12.22	-2.51	1.04	4.14	28.87	91.32
$\text{PMN}^{C\to C}$(3M)	3.465**	2.51	15.61	-32.49	-17.73	-2.17	2.53	6.69	27.69	68.21
$\text{PMN}^{C\to C}$(6M)	2.606*	1.74	16.92	-30.74	-19.72	-3.80	2.24	5.82	27.19	66.02
$\text{PMN}^{C\to C}$(12M)	2.32*	1.80	14.60	-28.12	-18.71	-2.98	1.83	5.28	25.55	64.47
$\text{FML}^{C\to C}$(1M)	-1.463	-1.25	13.21	-43.17	-20.83	-3.72	-0.60	3.20	12.37	35.30
$\text{FML}^{C\to C}$(3M)	0.642	0.40	18.03	-39.03	-18.63	-5.37	-0.78	4.65	31.06	71.93
$\text{FML}^{C\to C}$(6M)	2.819	1.55	20.60	-52.57	-15.17	-4.78	0.51	5.89	37.26	76.34
$\text{FML}^{C\to C}$(12M)	3.825*	1.92	22.59	-59.15	-17.74	-2.57	0.95	5.64	45.48	91.00

Table A.2: Fama-MacBeth Regression - Actual CDS Buyer's Return

Columns (1) to (8) show Fama-MacBeth regression results. The dependent variable is the actual CDS buyer's return (Eq.(13)) with the half of seller's margin requirement in Figure 1. The first-stage independent variables include conventional stock market research factors: Mkt^{Stock}-Rf, SMB, HML, CMA, and RMW (Fama and French, 2015), Intermediary Capital Risk Factor (ICRF) by He et al. (2017). The moment factors are constructed using the actual CDS buyer's return, following a procedure similar to that described in Table 3, and are estimated based on six-month rolling windows of daily return characteristics. The second-stage independent variables are risk exposures estimated in the first stage regression. We report the estimates from the second stage (price of risk). All statistics are computed using data from August 2009 to March 2020. Standard errors are estimated after Newey and West (1987) with 12 lags, and significance levels are 1% (***), 5% (**), and 10% (*).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β(Mkt^{CDS}-Rf)	-3.057	-3.16						-3.670*
	(-1.3)	(-1.46)						(-1.89)
β(UMD$^{C\to C}$($6M$))		0.982						3.005
		(0.43)						(1.48)
β(VMT$^{C\to C}$($6M$))		-5.997						-7.680**
		(-1.49)						(-2.1)
β(PMN$^{C\to C}$($6M$))		3.970**						3.110**
		(2.16)						(2.28)
β(FML$^{C\to C}$($6M$))		-0.11						-0.801
		(-0.06)						(-0.5)
β(Mkt^{Bond}-Rf)			0.270*	0.197*				0.022
			(1.87)	(1.78)				(0.27)
β(UMD$^{B\to C}$($6M$))				0.815				-0.570
				(0.42)				(-0.36)
β(VMT$^{B\to C}$($6M$))				-2.412				-3.803**
				(-1.46)				(-2.14)
β(PMN$^{B\to C}$($6M$))				0.481				0.021
				(0.37)				(0.02)
β(FML$^{B\to C}$($6M$))				0.927				-1.37
				(0.63)				(-0.82)
β(Rating$^{B\to C}$)				1.065				0.632
				(0.79)				(0.46)
β(Maturity$^{B\to C}$)				0.139				0.59
				(0.18)				(0.68)
β(Beta$^{B\to C}$)				0.729				0.923
				(0.41)				(0.57)
β(IlliQ$^{B\to C}$)				1.094				-0.075
				(0.75)				(-0.06)
β(Mkt^{Stock}-Rf)					0.391	0.334		0.391
					(1.03)	(0.9)		(1.58)
β(SMB)						0.083		0.194
						(0.31)		(0.98)
β(HML)						-0.17		-0.174
						(-0.47)		(-0.63)
β(RMW)						-0.134		-0.183
						(-0.75)		(-1.49)
β(CMA)						-0.245		-0.104
						(-1.08)		(-0.6)
β(ICRF)							0.926	0.589
							(1.23)	(1.34)
Intercept	-5.281***	-5.213***	-5.878***	-5.524***	-6.149***	-6.138***	-5.624***	-4.327***
	(-10.27)	(-16.96)	(-7.57)	(-10.7)	(-11.82)	(-13.38)	(-11.57)	(-12.52)
Rsq	0.037***	0.110***	0.028***	0.157***	0.037***	0.103***	0.038***	0.294***
	(7.85)	(9.15)	(7.05)	(13)	(6.8)	(11.51)	(8.59)	(15.39)
Adj. Rsq	0.035***	0.103***	0.027***	0.145***	0.035***	0.096***	0.036***	0.272***
	(7.49)	(8.48)	(6.64)	(11.73)	(6.5)	(10.61)	(8.2)	(13.72)

Table A.3: Fama-MacBeth Regression - Actual CDS Buyer's Return (Full Margin)

Columns (1) to (8) show Fama-MacBeth regression results. The dependent variable is the actual CDS buyer's return (Eq.(11)) with full margin requirement (i.e. $m^{Buy} = 1$). The first-stage independent variables include conventional stock market research factors: Mkt^{Stock}-Rf, SMB, HML, CMA, and RMW (Fama and French, 2015), Intermediary Capital Risk Factor (ICRF) by He et al. (2017). The moment factors are constructed using the actual CDS seller's return (with full margin), following a procedure similar to that described in Table 3, and are estimated based on six-month rolling windows of daily return characteristics. The second-stage independent variables are risk exposures estimated in the first stage regression. We report the estimates from the second stage (price of risk). All statistics are computed using data from August 2009 to March 2020. Standard errors are estimated after Newey and West (1987) with 12 lags, and significance levels are 1% (***), 5% (**), and 10% (*).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β(Mkt^{CDS}-Rf)	-0.095**	-0.087**						-0.086**
	(-2.13)	(-2.03)						(-2.08)
β(UMD$^{C\to C}(6M)$)		0.077						0.057
		(1.48)						(1.35)
β(VMT$^{C\to C}(6M)$)		-0.172*						-0.186**
		(-1.95)						(-2.25)
β(PMN$^{C\to C}(6M)$)		0.018						0.03
		(0.39)						(0.86)
β(FML$^{C\to C}(6M)$)		0.099*						0.093**
		(1.84)						(2.01)
β(Mkt^{Bond}-Rf)			0.356**	0.210*				0.238**
			(2.3)	(1.71)				(2.09)
β(UMD$^{B\to C}(6M)$)				-0.086				-0.113**
				(-1.56)				(-2.08)
β(VMT$^{B\to C}(6M)$)				-0.057				-0.064
				(-0.77)				(-0.81)
β(PMN$^{B\to C}(6M)$)				-0.021				-0.043*
				(-0.67)				(-1.74)
β(FML$^{B\to C}(6M)$)				-0.052				-0.041
				(-1.33)				(-1.2)
β(Rating$^{B\to C}$)				-0.170**				-0.172**
				(-2.3)				(-2.27)
β(Maturity$^{B\to C}$)				0.087**				0.081**
				(2.37)				(2.44)
β(Beta$^{B\to C}$)				-0.080*				-0.087*
				(-1.67)				(-1.81)
β(IlliQ$^{B\to C}$)				-0.014				-0.018
				(-0.43)				(-0.66)
β(Mkt^{Stock}-Rf)					0.785**	0.804**		0.521**
					(2.34)	(2.6)		(2.26)
β(SMB)						0.329		0.325*
						(1.53)		(1.91)
β(HML)						-0.169		0.018
						(-0.5)		(0.07)
β(RMW)						-0.185		-0.166
						(-1.2)		(-1.27)
β(CMA)						0.003		0.092
						(0.02)		(0.62)
β(ICRF)							1.377**	0.622
							(2.31)	(1.31)
Intercept	-0.171***	-0.172***	-0.186***	-0.171***	-0.177***	-0.176***	-0.179***	-0.168***
	(-9.95)	(-10.84)	(-10.12)	(-8.97)	(-10.19)	(-10.28)	(-10.55)	(-9.17)
Rsq	0.184***	0.259***	0.159***	0.333***	0.184***	0.249***	0.171***	0.452***
	(8.11)	(10.77)	(9.36)	(14.41)	(8.76)	(12.22)	(8.76)	(18.52)
Adj. Rsq	0.182***	0.253***	0.157***	0.324***	0.183***	0.243***	0.170***	0.434***
	(8.03)	(10.42)	(9.26)	(13.77)	(8.67)	(11.8)	(8.68)	(17.21)