The Predictive Power of Credit Spreads in Return and Risk

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Abstract This paper develops an empirical framework based on a parametric model that relates the initial credit spread to the two key inputs of mean–variance portfolio optimization: expected return and downside risk. We model credit spreads as a mean-reverting Ornstein–Uhlenbeck process and derive closed-form expressions for the expected return and expected shortfall of a credit default swap position. Using data on CDS indices across investment-grade, high-yield, financial, and emerging markets, we test these predictions in the cross section and over time. Our results show that higher initial spreads are systematically associated with higher future excess returns and less severe downside risk. Out-of-sample forecasting exercises confirm that spreads contain economically meaningful predictive content, improving portfolio allocation relative to simple benchmarks. These findings highlight the role of credit spreads not only as contemporaneous measures of credit risk but also as forward-looking decision variables in fixed income portfolio construction and risk management.

Keywords: Credit spreads; CDS; Return predictability; Expected shortfall; Fixed income risk

JEL codes: G12, G11, G13

1. Introduction

The foundations of modern portfolio theory were laid by Markowitz (1952), who formalized the trade-off between risk and return in asset allocation. In his framework, optimal portfolio choice requires prior knowledge of two key elements: the expected return of each asset and a measure of their joint risk, typically represented by the covariance matrix of returns. These inputs are not mere statistical artifacts—they summarize the investor's beliefs about future

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payoffs and risks, and thus drive allocation decisions. The challenge lies in identifying variables that can reliably forecast these inputs.

Within fixed income markets, the credit spread—defined as the difference between the yield of a corporate bond and that of a sovereign bond with similar maturity—has long been studied as a proxy for credit risk. Beyond this interpretation, a growing body of literature highlights the credit spread as a key state variable shaping the distribution of returns and risks in credit markets. Elton et al. (2001) demonstrate that credit spreads contain components beyond default risk, including tax effects and a systematic risk premium correlated with equity market returns. Similarly, Longstaff et al. (2005) decompose spreads into default and non-default components, showing that even after accounting for credit risk, a substantial portion of spreads reflects liquidity and systematic factors. More recent work, such as Thomas (2012) and Feng et al. (2025), shows that credit spreads are not only contemporaneous measures of risk but also forward-looking predictors of bond performance.

From a portfolio management perspective, the initial level of the credit spread serves as a concise statistic summarizing the market-implied compensation for bearing credit risk. A higher spread implies higher carry but also greater exposure to credit and liquidity risk—factors that directly influence both expected return and downside risk. If the spread can be mapped into these two quantities, it naturally becomes a candidate input for portfolio optimization in the spirit of Markowitz.

This paper develops a theoretical and empirical framework linking the initial credit spread to the two fundamental inputs of mean–variance optimization: the expected return and the expected downside risk. We focus on the total return of a short position in a credit default swap (CDS), which closely mirrors the payoff of a long position in a corporate bond. Modeling the credit spread as a mean-reverting Ornstein–Uhlenbeck process, we derive closed-form expressions for the expected return and Expected Shortfall (ES) of the strategy as explicit functions of the initial contractual spread s_0. We then test these theoretical predictions empirically, showing that initial spreads are strong and systematic predictors of future excess returns and downside risk across CDS indices.

Our central argument is that the credit spread should be viewed not merely as a measure of credit risk, but as a decision variable in portfolio construction. By linking a readily observable market quantity to the fundamental inputs of portfolio theory, we offer a bridge between credit risk modeling and optimal fixed income allocation.

2. Theoretical Framework

We analyze the excess return of an unfunded short position in a credit default swap (CDS) over the interval $[0,t]$, assuming no credit events during the period. Let s_0 denote the contractual spread agreed upon at initiation and s_t the prevailing market spread at time t. The mark-to-market return of the position reflects both the accrued carry and the revaluation of the contract due to movements in the CDS spread. Formally, the excess return at time t of an unfunded short position in a CDS, as protection seller, $ER_{\text{CDS}}(t)$, is given by:

$$\text{ER}_{\text{CDS}}(t) = s_0 \cdot t + (s_0 - s_t) \cdot \mathscr{A}(t), \tag{1}$$

where $\mathscr{A}(t)$ denotes the present value of the remaining premium leg—commonly referred to as the CDS annuity or risky PV01—as of time t. The first term represents the premium income accrued over the holding period. The second term captures the mark-to-market gain, which arises from the difference between the contractual and market-implied spreads. A decline in spreads increases the value of the position for the protection seller.

The CDS annuity $\mathscr{A}(t)$ is defined as the present value of future premium payments, weighted by survival probabilities and discounted at risk-free rates. In discrete form, assuming periodic payments at dates $\{t_1, t_2, \ldots, t_n\}$, it is expressed as:

$$\mathscr{A}(t) = \sum_{i=1}^{n} \Delta_i \cdot D(t,t_i) \cdot Q(t_i), \tag{2}$$

where Δ_i is the accrual fraction between payment dates, $D(t,t_i)$ is the discount factor from time t to payment date t_i, and $Q(t_i) = \mathbb{P}(\tau > t_i)$ denotes the survival probability of the reference entity.

Under a constant hazard rate λ and a constant interest rate r, and assuming continuous time with contractual maturity T, the annuity admits the closed-form expression:

$$\mathscr{A}(t) = \frac{1 - e^{-(r+\lambda)(T-t)}}{r+\lambda}, \tag{3}$$

where T denotes the maturity date of the CDS contract.

To model the dynamics of the credit spread s_t, we assume it follows a mean-reverting process of the Ornstein–Uhlenbeck (OU) type:

$$ds_t = \kappa(\theta - s_t)\,dt + \sigma\,dW_t, \tag{4}$$

where $\kappa > 0$ governs the speed of mean reversion, θ is the long-run mean level of the spread, σ is the volatility parameter, and W_t is a standard Brownian motion. This mean-reverting specification is adopted in the credit risk literature to reflect the empirical observation that credit spreads tend to revert to a long-term equilibrium level, as discussed by Pan and Singleton (2008) in the context of sovereign CDS spreads and by Longstaff et al. (2005) in the decomposition of corporate bond spreads.

Under the OU dynamics in Equation (4), the closed-form solution for the credit spread at time t is given by:

$$s_t = s_0 \cdot e^{-\kappa t} + \theta \cdot (1 - e^{-\kappa t}) + \sigma \int_0^t e^{-\kappa(t-u)}\, dW_u. \tag{5}$$

This expression implies that s_t is normally distributed with conditional mean and variance:

$$\mathbb{E}[s_t] = s_0 \cdot e^{-\kappa t} + \theta \cdot (1 - e^{-\kappa t}), \tag{6}$$

$$\operatorname{Var}[s_t] = \frac{\sigma^2}{2\kappa} \cdot \left(1 - e^{-2\kappa t}\right). \tag{7}$$

It follows that the spread change $\Delta s = s_0 - s_t$ is also normally distributed, with:

$$\mathbb{E}[\Delta s] = (s_0 - \theta)(1 - e^{-\kappa t}), \tag{8}$$

$$\operatorname{Var}[\Delta s] = \frac{\sigma^2}{2\kappa} \cdot (1 - e^{-2\kappa t}). \tag{9}$$

Under the OU process in Equation (4), the excess return of the CDS position in Equation (1) is normally distributed with conditional mean:

$$\mathbb{E}[\mathrm{ER}_{\mathrm{CDS}}(t)] = s_0 \cdot t + \mathscr{A}(t) \cdot (s_0 - \theta)(1 - e^{-\kappa t}), \tag{10}$$

and variance:

$$\operatorname{Var}[\mathrm{ER}_{\mathrm{CDS}}(t)] = \mathscr{A}(t)^2 \cdot \frac{\sigma^2}{2\kappa} \cdot (1 - e^{-2\kappa t}). \tag{11}$$

The expected shortfall at confidence level $\alpha \in (0,1)$ is given by:

$$\mathrm{ES}_\alpha[\mathrm{ER}_{\mathrm{CDS}}(t)] = \mathbb{E}[\mathrm{ER}_{\mathrm{CDS}}(t)] - \sqrt{\operatorname{Var}[\mathrm{ER}_{\mathrm{CDS}}(t)]} \cdot \frac{\phi(\Phi^{-1}(\alpha))}{\alpha}, \tag{12}$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ denote the standard normal density and cumulative distribution function, respectively.

Substituting the analytical expressions for the conditional mean and variance into Equation (12), we obtain an explicit formula for the expected shortfall of the CDS position:

$$\begin{aligned}\mathrm{ES}_{\alpha}[\mathrm{TR}_{\mathrm{CDS}}(t)] = {} & s_0 t + \mathscr{A}(t)(s_0-\theta)(1-e^{-\kappa t}) \\ & - \mathscr{A}(t)\sqrt{\frac{\sigma^2}{2\kappa}(1-e^{-2\kappa t})}\,\frac{\phi(\Phi^{-1}(\alpha))}{\alpha}.\end{aligned} \tag{13}$$

To better understand the impact of the initial contractual spread s_0 on the expected return and the expected shortfall, we rearrange Equations (10) and (13) as follows:

$$\begin{aligned}\mathbb{E}[\mathrm{ER}_{\mathrm{CDS}}(t)] = {} & s_0\left[t + \mathscr{A}(t)(1-e^{-\kappa t})\right] \\ & - \theta\mathscr{A}(t)(1-e^{-\kappa t}),\end{aligned} \tag{14}$$

$$\begin{aligned}\mathrm{ES}_{\alpha}[\mathrm{ER}_{\mathrm{CDS}}(t)] = {} & s_0\left[t + \mathscr{A}(t)(1-e^{-\kappa t})\right] \\ & - \theta\mathscr{A}(t)(1-e^{-\kappa t}) \\ & - \mathscr{A}(t)\sqrt{\frac{\sigma^2}{2\kappa}(1-e^{-2\kappa t})}\,\frac{\phi(\Phi^{-1}(\alpha))}{\alpha}.\end{aligned} \tag{15}$$

The rearranged expressions make explicit the linear relationship between the initial contractual spread s_0 and the risk and return measures of the CDS position—namely, the expected return and the expected shortfall. We investigate this linear relationship in detail and provide empirical evidence that variations in s_0 account for a substantial portion of the observed cross-sectional and time-series variation in these variables. This highlights the central role of the initial spread in shaping the performance and risk profile of a short CDS (long bond) position.

3. Data

Our empirical analysis is based on daily data for standardized credit default swap (CDS) indices and their associated excess return benchmarks, obtained from Bloomberg for the period November 21, 2013, to July 31, 2025.

Excess return indices measure the performance of an unfunded short position in a CDS index. They capture the excess return associated with selling protection on the underlying CDS basket, incorporating the carry from the contractual spread, mark-to-market gains or losses from spread movements, and realized credit events such as defaults and recoveries. These indices also account for periodic roll adjustments as expiring series are replaced by newly issued on-the-run contracts.

All CDS and excess return indices in our sample are administered by **S&P Global**, which manages the CDX and iTraxx families. These indices serve as standardized and liquid benchmarks for synthetic credit exposure across investment-grade, high-yield, and subordinated financial credit markets. Each index is composed of a fixed number of equally weighted single-name CDS contracts, selected semiannually based on liquidity, credit quality, and sectoral representation. Rebalancing typically occurs in March and September to ensure continued market relevance.

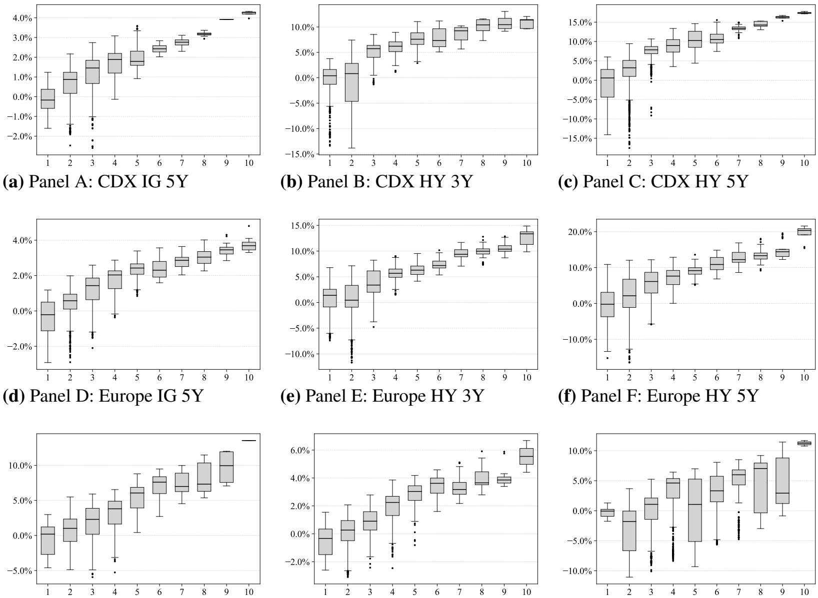
Table 1
CDS Indices and Corresponding Excess Return Benchmarks

CDS Index (Spread Level)	Excess Return Index	Description of Composition
CDX IG CDSI GEN 5Y	ERIXCDIG Index	U.S. investment-grade corporate CDS; 125 names; 5Y maturity
CDX HY CDSI GEN 3Y	CH3LERD5 Index	U.S. high-yield corporate CDS; 100 names; 3Y maturity
CDX HY CDSI GEN 5Y	ERINCDHY Index	U.S. high-yield corporate CDS; 125 names; 5Y maturity
iTraxx Europe IG CDSI GEN 5Y	ERIXITEU Index	Euro investment-grade corporate CDS; 125 names; 5Y maturity
iTraxx Europe Crossover CDSI GEN 3Y	IX3LERD5 Index	Euro high-yield CDS; 75 names; 3Y maturity
iTraxx Europe Crossover CDSI GEN 5Y	ERIXILXO Index	Euro high-yield CDS; 75 names; 5Y maturity
iTraxx Senior Financials CDSI GEN 5Y	IS5LERD5 Index	Euro senior debt of major banks; 30 names; 5Y maturity
iTraxx Subordinated Financials CDSI GEN 5Y	IU5LERD5 Index	Euro subordinated debt of major banks; 30 names; 5Y maturity
CDX EM CDSI GEN 5Y SPRD	UISYME5E Index	USD-denominated EM sovereign and quasi-sovereign CDS; 5Y maturity

This comprehensive dataset enables an analysis of the relationship between initial credit spreads and the realized returns of passive short CDS exposures across different maturities, geographies, and credit quality segments.

To examine how initial credit risk affects the return distribution of CDS exposures, we implement a binning strategy. For each index, the full historical range of observed spreads is partitioned into ten deciles. Daily observations are then assigned to a spread group based on the prevailing spread level, and the corresponding 12-month forward excess return is recorded.

We then construct boxplots of the resulting 12-month forward excess return distributions for each spread group. This approach allows us to visualize how the distribution of returns evolves with the initial spread, capturing both central tendency and downside risk conditional on ex-ante credit conditions.



(a) Panel A: CDX IG 5Y
(b) Panel B: CDX HY 3Y
(c) Panel C: CDX HY 5Y
(d) Panel D: Europe IG 5Y
(e) Panel E: Europe HY 3Y
(f) Panel F: Europe HY 5Y
(g) Panel G: Financial Subordinated Debt 5Y
(h) Panel H: Financial Senior Debt 5Y
(i) Panel I: Emerging Markets 5Y

Figure 1

Distribution of Excess Returns by Spread Group Across CDS Indices. Panel A–I show boxplots of excess return distributions for different CDS index families, grouped by deciles of initial credit spreads.

The boxplots in Figure 1 reveal a clear and consistent pattern across all CDS index families. As initial spreads increase, the median excess return tends to rise, while the lower tail of the return distribution becomes less severe. In other words, higher initial credit spreads are associated not only with greater central returns but also with reduced downside risk.

This visual evidence suggests a monotonic relationship between initial credit risk and both the location and shape of the return distribution. In the subsequent sections, we formally test whether this relationship is statistically significant and economically meaningful by estimating the conditional expectation and expected shortfall of excess returns as linear functions of initial spreads.

4. Empirical Strategy and Results

This section outlines the empirical strategy used to assess the predictive content of credit spreads for future returns and downside risk. We proceed in three steps. First, we implement a bin-based predictive regression design, grouping observations by quantiles of the initial spread and estimating the relationship with subsequent returns and expected shortfall. Second, we compare the coefficients obtained in these regressions to the closed-form predictions implied by the Ornstein–Uhlenbeck (OU) framework, testing the validity of the theoretical linear mapping between spreads and expected returns. Finally, we evaluate the forecasting performance of credit spreads in an out-of-sample setting, benchmarking their predictive accuracy against historical-mean models. Together, these exercises provide a comprehensive test of whether initial spreads serve as reliable and economically meaningful predictors of excess returns and downside risk across credit markets.

4.1 Bin-Based Predictive Regressions

We test whether the initial contractual spread s_0 predicts future excess returns using a bin-based regression design. For each CDS index, we partition the time-series of spreads into twenty quantile bins. Within each bin, we compute the average initial spread and the corresponding 12-month forward excess return. The resulting pairs $(\bar{s}, \bar{r})$ summarize the conditional relationship between spreads and returns.

For each index, we estimate the predictive regression

$$\bar{r}_{i,b} = \alpha_i + \beta\, \bar{s}_{i,b} + \varepsilon_{i,b}, \tag{16}$$

where $\bar{r}_{i,b}$ is the bin-averaged 12-month excess return of index i in bin b, and $\bar{s}_{i,b}$ is the corresponding average spread. We then pool all indices and estimate

$$\bar{r}_{i,b} = \alpha + \gamma_i + \beta\, \bar{s}_{i,b} + \varepsilon_{i,b}, \tag{17}$$

including asset fixed effects γ_i to absorb level differences across asset classes.

Table 2 reports the results. In the index-by-index regressions (Columns 1–9), slope estimates are uniformly positive, with R^2 ranging from 0.63 to 0.96. The pooled regression delivers a highly significant slope coefficient (t = 26.6), confirming strong statistical evidence that higher initial spreads predict higher future excess returns.

Table 2
Predictive Regressions of Excess Returns on Initial Spreads

	US IG 5Y	US HY 3Y	US HY 5Y	Europe IG 5Y	Europe HY 3Y	Europe HY 5Y	Senior Fin 5Y	Sub Fin 5Y	EM 5Y	Pooled (FE)
Spread (s_0)	4.7793	3.1505	4.9047	5.7236	3.0915	4.6930	6.1874	5.4498	2.7163	3.8394
	(0.3282)	(0.3992)	(0.4674)	(0.4379)	(0.2730)	(0.3317)	(0.3782)	(0.2535)	(0.4911)	(0.1450)
R^2	0.92	0.78	0.86	0.90	0.88	0.92	0.94	0.96	0.63	0.83
Observations	20	20	20	20	20	20	20	20	20	180
Asset Fixed Effects	No	No	No	No	No	No	No	No	No	Yes

This table reports predictive regressions of 12-month excess returns on initial spreads (s_0). Columns 1–9 present results for each CDS index estimated separately, using bin-averaged observations. Column 10 pools all indices and includes asset fixed effects (FE) to account for level differences. Standard errors are reported in parentheses. All regressions are estimated by OLS.

We repeat the same bin-based design using the 12-month forward expected shortfall, $\bar{es}_{i,b}$, computed for each observation and averaged within bins. The estimating equations are fully analogous:

$$\bar{es}_{i,b} = \alpha_i^{ES} + \beta^{ES}\,\bar{s}_{i,b} + u_{i,b}, \qquad \bar{es}_{i,b} = \alpha^{ES} + \gamma_i^{ES} + \beta^{ES}\,\bar{s}_{i,b} + u_{i,b}. \quad (18)$$

Table 3 shows that the ES is also strongly and positively related to the initial spread. Index-by-index slopes are all positive and statistically significant (t-stats between 4.04 and 11.06), with R^2 between 0.48 and 0.87. The pooled FE regression yields $\hat{\beta}^{ES} = 5.1611$ (s.e. $=$ 0.3090; $t = 16.68$), with $R^2 = 0.69$ and an intercept of -0.1850. Economically, higher initial spreads are associated with *less severe* left tails (ES moves upward), consistent with the theoretical linear mapping in Section 1.

Table 3
Predictive Regressions of Expected Shortfall (ES) on Initial Spreads

	US IG 5Y	US HY 3Y	US HY 5Y	Europe IG 5Y	Europe HY 3Y	Europe HY 5Y	Senior Fin 5Y	Sub Fin 5Y	EM 5Y	Pooled (FE)
Spread (s_0)	5.5334	3.9942	6.7454	7.8665	4.5781	7.1844	6.7771	6.3164	2.3105	5.1611
	(0.8787)	(0.9823)	(1.1259)	(0.7114)	(0.7619)	(0.7883)	(0.6483)	(0.5934)	(0.5715)	(0.3090)
R^2	0.6900	0.4800	0.6700	0.8700	0.6700	0.8200	0.8600	0.8600	0.4800	0.6900
Observations	20	20	20	20	20	20	20	20	20	180
Asset Fixed Effects	No	No	No	No	No	No	No	No	No	Yes

This table reports predictive regressions of 12-month forward expected shortfall (ES) on initial spreads (s_0), using the same bin-based design as in Table 2. Columns 1–9 present index-by-index regressions; Column 10 reports the pooled regression with asset fixed effects (FE). Standard errors are reported in parentheses. All regressions are estimated by OLS.

4.2 Testing the Linear Mapping of Expected Return

Building on the analytical framework developed in Section 1, we now turn to testing the model's implications for expected returns. Equation (14) delivers a closed-form expression linking the initial contractual spread s_0 to the expected excess return of a CDS position. The model predicts a linear mapping of the form

$$\mathbb{E}[ER] = \alpha^{theo} + \beta^{theo} \cdot s_0,$$

where the slope and intercept are explicitly determined by the structural parameters of the Ornstein–Uhlenbeck (OU) process. From Equation (14), we obtain

$$\beta^{theo} = t + \mathscr{A}(t)\,(1 - e^{-\kappa t}), \tag{19}$$

$$\alpha^{theo} = -\,\theta \cdot \mathscr{A}(t)\,(1 - e^{-\kappa t}), \tag{20}$$

where κ and θ are the OU speed of mean reversion and long-run mean of the spread, respectively, and $\mathscr{A}(t)$ is the risky annuity.

In discrete time, the OU dynamics in Equation (4) admit an AR(1) representation:

$$s_t = a + \rho s_{t-1} + \varepsilon_t,$$

with autoregressive coefficient $\rho = e^{-\kappa\Delta}$, where Δ is the observation frequency. Ordinary least squares applied to daily spreads yields estimates $\hat{a}$ and $\hat{\rho}$. From these, we recover the continuous-time parameters:

$$\hat{\kappa} = -\frac{\ln\hat{\rho}}{\Delta}, \quad \hat{\theta} = \frac{\hat{a}}{1-\hat{\rho}}, \quad \hat{\sigma}^2 = \frac{2\hat{\kappa}}{1-\hat{\rho}^2}\,\widehat{\mathrm{Var}}(\varepsilon_t).$$

This mapping ensures internal consistency between the AR(1) fit and the continuous-time OU process used for theoretical predictions.

To evaluate the empirical validity of this mapping, we estimate bin-based regressions of the form

$$\bar{r}_{i,b} = \hat{\alpha}_i + \hat{\beta}_i\,\bar{s}_{i,b} + \varepsilon_{i,b},$$

as described above, and directly compare the estimated coefficients $(\hat{\alpha}_i, \hat{\beta}_i)$ to their theoretical counterparts $(\alpha^{theo}, \beta^{theo})$. The comparison is summarized in Table 4, which reports empirical slopes and intercepts alongside the corresponding theoretical predictions, together with Wald test p-values for the null hypotheses $\hat{\beta}_i = \beta^{theo}$ and $\hat{\alpha}_i = \alpha^{theo}$.

Overall, the results reveal a high degree of consistency between theory and data for most CDS indices. For U.S. and European high-yield and financials, the empirical slopes are statistically indistinguishable from their theoretical values, and the intercept restrictions cannot be rejected at conventional levels.

In the case of investment-grade indices, the slope estimates appear somewhat lower than the theoretical benchmark, but this deviation is largely explained by the narrow range of spreads observed in IG markets. Because spreads fluctuate within a tight band, small differences in the slope translate into relatively larger p-values, even though the overall fit remains broadly consistent with the theoretical mapping.

By contrast, Emerging Markets (EM) show a clear and systematic departure from the model. Unlike the corporate-based indices, the EM index aggregates a smaller number of sovereign names and is far less diversified. Moreover, country weights are uneven, with China, South Africa, Brazil, Turkey, and Mexico together accounting for nearly 45% of the benchmark. This concentration amplifies idiosyncratic country-specific shocks relative to the common credit-risk channel captured by the OU framework. As a result, EM returns are less aligned with the theoretical predictions, reflecting the predominance of local risk factors over the broader asset-class dynamics that dominate in corporate credit indices.

Table 4

Theory vs. empirics: slope and intercept of $E[ER]$ with respect to s_0.

Asset	$\hat{\beta}$	β^{theo}	p-val β	$\hat{\alpha}$	α^{theo}	p-val α
US IG 5Y	4.779	5.573	0.026	-0.022	-0.030	0.003
US HY 3Y	3.151	3.189	0.925	-0.078	-0.067	0.412
US HY 5Y	4.905	4.950	0.924	-0.148	-0.148	0.965
Europe IG 5Y	5.724	5.363	0.421	-0.027	-0.029	0.592
Europe HY 3Y	3.092	2.937	0.579	-0.048	-0.048	0.997
Europe HY 5Y	4.693	4.726	0.922	-0.110	-0.118	0.469
Senior Financials 5Y	6.187	5.503	0.087	-0.034	-0.034	0.997
Sub. Financials 5Y	5.450	5.299	0.559	-0.056	-0.064	0.061
Emerging Markets	2.716	4.770	0.001	-0.053	-0.083	0.019

Notes: This table compares empirical slopes and intercepts from bin-based regressions of 12-month excess returns on initial spreads with theoretical predictions implied by the OU process. Wald test p-values assess whether coefficients are statistically different from theory.

4.3 Out-of-Sample Predictive Performance

To complement the bin-based evidence, we evaluate the predictive ability of initial spreads s_0 in an out-of-sample (OOS) setting. Using an expanding-window design, we estimate predictive regressions with the first five years reserved for initial training. At each subsequent date, we re-estimate the model and generate one-step-ahead forecasts of 12-month cumulative excess returns.

Forecast errors are benchmarked against a simple historical-mean model, and we compute the cumulative R^2_{OOS} measure of Campbell and Thompson (2008).

Table 5 reports the final cumulative R^2_{OOS} for each CDS index. The results reveal a striking degree of predictive content in credit spreads. Investment-grade indices deliver particularly strong performance, with R^2_{OOS} estimates above 50%. High-yield and financial indices also show robust out-of-sample gains, in the 40–60% range. Even in Emerging Markets, where country-specific shocks play a larger role, the model achieves a non-trivial R^2_{OOS} of 24.8%. These magnitudes stand well above those typically documented in the equity return predictability literature, underscoring the forecasting value of credit spreads.

Table 5
Out-of-Sample Predictive Performance

	US IG 5Y	US HY 3Y	US HY 5Y	Europe IG 5Y	Europe HY 3Y	Europe HY 5Y	Senior Fin 5Y	Sub. Fin 5Y	EM 5Y
Final R^2_{OOS}	53.8%	39.4%	42.5%	61.0%	58.7%	56.9%	54.1%	58.4%	24.8%

This table reports out-of-sample predictive performance of contractual spreads. For each CDS index, we estimate expanding-window regressions of 12-month cumulative excess returns on initial spreads, using the first five years for model training. The R^2_{OOS} statistic is computed relative to a historical-mean benchmark following Campbell and Thompson (2008). Values correspond to the final cumulative R^2_{OOS} at the end of the sample.

Figure A3 plots the full trajectories of cumulative R^2_{OOS} over time. The upward-sloping paths observed for most indices indicate that predictive accuracy improves steadily as the evaluation window expands, rather than being concentrated in a single subperiod. This stability underscores that credit spreads not only correlate with future returns ex post, but also embed information exploitable in real-time forecasting. The robustness across asset classes provides strong empirical support to the theoretical linear mapping developed in Section 1.

5. Conclusion

This paper establishes both theoretically and empirically that credit spreads are powerful predictors of fixed income returns and downside risks. Building on a structural mapping derived from an Ornstein–Uhlenbeck process for spread dynamics, we show that the initial contractual spread provides a linear approximation to expected return and expected shortfall of CDS positions. Empirical tests confirm this theoretical prediction across a wide range of CDS indices, with strong and robust statistical evidence. Out-of-sample results further demonstrate that spreads contain exploitable forecasting information that improves portfolio allocation beyond simple historical benchmarks.

The findings underscore the importance of interpreting credit spreads not only as contemporaneous measures of credit risk, but as forward-looking decision variables in portfolio construction. By linking an observable market price to the two fundamental inputs of mean–variance optimization—expected return and downside risk—our framework provides a tractable and economically meaningful tool for credit investors and risk managers.

Future research may focus on applying this framework within a portfolio optimization setting, examining how the predictive content of credit spreads can be integrated into allocation rules, risk management practices, and the design of fixed income investment strategies.

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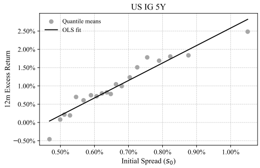
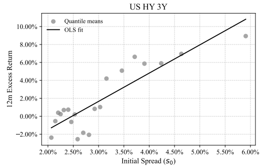
A. Additional tables and figures

Figure A1
Predictive regressions by CDS index (bin-based).



(a) US IG 5Y



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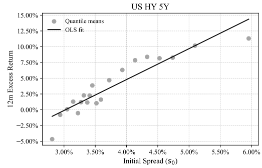

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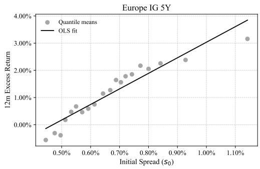

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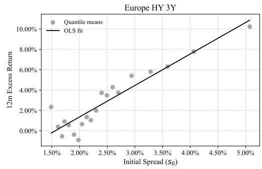

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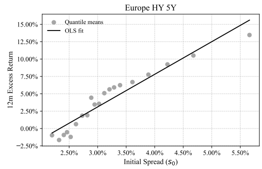

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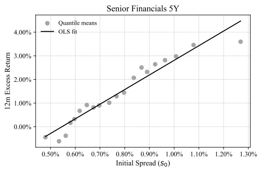
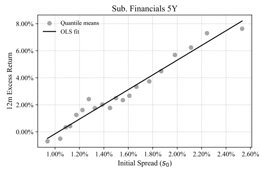
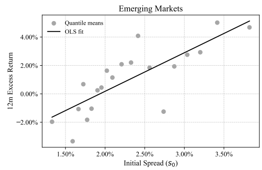


(g) Senior Financials 5Y



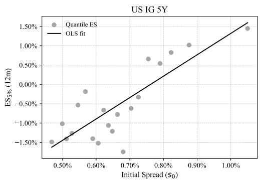
(h) Sub. Financials 5Y



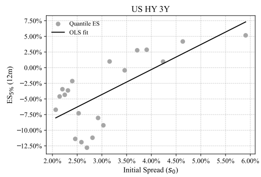
(i) Emerging Markets

***E*ach panel plots the bin-averaged 12-month forward excess return against the average initial spread for a given CDS index. The fitted line corresponds to the OLS predictive regression estimated on the 20 spread bins. The figure illustrates the positive relationship between initial spreads and subsequent excess returns across indices.**

Figure A2
Predictive regressions by CDS index (bin-based) – Expected Shortfall.



(a) US IG 5Y



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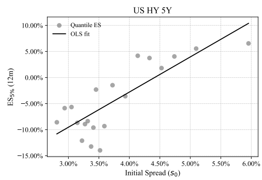

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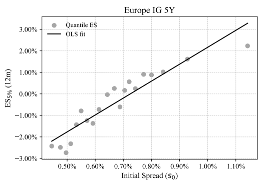
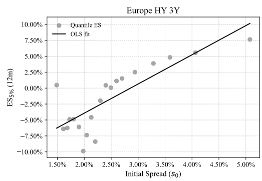
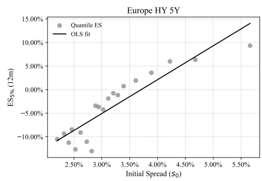


(d) Europe IG 5Y



(e) Europe HY 3Y



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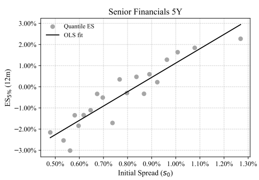
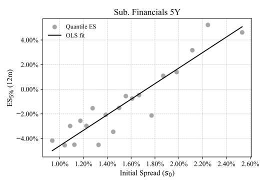
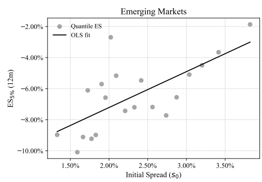


(g) Senior Financials 5Y



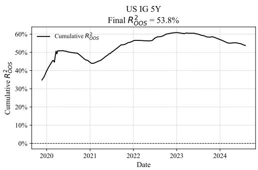
(h) Sub. Financials 5Y



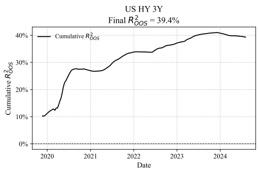
(i) Emerging Markets

***E*ach panel plots the bin-averaged 12-month forward expected shortfall against the average initial spread for a given CDS index. The fitted line corresponds to the OLS predictive regression estimated on the 20 spread bins. The figure shows that higher initial spreads are associated with less adverse downside outcomes, consistent with the theoretical mapping.**

Figure A3
Out-of-sample predictive performance by CDS index.



(a) US IG 5Y



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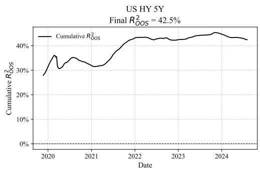

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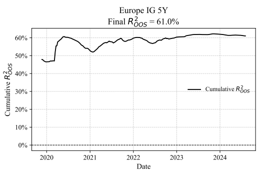
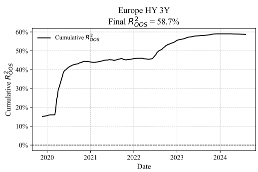


(d) Europe IG 5Y



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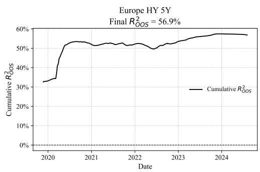

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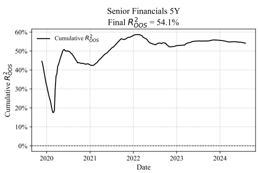
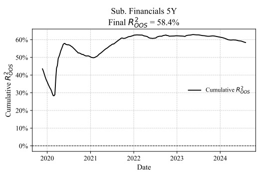
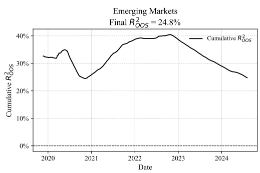


(g) Senior Financials 5Y



(h) Sub. Financials 5Y



(i) Emerging Markets

***E*ach panel shows the cumulative out-of-sample R^2_{OOS} of the predictive regression model using initial spreads, relative to a historical-mean benchmark. Forecasts are generated recursively using an expanding estimation window with the first five years reserved for initial training. Positive and upward-sloping paths indicate sustained forecasting gains over time.**