DEBT REFINANCING AND CROSS-MARKET SPILLOVERS INTO CREDIT SPREADS

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Abstract:

This paper examines whether the timing of corporate debt maturities influences credit spread pricing and the transmission of refinancing stress across markets. Using U.S. firm-level data from 2002 to 2024, we study how refinancing intensity (RI), the share of debt maturing within three years, affects credit default swap (CDS) and corporate bond spreads. RI commands a significant premium in CDS markets once firm characteristics are controlled for, yet its influence on bond spreads is negligible. RI also fails to predict future changes in credit spreads, indicating that rollover exposure is priced only when conditions deteriorate. Residual refinancing risk factors that remove size, value, and bond-market liquidity show that refinancing stress originates in CDS markets and later reaches bonds, while equity signals are short-lived. Our results identify refinancing stress as a credit-market state variable, most clearly reflected in CDS spreads and only weakly visible in bond spreads or equity returns.

Keywords:

Refinancing risk, Debt maturity structure, Credit default swaps, Corporate bond spreads, Cross-market spillovers

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I Introduction

The onset of the COVID-19 pandemic in March 2020 revealed how corporate debt structures expose firms to sudden funding disruptions. As global credit markets froze and liquidity conditions deteriorated, many firms faced surging credit risk premia despite stable operating performance. Figure 1 illustrates that average CDS spreads and average corporate bond spreads rose sharply during this period and co-moved in earlier episodes of financial stress such as the global financial crisis and the eurozone debt crisis. This co-movement suggests that shifts in funding conditions affect multiple credit instruments simultaneously, indicating that refinancing pressures are not confined to a single segment of the credit market.

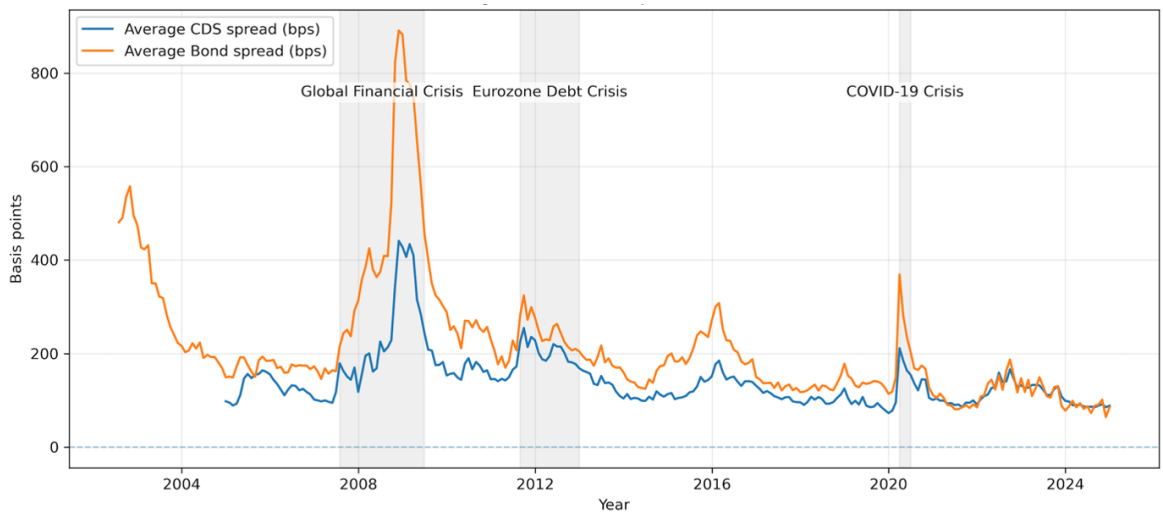


Figure 1. Average CDS and Bond Spreads, 2002–2024
This figure plots monthly average corporate CDS spreads and matched corporate bond spreads over the period July 2002 to December 2024, measured in basis points. CDS data are available from December 2004 onward. For each month, firm-level CDS and bond spreads are averaged across all issuers with observations in both markets. Bond spreads are defined relative to U.S. Treasury yields of equivalent remaining maturity based on Federal Reserve H.15 constant-maturity benchmarks. Shaded regions mark episodes of financial stress: the global financial crisis (2007–2009), the eurozone debt crisis (2011–2012) and the COVID-19 shock (2020).

From a corporate finance perspective, issuing short-term debt can reduce borrowing costs and create flexibility in capital structure decisions. It exposes firms to refinancing risk because liabilities must be rolled over more frequently. When a substantial share of outstanding debt nears maturity, firms become particularly sensitive to changes in credit conditions. Investors may require compensation for bearing the risk that refinancing occurs when liquidity weakens or credit spreads widen. Friewald, Nagler and Wagner (2022) formalise this mechanism and show that firms with higher refinancing intensity

(RI), defined as the share of total debt maturing within three years, earn higher equity returns. Their results suggest that RI captures a dimension of risk that is distinct from overall leverage and not fully reflected in traditional measures of financial distress.

In this paper, we extend the work of Friewald et al. (2022) in two ways. First, we broaden the empirical setting by focusing on corporate credit markets rather than equities, thereby shifting the lens from realised compensation to the forward-looking pricing of RI. Credit spreads incorporate refinancing risk at the point of funding, making them the relevant ex ante measure for identifying whether rollover exposure is priced before conditions deteriorate. Second, we examine whether RI behaves as a distinct component of credit risk premia that remains after controlling for standard firm attributes, and whether this refinancing-related component persists across instruments. We address three central research questions:

(i) Do firms with higher RI exhibit wider credit spreads once observable firm characteristics are controlled for?

(ii) Does RI predict subsequent changes in credit spreads, indicating that credit markets anticipate rollover risk?

(iii) Does RI function as an independent state variable whose innovations transmit across markets?

Recent research addresses parts of these questions but leaves two critical issues unresolved. Li, Wang, Wu, and Zhang (2023) show that firms with high RI earn higher realised bond returns, demonstrating that rollover pressure is compensated ex post once refinancing constraints materialise. Liu, Qiu, and Wang (2021) document that firms with significant near-term debt relative to cash experienced pronounced increases in CDS spreads during the COVID-19 crisis, indicating that RI can be priced ex ante under stressed credit conditions. These studies establish that RI and related rollover measures can affect credit premia when refinancing needs become material, but they do not show that RI is systematically embedded in credit spreads under non-stressed conditions or that refinancing-related pricing operates as an independent and persistent component of credit premia across instruments.

These distinctions have material implications. If RI raises credit risk premia today rather than only when refinancing costs spike, firms face incentives to maintain smoother maturity structures. They also have reasons to avoid concentrated rollover profiles and to preserve liquidity buffers that mitigate refinancing shocks. If RI behaves as an independent state variable, refinancing stress, defined as the component of credit spreads associated with RI after removing characteristic-driven variation, is not only a firm-specific attribute. It also functions as a systematic pricing force that shapes funding costs across credit markets. Determining whether RI carries such characteristics is therefore essential for understanding how maturity structure influences the cost of capital and how refinancing

shocks propagate.

To address these questions, we construct a comprehensive dataset of U.S. non-financial firms with traded 5-year CDS contracts, measured by par-mid spreads (henceforth "CDS spreads"), and matched corporate bonds, where bond spreads are defined relative to maturity-matched U.S. Treasury yields. First, we analyse how refinancing intensity relates to both the levels and the changes in CDS and bond spreads. Second, we isolate refinancing-related pricing components by removing variation attributable to firm size, leverage, value characteristics and bond-market illiquidity. The resulting residual refinancing risk (RRI) factors allow us to assess whether refinancing exposure contains independent pricing information and whether related shocks propagate across markets.

Our findings show that RI is priced in CDS spreads only after controlling for observable firm characteristics, while its effect on bond spreads is small and statistically insignificant. RI does not predict short horizon changes in credit spreads, indicating that rollover exposure is incorporated contemporaneously rather than forecasted in advance. Finally, innovations in RRI factors originate primarily in CDS markets and transmit to bond markets, consistent with the view that refinancing stress behaves as an independent state variable within credit markets.

The paper proceeds as follows: Section II outlines the theoretical foundations, reviews related literature and positions our contribution. Section III details the data sources, variable construction and sample filtering. Section IV presents the empirical analysis, including the pricing tests for RI and the construction of residual risk factors, and the subsequent spillover analysis. Section V reports robustness checks. Section VI concludes and discusses implications for credit pricing and corporate financing decisions.

II Theoretical Background and Related Literature

The maturity structure of corporate debt determines when firms must confront credit market conditions. Rather than holding a single long-dated liability, firms issue debt with varying maturities, which creates refinancing needs at particular points in time. If a large share of this debt falls due when credit spreads widen or liquidity tightens, refinancing costs can rise sharply despite stable fundamentals. This exposure reflects the timing of debt rollover, not the overall level of indebtedness.

Traditional capital structure theory, beginning with Modigliani and Miller (1958), treats leverage as a static aggregate and consequently overlooks differences in when firms must refinance. Two firms may have identical leverage but face distinct risks if one relies on short maturities while the other does not. Maturity composition therefore introduces an intertemporal element that leverage alone cannot capture.

This distinction aligns with structural credit models. In Merton's (1974) framework, debt values depend on asset volatility and the schedule of liabilities. Firms with concentrated short-term maturities are more sensitive to adverse market shocks because they must re-enter funding markets more frequently. Debt maturity therefore acts as a separate state variable in the analysis of credit risk.

Friewald, Nagler, and Wagner (2022) provide one of the most comprehensive treatments of this idea. They decompose total leverage into short-term and long-term components and introduce refinancing intensity (RI), defined as the share of total debt maturing within three years. Firms with high RI must roll over debt more often, exposing them to funding shocks when market conditions deteriorate. Because firms actively choose their maturity profiles, RI may also reflect managerial expectations about future financing conditions rather than a purely exogenous risk exposure. Friewald et al. (2022) suggest two counteracting channels. Short-term debt offers flexibility and can discipline management, yet it increases vulnerability to sudden tightening in credit conditions. Their empirical results show that the risk component dominates. Firms with high RI earn higher expected stock returns. This suggests that equity investors require compensation for bearing refinancing risk, and it positions RI as a distinct priced factor in equity markets.

He and Xiong (2012) provide a complementary theoretical channel that places refinancing conditions at the centre of credit risk. In their framework, creditors may decline to roll over maturing debt when funding markets tighten, even if the firm remains economically solvent. Default risk therefore arises not solely from deteriorating firm value but from the interaction between short-term liabilities and market liquidity. RI thus becomes a direct determinant of credit risk premia, and the pricing of debt instruments reflects both solvency considerations and the prospect of future rollover constraints.

These observations align with established empirical patterns in credit spreads. Elton, Gruber, Agrawal and Mann (2001) show that corporate bond yields contain sizeable components that are not explained by expected default losses. Collin Dufresne, Goldstein and Martin (2001) find that most time series variation in spreads is driven by a single latent factor that standard credit risk fundamentals cannot account for. Refinancing needs concentrate debt maturities at precisely the moments when liquidity conditions tighten, and they provide a credible channel through which this residual variation may arise. Short maturity structures compress refinancing decisions into narrow intervals. They leave firms exposed to adverse movements in credit conditions regardless of their ongoing profitability. Understanding where this refinancing channel is reflected, and whether it is priced in advance or only upon realisation, requires separating the mechanisms embedded in spreads from those observed in returns.

The difference between ex ante pricing and ex post realisation clarifies why RI appears differently across measures. Credit spreads represent the premium investors require upfront for bearing rollover exposure. Realised returns compensate investors only when refinancing

costs actually materialise. Li, Wang, Wu, and Zhang (2023) show that firms with high RI earn higher bond returns. Whether a similar premium is embedded directly in credit spreads remains less explored. Liu, Qiu, and Wang (2021) examine the COVID-19 crisis and show that firms with a large share of near-term debt relative to cash experienced larger increases in credit default swap (CDS) spreads when funding markets tightened. Rollover pressure can therefore be priced immediately under stress. These results highlight that refinancing risk may affect credit premia when refinancing needs become material, but they do not establish that RI systematically predicts the evolution of credit spreads in normal conditions.

Market structure further shapes how RI is incorporated across instruments. CDS contracts trade in liquid markets and offer direct protection against credit events. They therefore adjust quickly when perceptions of refinancing pressure change. Corporate bond spreads embed both credit and liquidity premia, which depend on trading frictions. Longstaff, Mithal, and Neis (2005) show that non-default components form a substantial part of bond spreads. Information unrelated to fundamental default risk can therefore affect bond pricing and obscure signals that pass through CDS markets more clearly. Norden and Weber (2009) show that equity markets adjust first, CDS follows shortly after, and bond markets react with a lag. This sequence implies that refinancing-related information should appear most strongly in CDS spreads and only later in bonds. These dynamics clarify why RI is more visible in some instruments than others, but they do not show whether the refinancing channel can be detected within spreads themselves.

Identifying this channel is challenging. Credit spreads combine several priced components that can mask refinancing effects. Larger and more profitable firms typically have lower spreads because they are perceived as safer borrowers, regardless of when their debt matures. Expected returns reflect realised compensation for risk and are less influenced by these additional components. This makes refinancing effects more visible in return based tests. Kozak, Nagel and Santosh (2020) argue that asset pricing tests should first remove characteristic driven variation before assessing whether an additional variable contains independent pricing information. Applying this logic to credit markets requires stripping away the firm level characteristics and pricing components that systematically influence spreads. Only then can RI be examined as a distinct source of variation. The resulting residual is an empirical proxy rather than a perfectly isolated refinancing factor, but it sharpens identification.

Although RI is recognised as a priced component in equity markets, its role in credit markets remains largely unexplored. Existing evidence shows that rollover exposure affects realised bond returns and that credit spreads embed variation unrelated to default fundamentals. Prior work has not shown whether RI is priced in the cross section of credit spreads, whether it influences their short horizon dynamics outside crisis periods, or whether refinancing related information transmits across financial markets. To address this

gap, we examine whether RI is reflected in credit spreads once standard firm characteristics are controlled for. We also study whether RI predicts changes in credit premia and whether a refinancing related pricing component persists and propagates across markets once characteristic driven variation has been removed. This approach allows us to assess whether refinancing risk operates as an independent mechanism in credit pricing rather than a feature confined to equity returns or crisis periods.

III Data

We construct two firm-level datasets that merge equity data with credit default swap (CDS) spreads and with corporate bond spreads at the monthly frequency. Accounting variables come from Compustat North America. Stock returns, prices, and shares outstanding are obtained from CRSP. Corporate bond trades and bond characteristics, including coupon rate, maturity date, issue size, and TRACE credit grades, are drawn from FINRA TRACE. Single-name CDS spreads come from Refinitiv via LSEG Workspace. Constant-maturity Treasury yields used to construct bond spreads are sourced from the Federal Reserve H.15 release. Monthly risk-free rates and Fama-French factor returns are retrieved from the Kenneth French Data Library. The CDS-equity sample spans December 2004 to December 2024, and the bond-equity sample spans July 2002 to December 2024.

Both datasets are aligned at the monthly frequency. Following Friewald, Nagler, and Wagner (2022), accounting figures are matched to monthly stock returns using a six-month reporting lag. Financial statements for the fiscal year ending in December 2020 therefore enter the sample from July 2021. This lag ensures that the accounting information reflects data available to investors.

The sample contains common stocks listed on NYSE, NASDAQ, and AMEX, identified using CRSP share codes 10 or 11 and exchange codes 1, 2, or 3. Financial firms (SIC 6000-6999) are excluded. Observations with non-positive total assets, book equity, or market equity are removed, and firms must have positive leverage. The construction of the debt-maturity variables follows Friewald et al. (2022). Missing short-term debt due within one year (DD1) and long-term debt (DLTT) are set to zero. For the intermediate maturity buckets DD2 to DD5, which record debt maturing in years two to five, missing entries are set to zero if at least one value in the sequence is reported. Observations with negative debt values are removed. Total debt defined as DD1 + DLTT must not exceed total assets. Long-term debt must be at least as large as the sum of debt maturing in years two to five (DD2 + DD3 + DD4 + DD5). Refinancing intensity (RI) follows Friewald et al. (2022) and measures the share of total debt maturing within three years:

$$RI_{i,t} = \frac{DD1_{i,t} + DD2_{i,t} + DD3_{i,t}}{DD1_{i,t} + DLTT_{i,t}} \tag{3.1}$$

Leverage (LEV) is defined as total debt scaled by total assets:

$$LEV_{i,t} = \frac{DD1_{i,t} + DLTT_{i,t}}{AT_{i,t}} \tag{3.2}$$

Book-to-market equity (BM) is defined as book equity divided by market equity. Book equity is constructed following Davis, Fama, and French (2000) from Compustat stockholders' equity, deferred taxes and investment tax credits, and preferred stock. Market equity (ME) is calculated as the CRSP month-end share price multiplied by shares outstanding. Profitability is measured as return on assets (ROA), defined as income before extraordinary items divided by total assets. Excess stock returns are computed as the CRSP monthly stock return minus the corresponding monthly risk-free rate from the Fama-French Research Factors.

TRACE bond transactions are cleaned following Dick-Nielsen (2009, 2014) and Bao, Pan, and Wang (2011). Administrative messages including late, cancelled, corrected, volume-weighted, and portfolio trades are excluded. Near-identical prints are removed to avoid double counting. Implausible price and yield observations are trimmed using a median absolute deviation filter applied within each bond and day. Historical TRACE trade-size caps (USD 5 million for investment-grade bonds and USD 1 million for high-yield bonds before 2013) are adjusted. The sample is then restricted to straight U.S. fixed-rate corporate bonds, excluding floaters, convertibles, Rule 144A issues, and asset-backed securities. We retain only bonds with a remaining maturity of two to ten years. These steps ensure that bond prices reflect actual trading behaviour rather than microstructure noise.

Cleaned TRACE transactions are aggregated in two steps. First, all trades within a given day are collapsed into a single bond-day observation by computing volume-weighted average prices and yields. This gives more weight to larger trades and reduces noise from individual prints:

$$P_d^{VW} = \frac{\sum_i p_i \,\mathrm{vol}_i}{\sum_i \mathrm{vol}_i} \qquad Y_d^{VW} = \frac{\sum_i y_i \,\mathrm{vol}_i}{\sum_i \mathrm{vol}_i} \tag{3.3}$$

The total traded volume $V_d = \sum_i \mathrm{vol}_i$ and the number of trades N_d are recorded as indicators of trading activity and liquidity.

Second, the daily observations are converted to the monthly frequency, following Dick-Nielsen, Feldhütter, and Lando (2012). The primary monthly yield corresponds to the last trading day of the month. If no trade occurs on that day, the yield is based on volume-weighted averages of all trades in the month, and simple averages are used only as a fallback:

$$\bar{P}_m^{VW} = \frac{\sum_{d \in m} P_d^{VW} V_d}{\sum_{d \in m} V_d} \qquad \bar{Y}_m^{VW} = \frac{\sum_{d \in m} Y_d^{VW} V_d}{\sum_{d \in m} V_d} \tag{3.4}$$

This procedure produces a single yield observation for each bond month and ensures that monthly spreads reflect the most recent available price information. Bond illiquidity is measured using an Amihud style price impact metric, originally introduced by Amihud (2002) and adapted to corporate bonds by Dick-Nielsen et al. (2012). The measure is computed as the absolute daily return scaled by trading volume, using the preaggregated volume-weighted bond-day prices:

$$r_d = \left| \frac{P_d^{VW}}{P_{d-1}^{VW}} - 1 \right| \qquad \text{Amihud}_m = \text{median}_{d \in m} \left(\frac{|r_d|}{V_d} \right) \tag{3.5}$$

This approach captures how sensitive prices are to trading activity and provides a simple proxy for short horizon transaction costs and market depth. Monthly bond spreads are expressed in basis points as the difference between each bond's yield and the maturity matched U.S. Treasury yield. The Treasury benchmarks are taken from constant maturity yields in the Federal Reserve H.15 release and are interpolated following the method of Collin Dufresne, Goldstein and Martin (2001):

$$\text{Spread}_{i,t}^{\text{bond}} = \left(\text{YTM}_{i,t}^{\text{bond}} - \text{YTM}_t^{\text{Treasury}}(\text{Maturity}_{i,t}) \right) \times 10{,}000 \tag{3.6}$$

$$\Delta\text{Spread}_{i,t}^{\text{bond}} = \text{Spread}_{i,t}^{\text{bond}} - \text{Spread}_{i,t-1}^{\text{bond}} \tag{3.7}$$

Observations with absolute spreads below five basis points are removed, as they typically indicate stale or near risk-free prices. To limit the effect of extreme movements, both spread levels and changes are winsorised at the 1st and 99th percentiles within each calendar year. This produces spread series that reflect economically meaningful variation in credit risk. Credit quality is identified using TRACE's internal grade code, which classifies bonds as investment grade (IG), high yield (HY), unrated (U), or not classified (N). We construct a binary indicator equal to 1 for investment-grade bonds and 0 otherwise:

$$\text{IG_dummy}_{i,t} = \mathbf{1}\{\text{TRACE grade begins with "IG"}\} \tag{3.8}$$

This coarse classification avoids the noise associated with finer rating transitions while still capturing the separation between investment-grade and high-yield segments of the bond market.

CDS data are obtained from Refinitiv's single name par mid quotes. These quotes represent the annual premium required to buy credit protection on a given firm. For each

firm, tenor and month, the CDS spread corresponds to the last available quotation in that month. This ensures consistency with the monthly frequency of the equity and accounting data:

$$\text{CDS}_{i,k,t} = \text{PAR_MID_SPREAD}_{i,k,d^*} \qquad d^* = \max\{d \in t : \text{data available}\} \tag{3.9}$$

The underlying daily quotes are cleaned following Fontana and Scheicher (2016). Observations with non-positive values or extreme entries above 10,000 basis points are removed, and duplicate quotes are dropped. CDS tenors are standardised. Extreme values are winsorised at the 1st and 99th percentiles within each year. The analysis is restricted to 5-year contracts to ensure comparability across firms. Monthly changes in CDS spreads are defined as the difference between the month-end quotation and its value in the previous month:

$$\Delta\text{CDS}_{i,k,t} = \text{CDS}_{i,k,t} - \text{CDS}_{i,k,t-1} \tag{3.10}$$

The resulting bond-equity panel contains 311,919 firm-month observations across 1,060 firms, while the CDS-equity panel includes 150,570 observations across 326 firms.

Table I
Summary Statistics

This table reports summary statistics for the variables used in the empirical analysis. Panel A presents the credit default swap (CDS), CDS–equity sample, and Panel B reports the bond–equity sample. Reported values include means and standard deviations for refinancing intensity (RI), leverage (LEV), market equity measured in natural logarithms (Log ME), and in billions (ME), book-to-market equity (BM), return on assets (ROA), and excess stock returns. Credit variables consist of CDS and bond spreads, both measured in basis points, together with their monthly changes. Additional bond characteristics include coupon rates, remaining maturity, an Amihud-style illiquidity measure (scaled by 10^6), and an indicator for investment-grade status. All figures are based on firm-level observations at the month-end frequency. Credit spreads and liquidity measures are winsorised at the 1st and 99th percentiles. The CDS sample covers the years 2004-2024, and the bond sample the years 2002-2024.

Variable	**Panel A: CDS–equity sample**		**Panel B: Bond–equity sample**	
	Mean	Std. Dev.	Mean	Std. Dev.
CDS spread (bps)	139.124	198.954		
Δ CDS spread (bps)	−0.194	39.885		
BM	0.543	0.773		
LEV	0.312	0.140	0.331	0.137
ME (billion USD)	50.932	144.553	67.104	204.493
RI	0.247	0.171	0.224	0.159
Excess return (%)	1.095	10.357	0.970	10.793
ROA	0.051	0.074	0.051	0.073
Log ME	23.571	1.500	23.511	1.794
Amihud illiquidity			0.050	0.198
Coupon rate (%)			5.482	6.705
Δ bond spread (bps)			−0.289	75.432
Remaining maturity			5.712	2.243
IG dummy			0.457	0.498
Bond spread (bps)			199.258	263.641
Observations	150,570		311,919	
Firms	326		1,060	

Table I reports summary statistics for the CDS-equity panel (Panel A) and the bond-equity panel (Panel B). RI averages 0.25 in the CDS sample and 0.22 in the bond sample, below the value of 0.40 reported by Friewald et al. (2022). This difference reflects the composition of our datasets, which contain larger and more profitable issuers: mean market equity is USD 51 billion in the CDS panel and USD 67 billion in the bond panel, compared with USD 3.32 billion in their sample. These firms generally have broader access to bond financing, which reduces their reliance on short-horizon refinancing.

Leverage averages 0.31 in the CDS sample and 0.33 in the bond sample, levels close to those in Friewald et al. (2022) and indicative of firms with not excessive balance-sheet

exposure. Credit spreads exhibit wide dispersion. The mean CDS spread is 139 basis points, whereas bond spreads average 199 basis points, reflecting liquidity premia and trading frictions in secondary bond markets. This spread differential aligns with the evidence in Longstaff, Mithal and Neis (2005), who document that a significant portion of corporate bond spreads reflects nondefault components unrelated to fundamental credit risk.

Firm size is highly skewed. Although the average issuer is large, the distribution is dominated by a limited number of very large firms. As shown in Figure A.1, this motivates the use of log-market equity in the regressions. Profitability and excess equity returns are similar across the two samples.

Panel B reports additional bond characteristics. Approximately 46 percent of issues are investment-grade, the average coupon rate is 5.5 percent, and the mean remaining maturity is 5.7 years. These characteristics imply that the bonds in our sample sit at maturities where refinancing decisions are relevant for firms' capital structure decisions, making them suitable for studying rollover-related pricing effects.

Table II
Correlation Matrix

This table reports pairwise Pearson correlations for the variables used in the empirical analysis. The correlation matrix is constructed by merging the credit default swap (CDS), CDS-equity and bond-equity panels on firm identifiers (PERMNO) and month-end dates, retaining only overlapping firm-month observations. The variables include refinancing intensity (RI), leverage (LEV), firm size measured as the natural logarithm of market equity (Log ME), profitability (ROA), book-to-market equity (BM), excess stock returns, CDS spreads and their monthly changes, as well as bond spreads and their monthly changes, all measured in basis points. All variables are aligned to the month-end frequency before merging. Credit spreads are winsorised at the 1st and 99th percentiles within each calendar year. The panel contains 118,651 firm-month observations across 273 firms between the years 2004-2024.

Variable	RI	LEV	Log ME	ROA	CDS spread	ΔCDS	Bond spread	ΔBond	Excess return	BM
RI	1.000	-0.048	0.027	-0.011	0.025	-0.009	-0.012	-0.010	0.004	0.003
LEV	-0.048	1.000	-0.138	-0.157	0.202	-0.010	0.158	-0.012	0.004	-0.071
Log ME	0.027	-0.138	1.000	0.357	-0.512	-0.009	-0.571	-0.007	0.019	-0.294
ROA	-0.011	-0.157	0.357	1.000	-0.277	0.025	-0.278	0.024	-0.030	-0.272
CDS spread	0.025	0.202	-0.512	-0.277	1.000	0.131	0.832	0.093	-0.032	0.479
ΔCDS	-0.009	-0.010	-0.009	0.025	0.131	1.000	0.081	0.538	-0.466	0.072
Bond spread	-0.012	0.158	-0.571	-0.278	0.832	0.081	1.000	0.186	-0.039	0.493
ΔBond	-0.010	-0.012	-0.007	0.024	0.093	0.538	0.186	1.000	-0.396	0.070
Excess return	0.004	0.004	0.019	-0.030	-0.032	-0.466	-0.039	-0.396	1.000	-0.077
BM	0.003	-0.071	-0.294	-0.272	0.479	0.072	0.493	0.070	-0.077	1.000

Table II reports pairwise correlations across firm characteristics, RI, and credit spread measures in the merged CDS-bond-equity sample. RI exhibits negligible correlations with leverage (-0.048), firm size (0.027), and profitability (-0.011), value (0.003). This indicates that short horizon refinancing needs are not directly tied to standard balance sheet indicators. Friewald et al. (2022) show that RI contains information beyond leverage

in explaining return differentials, which underscores that the maturity profile of debt represents a distinct dimension of firms' financing choices. RI is also only weakly correlated with contemporaneous credit spreads, which indicates that it does not map directly into spread levels and instead interacts with broader firm characteristics. As a result, its pricing implications cannot be inferred from simple correlations alone.

Leverage is positively related to both CDS and bond spreads, with correlations of 0.202 and 0.158. Firms with higher leverage exhibit greater exposure to credit risk, which is reflected in wider spreads. Firm size and profitability, by contrast, are negatively correlated with credit spreads. Larger and more profitable firms are perceived as safer borrowers and typically refinance under more favourable conditions, consistent with their lower spread levels. These relationships follow the idea that stronger fundamentals ease financing constraints and reduce the compensation required for bearing credit risk.

CDS and bond spreads exhibit a high correlation of 0.832, indicating that both instruments reflect similar assessments of underlying credit risk. The correlation between their monthly changes is lower at 0.538, suggesting that the two markets do not adjust contemporaneously to new information. Periods with rising credit premia coincide with weaker equity performance, as shown by the negative correlations between excess equity returns and changes in credit spreads (-0.466 for CDS and -0.396 for bonds). This pattern indicates that equity and credit markets react asymmetrically to shifts in perceived corporate risk. When investors revise a firm's outlook downward, equity prices fall because shareholders absorb residual downside risk, whereas credit spreads widen as lenders require greater compensation for elevated default risk.

Additional descriptive statistics for the merged CDS-bond-equity sample are presented in Table A.I. This integrated panel contains all firm-month observations common to both markets and forms the basis for the spillover analysis. The distributional properties resemble those in Table I, confirming that the merged dataset maintains the key characteristics of the underlying samples.

IV Empirical analysis

The empirical analysis proceeds in four steps. First, we examine whether firms with higher refinancing intensity (RI) are associated with wider credit spreads once standard firm characteristics such as leverage, size, and profitability are controlled for. Second, we test whether RI contains predictive power for subsequent changes in credit spreads, which allows us to assess whether RI is reflected contemporaneously or anticipated by credit markets. Third, we isolate the refinancing risk component of pricing by constructing residual refinancing risk (RRI) factors. Finally, we examine whether shocks to the RRI factor originate in one market and transmit to others.

A. Refinancing intensity and the level of credit spreads

To examine whether RI is reflected in credit spreads, we estimate Fama-MacBeth (1973) cross-sectional regressions using monthly panels of 5-year credit default swap (CDS) spreads and corporate bond spreads, both expressed in basis points. In each month, CDS spreads or bond spreads over U.S. Treasuries are regressed on RI and firm characteristics such as leverage, log market equity, return on assets, and book-to-market equity. For bonds, we additionally include an investment-grade indicator, remaining maturity, coupon rate, and the Amihud illiquidity measure. To test whether the pricing of RI varies with liquidity conditions or the maturity structure of debt, we extend the bond specification with interaction terms between RI and Amihud or remaining maturity. RI, Amihud, and maturity are mean centred before interaction, and the Amihud variable is winsorised and scaled by 10^6. Monthly slope coefficients are averaged over time, and inference is based on Newey-West (1987) heteroskedasticity-robust and autocorrelation-robust t-statistics from time series regressions of the coefficient series on a constant using three lags.

Table III
Cross-Sectional Regression on Credit Spreads

This table reports Fama-MacBeth (1973) cross-sectional regressions of credit spreads on refinancing intensity (RI) and firm characteristics. Panel A uses five-year credit default swap (CDS) spreads, and Panel B uses corporate bond spreads over U.S. Treasuries matched by remaining maturity, restricted to bonds with two to ten years to maturity. Control variables include leverage (LEV), natural logarithm of market equity (Log ME), return on assets (ROA), and book-to-market equity (BM). Bond regressions further control for investment-grade status, remaining maturity, coupon rate, and an Amihud illiquidity measure that is winsorised and scaled by 10^6. Interaction terms between RI and illiquidity or maturity are included only in the bond specifications, with all variables mean centred before interaction. The table reports time-series averages of the monthly coefficients, with Newey-West (1987) heteroskedasticity-robust and autocorrelation-robust t-statistics obtained from time-series regressions of the coefficient series on a constant using three lags. Credit spreads and the illiquidity measure are winsorised at the 1st and 99th percentiles. The CDS sample contains 241 monthly cross-sections from 2004-2024, and the bond sample contains 270 from 2002-2024. The final rows report average cross-sectional R^2 values and the number of estimation months.

Panel A: CDS spreads

	1	2	3	4
Intercept	142.887 (19.64)	12.421 (2.98)	1283.908 (17.77)	888.964 (20.85)
RI	-4.202 (-0.45)	22.496 (2.88)	28.734 (6.64)	27.204 (6.97)
LEV		419.667 (12.47)	260.725 (14.97)	271.063 (14.88)
Log ME			-52.653 (-17.26)	-37.218 (-20.96)
ROA				-168.078 (-4.30)
BM				71.285 (11.25)
Average R^2	0.006	0.131	0.324	0.399
Months	241	241	241	241

Panel B: Bond spreads

	1	2	3	4
Intercept	214.760 (13.65)	30.289 (6.09)	1215.909 (13.04)	1214.750 (13.01)
RI	-127.558 (-7.55)	-98.607 (-6.01)	14.446 (1.56)	13.560 (1.46)
LEV		576.491 (11.12)	166.173 (14.65)	166.479 (14.63)
Log ME			-46.708 (-13.04)	-46.665 (-13.01)
ROA			-259.446 (-8.40)	-258.797 (-8.38)
BM			73.857 (16.96)	73.971(16.97)
IG dummy			-78.493 (-10.87)	-78.336(-10.86)
Remaining maturity			3.040 (3.00)	3.079 (3.06)
Coupon rate			5.951 (5.60)	5.919 (5.63)
Amihud illiquidity			18.670 (3.05)	16.763 (2.76)
RI × illiquidity				-29.449 (-1.12)
RI × maturity				-1.891 (-1.69)
Average R^2	0.020	0.154	0.649	0.651
Months	270	270	270	270

Table III reports Fama-MacBeth estimates of credit spreads on RI and a set of control variables. Panel A examines CDS spreads, and Panel B turns to bond spreads over Treasuries. Specifications 1–4 progressively add firm characteristics; in Panel B, specification 4 also

includes the investment-grade indicator, remaining maturity, the coupon rate, Amihud illiquidity measure, and the interaction terms.

In the CDS regressions, RI is insignificant in the univariate specification but becomes positive and significant once leverage and size are included. The coefficient stabilises around 27 basis points in the fully controlled models, which suggests that RI is priced once differences in fundamentals have been accounted for. This reversal follows from the idea that credit spreads can mask RI until firm characteristics correlated with funding capacity are removed. This pattern reflects the nature of CDS spreads. CDS contracts insure against credit deterioration, so protection costs rise when short-dated liabilities increase the likelihood that refinancing needs coincide with adverse market conditions. Firm characteristics associated with strong funding capacity, such as size or profitability, can mitigate these concerns and suppress the unconditional relation between RI and CDS spreads. Once these mitigating influences are controlled for, RI captures rollover exposure that is no longer tempered by firm strength and therefore enters as a priced component of credit protection.

The bond spread regressions yield a different outcome. RI loads negatively in the univariate specification, but the effect disappears once firm characteristics are added, and the coefficients turn positive, small, and insignificant. Leverage, by contrast, remains large and stable across all specifications. This result differs from the findings of Friewald, Nagler, and Wagner (2022) and Li, Wang, Wu, and Zhang (2023), who do not document leverage as a priced factor in equity or bond returns. In the context of spread determination, this pattern indicates that the cross-section of yields is shaped by the total scale of outstanding liabilities rather than by the timing at which these liabilities fall due. The level of indebtedness influences the perceived likelihood that a firm may be unable to honour its fixed commitments, whereas the maturity structure determines when such pressures may surface. The interaction terms with illiquidity and maturity are also economically small and insignificant, so neither trading frictions nor the refinancing horizon strengthens the pricing of RI in bonds.

The contrast with Li et al. (2023) concerns the nature of the pricing channel. Their study shows that firms with higher RI earn higher realised bond returns. The difference arises because returns capture compensation that materialises over the holding period, whereas spreads reflect the cost of debt at issuance or secondary-market trade. A characteristic may therefore yield a return premium ex post without commanding an ex-ante spread premium if markets adjust to refinancing pressures only once they occur. The two findings are thus complementary: RI generates compensation when rollover costs emerge, but bond spreads do not incorporate this risk ex ante because the market recognises it only when conditions deteriorate.

The remaining control variables display patterns consistent with established credit-pricing intuition. Larger and more profitable firms exhibit narrower spreads, reflecting a

lower likelihood of financial distress and greater internal capacity to meet debt obligations. Securities of weaker credit quality or inferior liquidity command higher premia, as investors require compensation for holding instruments that are more difficult to trade or more exposed to adverse selection. Graham-Rozen, Vieder, and Michelson (2024) document similar relations in their study of Israeli corporate bonds. Although market structures differ, the directional agreement across settings suggests that spreads incorporate information about firms' solvency and the frictions associated with trading their debt, even if magnitudes vary between samples.

While Table III documents the statistical pricing of RI and firm characteristics, the size of these effects is not immediately apparent. Table IV converts the estimated coefficients into economic magnitudes based on representative changes in the underlying variables.

Table IV
Economic Magnitudes of Refinancing Intensity and Credit Spreads Determinants

This table reports the economic magnitudes implied by the fully specified Fama-MacBeth (1973) regressions of credit spreads on refinancing intensity (RI) and control variables. Panel A presents the results for 5-year credit default swap (CDS) spreads. Panel B presents the results for bond spreads over maturity-matched U.S. Treasuries. Coefficients are taken from the final specifications in Table III, where the CDS regressions include RI and all firm-level controls, and the bond regressions additionally incorporate remaining maturity, coupon rate, the investment-grade indicator, and the Amihud illiquidity measure. Interaction terms are excluded to focus on the direct effects. For each variable, the table shows the average coefficient in basis points, a representative change (Δ), and the implied effect $\beta \times \Delta$. Representative changes reflect realistic variation: the interquartile range for firm characteristics, one standard deviation for the Amihud measure, and the sample mean share of investment-grade bonds for the investment-grade dummy. Other variables include leverage (LEV), the natural logarithm of market equity (Log ME), return on assets (ROA), book-to-market equity (BM), remaining maturity, coupon rate, and the Amihud ratio, which is winsorised within calendar years and scaled by 10^6. Credit spreads are winsorised at the 1st and 99th percentiles. The CDS sample covers the years 2004-2024, and the bond sample the years 2002-2024.

Panel	Variable	Beta (bps/unit)	Shock type	Shock size	Implied Δ (bps)
CDS	RI	27.204	p75–p25	0.214	5.829
CDS	LEV	271.063	p75–p25	0.199	53.818
CDS	log(ME)	-37.218	p75–p25	2.022	-75.244
CDS	ROA	-168.078	p75–p25	0.057	-9.607
CDS	BM	71.285	p75–p25	0.474	33.778
Bonds	RI	13.560	p75–p25	0.192	2.603
Bonds	LEV	166.479	p75–p25	0.185	30.789
Bonds	log(ME)	-46.665	p75–p25	2.373	-110.744
Bonds	ROA	-258.797	p75–p25	0.061	-15.816
Bonds	BM	73.971	p75–p25	0.474	35.049
Bonds	IG dummy	-78.336	Mean	0.468	-36.638
Bonds	Maturity	3.079	p75–p25	3.751	11.550
Bonds	Amihud	16.763	1 SD	0.203	3.399
Bonds	Coupon rate	5.919	p75–p25	3.400	20.125

Table IV reports the economic magnitudes implied by the fully specified Fama–MacBeth regressions. An interquartile increase in RI raises CDS spreads by 5.829 basis points, while the corresponding effect in bonds is 2.603 basis points. These magnitudes are modest when compared with the core determinants of credit risk. For example, an interquartile increase in leverage widens CDS spreads by 53.818 basis points and bond spreads by 30.789 basis points, and a similar increase in the book-to-market ratio raises spreads by 33.778 basis points in CDS and 35.049 basis points in bonds. The comparison indicates that RI is priced in CDS but remains small relative to leverage and book-to-market, which are the principal drivers of cross-sectional variation in credit spreads.

Taken together, the evidence shows that RI affects credit pricing, but only in specific segments of the market. CDS spreads incorporate RI once differences in firm characteristics are accounted for. The magnitudes in Table IV indicate that this effect, although limited, is comparable to other secondary determinants such as profitability. Bond spreads, by contrast, are shaped by the overall scale of indebtedness. Their response to RI is weak and statistically insignificant. This implies that bond markets price the likelihood of distress associated with the size of outstanding obligations rather than the timing at which these obligations must be refinanced. Refinancing risk is therefore visible in CDS spreads but does not appear as a distinct component of corporate bond spreads. The modest impact in CDS remains relevant because protection premia adjust swiftly when funding conditions deteriorate. Bond prices react more slowly due to issuance frictions and infrequent trading, which limits the extent to which RI is incorporated in advance.

B. Refinancing intensity and the predictability of credit spreads

We now turn to the time-series dimension and examine whether RI has predictive power for future movements in credit spreads. To address this question, we estimate monthly Fama–MacBeth (1973) predictive regressions using the one month ahead change in 5-year CDS spreads or bond spreads as the dependent variable. The specification mirrors the cross-sectional tests but shifts the focus from levels to spread dynamics. In each month, changes in CDS or bond spreads are regressed on RI together with the standard firm characteristics used previously: leverage, log market equity, profitability, and book-to-market equity. For bonds, the controls also include investment-grade status, remaining maturity, coupon rate, and the Amihud illiquidity measure. The specifications are introduced sequentially to determine whether RI contributes predictive content once firm and bond fundamentals are accounted for. The monthly slope coefficients are averaged over time, and inference is based on Newey–West (1987) heteroskedasticity-robust and autocorrelation-robust t-statistics using three lags.

Table V
Cross-Sectional Regression on Credit Spread Changes

This table reports Fama–MacBeth (1973) predictive regressions of next-month changes in credit spreads on refinancing intensity (RI) and firm characteristics. Panel A examines monthly changes in 5-year credit default swap (CDS) spreads, and Panel B reports results for monthly changes in bond spreads relative to maturity-matched U.S. Treasuries. Control variables include leverage (LEV), the natural logarithm of market equity (Log ME), return on assets (ROA), and book-to-market equity (BM). The bond regressions also incorporate investment-grade status, remaining maturity, coupon rate, and the Amihud illiquidity measure. The Amihud variable is winsorised at the 1st and 99th percentiles and scaled by 10^6. Specifications are introduced sequentially to evaluate whether RI adds predictive power beyond standard fundamentals. The table reports time-series averages of the monthly coefficients, with Newey–West heteroskedasticity-robust and autocorrelation-robust t-statistics (three lags) in parentheses. The CDS sample contains 241 monthly cross-sections between 2004–2024, and the bond sample contains 270 between 2002–2024. The final rows of each panel show the average cross-sectional R^2 and the number of usable months.

Panel A: CDS spread changes

	1	2	3	4
Intercept	-0.030 (-0.03)	-0.024 (-0.05)	6.223 (0.61)	-2.814 (-0.38)
RI	1.119 (1.07)	1.241 (1.17)	1.278 (1.27)	1.040 (1.03)
LEV		0.224 (0.05)	-0.306 (-0.11)	1.908 (0.68)
Log ME			-0.270 (-0.63)	0.009 (0.03)
ROA				14.739 (2.84)
BM				2.273 (2.88)
Average R^2	0.007	0.029	0.054	0.082
Months	241	241	241	241

Panel B: Bond spread changes

	1	2	3	4	5
Intercept	0.453 (0.15)	-0.391 (-0.32)	16.374 (0.62)	11.155 (0.54)	14.071 (0.70)
RI	-1.424 (-0.61)	-1.048 (-0.47)	1.082 (0.66)	0.935 (0.62)	1.346 (0.92)
LEV		2.883 (0.37)	-1.484 (-0.52)	-0.761 (-0.33)	-0.821 (-0.35)
Log ME			-0.694 (-0.65)	-0.553 (-0.69)	-0.699 (-0.88)
ROA				14.444 (2.22)	14.340 (2.34)
BM				2.166 (2.09)	2.460 (2.30)
IG dummy				-0.088 (-0.09)	0.480 (0.51)
Remaining maturity (yrs)					0.108 (0.93)
Coupon rate					-0.088 (-0.89)
Amihud illiquidity					-5.034 (-3.23)
Average R^2	0.007	0.025	0.065	0.105	0.123
Months	270	270	270	270	270

Table V presents Fama–MacBeth predictive regressions of next-month changes in credit spreads on RI and firm characteristics. Panel A shows the results for CDS spreads, and Panel B shows the results for bond spreads. Across all specifications, RI lacks predictive power. The coefficients are economically negligible and statistically insignificant, which implies that firms with greater refinancing needs do not face systematic short-term increases in CDS spreads or bond spreads. This pattern contrasts with the earlier cross-

sectional results, where RI was priced in CDS levels, and suggests that RI is incorporated contemporaneously rather than anticipated by credit markets. RI is therefore a static pricing characteristic in CDS markets rather than a time-varying predictor of spread dynamics.

The behaviour of the control variables does not overturn this conclusion. Profitability and book-to-market ratios display modest effects in the CDS regressions, yet the explanatory power remains low, with average cross-sectional R^2 values below 0.1. The bond results mirror those in CDS markets. RI remains economically small and statistically insignificant even after controlling for investment-grade status, remaining maturity, coupon rate, and bond illiquidity, while profitability and book-to-market exhibit similar predictive patterns. The Amihud coefficient turns negative and significant in the fully specified model, indicating short-term mean reversion in bond illiquidity.

The lack of predictability in RI gains context when viewed alongside the evidence in Liu, Qiu, and Wang (2021), who document short-term spread widening during the COVID-19 crisis when near-term debt obligations coincided with limited liquidity. Their rollover-pressure measure combines impending maturities with firms' cash holdings, which captures whether refinancing needs are immediate and difficult to meet. RI, by contrast, reflects the maturity structure of outstanding debt without conditioning on liquidity buffers. It therefore identifies exposure to refinancing conditions but does not indicate when such exposure becomes a binding constraint. In a non-crisis environment and without liquidity interaction, RI offers no systematic forecast of short-term spread changes.

Overall, the results show that refinancing risk influences the level of credit spreads but carries no information about their short-term dynamics. Markets acknowledge that concentrated maturities warrant higher compensation, yet RI does not indicate when refinancing pressures will arise. Credit spreads therefore embed RI contemporaneously, while monthly spread changes reflect forces unrelated to the timing of future debt rollovers.

C. Isolating refinancing stress from firm characteristics

The previous results show that RI is priced in CDS spreads once firm characteristics are controlled for, whereas the corresponding effect in corporate bond spreads remains economically small and statistically weak. Because credit spreads combine several priced components related to firm size, value, liquidity, and other dimensions of credit risk, the refinancing signal may be obscured even when RI is economically relevant. This creates the need to separate characteristic driven components from spreads and returns to isolate a residual refinancing metric that can reveal whether refinancing stress operates as a distinct state variable. Refinancing stress denotes the component of credit spreads attributable to refinancing pressure after characteristic driven variation has been removed. Establishing such a measure is essential for the subsequent spillover analysis, since cross-

market transmission can only be identified once this common co-movement has been filtered out.

To address this, we adopt the characteristics-first framework of Kozak, Nagel, and Santosh (2020), combined with the view of RI as a separate channel of fragility proposed by He and Xiong (2012). The objective is not to construct a tradable factor but to extract a residual refinancing metric that captures the component of pricing that aligns with refinancing pressure once unrelated pricing influences have been accounted for. However, the residual may still reflect latent credit-quality variation, so it should be viewed as consistent with refinancing stress rather than a definitive measure of it.

The rationale for this construction can be illustrated by considering two firms that are similar along priced characteristics such as size, value, and, for bonds, liquidity, yet differ in the share of debt maturing in the near–term. If refinancing stress operates as an independent source of pricing variation, the firm with greater rollover exposure should exhibit distinctive residual pricing outcomes after adjusting for these characteristics. We therefore construct residual refinancing risk (RRI) factors for CDS spreads, bond spreads, and equity excess returns. These factors isolate the pricing component associated with RI after removing systematic variation attributable to firm characteristics, providing a clearer view of how refinancing conditions are reflected in market valuations.

C.1 Factor construction

The RRI factors are constructed using the merged sample of firms for which CDS, bond, and equity data are jointly available. Summary statistics for this merged dataset are reported in Table A.I. For each month t and each market $m \in \{\text{CDS}, \text{Bonds}, \text{Equities}\}$, we estimate cross-sectional regressions of the form:

$$y_{i,t}^{(m)} = \alpha_t^{(m)} + \delta_{1,t}^{(m)} \log(ME_{i,t}) + \delta_{2,t}^{(m)} BM_{i,t} + \delta_{3,t}^{(m)} Amihud_{i,t} \cdot \mathbf{1}\{m = \text{Bonds}\} + \widehat{\varepsilon}_{i,t}^{(m)} \quad (4.1)$$

Here, $y_{i,t}^{(m)}$ denotes the CDS spread in basis points, the corporate bond spread in basis points, or the equity excess return in percent. Log market equity and book to market equity are included in all regressions to remove size and value effects. The Amihud measure is added only in the bond regressions because liquidity premia are an important component of corporate bond spreads and can mask pricing differences that arise from RI. Leverage is retained because it captures the scale of outstanding obligations, which shapes how RI translates into pricing. Removing it would collapse RI into a pure maturity structure measure and eliminate the distinction between rollover concentration and overall indebtedness. Other controls are not residualised because doing so would remove substantial variation in spreads and leave too little unexplained pricing heterogeneity to isolate refinancing related effects. The resulting residuals $\widehat{\varepsilon}_{i,t}^{(m)}$ therefore reflect the component of spreads or returns that remains after removing the influence of size, value and, for bonds,

liquidity. Table A.II reports the coefficient estimates from these regressions.

Based on these residuals, firms are sorted each month into terciles by RI using NYSE breakpoints for the 33rd and 66th percentiles. These thresholds are applied to the full CDS–bond–equity sample. For each market m, the RRI is defined as:

$$RRI_t^{(m)} = \bar{\widehat{\varepsilon}}^{(m)}_{\text{High RI},t} - \bar{\widehat{\varepsilon}}^{(m)}_{\text{Low RI},t} \tag{4.2}$$

This produces three non-tradable series: RRI_t^{CDS} and RRI_t^{Bond} in basis points, and RRI_t^{Equity} in percentage excess returns.

C.2 Properties of the residual refinancing risk factor

Having constructed the RRI factors, we now examine whether they exhibit properties consistent with a refinancing risk state variable. A variable that drives cross-market transmission should display persistent time-series variation, differences across refinancing portfolios that remain after characteristic adjustment, and sensitivity to funding conditions. Establishing these properties ensures that any subsequent impulse responses or variance decompositions reflect the propagation of refinancing stress itself rather than co-movement induced by size, value, or liquidity premia.

Table VI
Residual Refinancing Portfolios

This table presents time-series averages of portfolio characteristics for firms sorted each month into terciles based on refinancing intensity (RI). Sorting relies on NYSE breakpoints, where the 33rd and 66th percentiles of RI are computed from NYSE-listed firms and then applied to the full CDS–bond–equity sample. For each tercile (Low, Mid, High), the table reports average RI, residual credit default swap (CDS) spreads, residual bond spreads, residual equity excess returns, the natural logarithm of market equity (Log ME), book-to-market equity (BM), and the Amihud illiquidity measure (scaled by 10^6). Residual spreads and returns are obtained from monthly cross-sectional regressions of each pricing variable on log market equity and book-to-market equity; the Amihud measure is included only in the bond regressions. This procedure removes variation driven by size, value, and liquidity. The high-minus-low (H–L) row reports the difference between the High and Low portfolios and defines the residual refinancing risk (RRI) factors used in the subsequent analysis.

Portfolio	RI	Resid. CDS	Resid. Bond	Resid. Equity	Log ME	BM	Amihud
Low	0.077	-5.389	-1.259	0.101	23.242	0.521	0.062
Mid	0.210	-2.011	-0.243	0.082	23.748	0.529	0.054
High	0.410	7.710	1.953	-0.168	23.511	0.501	0.062
H–L	0.333	13.100	3.212	-0.269	0.270	-0.021	0.000

Table VI reports average residual spreads, returns, and firm characteristics across RI portfolios after controlling for size, book-to-market equity, and, for bonds, Amihud illiquidity.

Because spreads and returns have already been adjusted for characteristic driven variation in the first-stage regressions, the High and Low portfolios exhibit virtually no differences in the attributes used for adjustment. This ensures that any spread differentials are not mechanically driven by these characteristics. The high-minus-low differences show that firms with higher RI have higher residual CDS spreads (13.100 bps) and moderately higher residual bond spreads (3.212 bps). The stronger effect in CDS is consistent with earlier results, indicating that RI is more clearly reflected in CDS spreads than in corporate bond spreads once characteristic driven variation has been removed.

These results demonstrate that RI contributes to systematic variation in credit premia once characteristic driven components have been removed, which indicates that refinancing stress contains pricing information distinct from standard firm attributes. The residual equity return is slightly negative (-0.270 percent) for the high-minus-low portfolio. This should not be interpreted as evidence against a refinancing premium. Friewald et al. (2022) document a positive premium in broader equity samples, whereas the present sample consists only of firms with traded CDS and bonds, which are larger, more profitable, and less financially constrained than the typical equity issuer. For such firms, short-term debt can be used strategically to exploit favourable financing conditions, which weakens the link between RI and realised equity returns in normal market environments. Table A.III shows that extending the analysis to a wider equity sample restores the expected positive relation. The negative residual return in Table VI therefore reflects the composition of the merged CDS–bond–equity sample rather than the absence of refinancing related pricing in equities. While these cross-sectional differences confirm that RI remains visible after characteristic adjustment, they do not indicate whether such effects persist over time. We therefore next analyse the time-series properties of the residual factors.

Table VII
Summary Statistics for Residual Refinancing Risk Factors

This table reports summary statistics for the residual refinancing risk (RRI) factors constructed from credit default swap (CDS) spreads, bond spreads, and equity excess returns. For each market, the RRI factor is defined as the monthly difference between the High and Low refinancing-intensity terciles, where portfolios are formed using NYSE breakpoints. Spreads and returns are first residualised with respect to firm size and book-to-market equity, and for bonds also Amihud illiquidity, ensuring that the RRI factors capture variation unrelated to these characteristics. The table reports the time-series mean and standard deviation (SD) of each factor, the Newey–West (1987) t-statistic of the mean, first-order (AR(1)), and the Sharpe or signal-to-noise (SN) ratio. CDS and bond RRI are measured in basis points, and equity RRI is expressed in percentage excess returns.

Factor	Mean	SD	t-stat	AR(1)	Sharpe/SN
RRI CDS	13.100	35.861	5.671	0.927	0.365
RRI Bond	3.358	38.150	1.366	0.924	0.088
RRI Equity	-0.269	2.302	-1.811	0.027	-0.117

Table VII summarises the time-series properties of the three RRI factors. The CDS-based factor has a mean of 13.100 basis points and a Newey–West t-statistic of 5.671, which indicates that firms with high RI consistently exhibit higher residual CDS spreads. The factor also displays strong persistence, with an AR(1) coefficient of 0.937 and a signal-to-noise ratio of 0.365. These properties suggest that refinancing stress enters CDS spreads as a systematic component rather than episodic noise, which is consistent with theoretical arguments that rollover exposure generates persistent credit concerns (He and Xiong, 2012).

The bond-based RRI has a mean of 3.358 basis points and is statistically indistinguishable from zero. Its autocorrelation is similar to that of the CDS factor, but the signal-to-noise ratio is low. This indicates that refinancing related variation is difficult to detect in bonds. The pattern is consistent with the interpretation that other priced components in bond spreads, such as liquidity premia and trading frictions documented by Longstaff, Mithal and Neis (2005) and Norden and Weber (2009), may obscure refinancing related variation and make it harder for RI to appear as a distinct residual component.

The equity-based RRI has a mean of -0.269 percent, a negative Sharpe ratio, and negligible persistence. Once characteristic driven variation is removed, RI does not persist in equities in a way that reflects systematic pricing. Any refinancing related information that enters equity valuations dissipates rapidly, leaving no indication that equity markets embed refinancing pressure as a stable source of risk.



Figure 2. Refinancing Risk Factors Across Credit and Equity Markets
Residual refinancing risk (RRI) factors constructed from credit default swap (CDS) spreads, bond spreads, and equity excess returns. Each month, firms are sorted into terciles based on refinancing intensity (RI), with NYSE firms determining the 33rd and 66th percentile breakpoints that are applied to the full sample. Residual spreads and returns are obtained from cross-sectional regressions of CDS spreads, bond spreads, or equity excess returns on the natural logarithm of market equity, and book-to-market equity, and for bonds also the Amihud illiquidity measure. These residuals isolate the component of pricing unrelated to size, value, or liquidity. Panel A plots the high-minus-low residual series in basis points (CDS and bonds) or percent (equities). Panel B applies a signed log transformation, $\log(1 + |RRI|) \times \text{sign}(RRI)$, to limit the impact of extreme values while retaining direction. Both panels span the full sample period from 2004 to 2024.

Figure 2 plots the RRI factors over time. In Panel A, the CDS-based RRI is predominantly positive and rises sharply during known episodes of funding stress, including the 2008-2009 financial crisis and the 2011-2012 eurozone debt crisis. The bond-based RRI moves in the same direction but with lower amplitude, indicating that refinancing stress is present in bond spreads although less strongly than in CDS spreads. The equity-based RRI fluctuates around zero, consistent with earlier evidence that refinancing risk is difficult to detect in equities within the merged sample. Panel B applies a signed logarithmic transformation to the same series to reduce the influence of extreme observations while

preserving directional movements. The relative ordering remains unchanged. The CDS factor displays the strongest and most persistent dynamics, the bond factor is more muted, and the equity factor shows no systematic pattern. The figure also reveals episodes in which the CDS-based and bond-based factors assume negative values. These patterns suggest that, during periods of favourable financing conditions, rollover considerations may lose relevance, allowing firms with shorter maturity structures to avoid pricing penalties and, in some cases, be viewed as more flexible. Friewald et al. (2022) argue that RI embeds both fragility and flexibility, and the balance between these components varies with market conditions. When funding becomes scarce, the fragility channel dominates, and RI once again commands a premium, which coincides with the return of the RRI factors to positive territory.

D. The cross-market dynamics of refinancing stress

The previous section constructed residual refinancing risk (RRI) factors for equities, CDS, and bonds after removing variation linked to firm size, value, and bond-market liquidity. The results revealed a clear divergence. The CDS-based RRI displays pronounced persistence, the bond-based RRI moves in the same direction but with lower intensity, and the equity RRI is effectively serially uncorrelated and behaves like noise. Only the credit market measures therefore exhibit the temporal structure required of a state variable capable of transmitting shocks. Equity RRI is nevertheless retained to test whether refinancing related information first appears in equity markets before it is reflected in credit spreads, which aligns with documented information hierarchies across asset classes (Norden and Weber, 2009).

Having established that refinancing stress persists in credit markets but not in equities, we next examine whether refinancing pressures in one market affect the others over time. This matters because pricing in levels does not show whether refinancing shocks remain isolated or transmit across markets. If RI functions as a state variable, shocks should spread from the markets where they first appear. Studying this transmission allows us to link the cross-sectional pricing results to how refinancing conditions influence the evolution of credit premia.

Accordingly, we estimate a vector-autoregression (VAR) in which each RRI series depends on its own lags and on the lagged values of the others. Unit-root tests confirm that the series do not contain stochastic trends. Augmented-Dickey-Fuller (1979) tests reject the presence of unit roots, while KPSS (1992) statistics reflect the high persistence of the CDS- and bond-based measures rather than evidence of explosive behaviour. The equity RRI is strictly stationary. Although the credit market RRIs are highly persistent, their autoregressive coefficients remain below unity (Table A.IV), which makes them suitable for estimation in levels. Because the factors differ in scale, all series are standardised to mean

zero and unit variance. Lag length is selected using the Bayesian Information Criterion (Schwarz, 1978), which favours a VAR(1) specification (Table A.V). Orthogonal shocks are identified using a recursive Cholesky ordering Equity → CDS → Bond, which aligns with evidence that information is incorporated first in equities, then in CDS markets, and only subsequently in bonds (Norden and Weber, 2009).

D.1 Directional transmission of refinancing stress

We begin by examining whether refinancing stress in one market helps predict future movements in another. Granger causality tests provide an initial assessment of directional linkages before the impulse response analysis.

Table VIII

Cross-Market Granger Causality Tests

This table reports Granger causality tests based on a three-variable VAR model estimated on monthly residual refinancing risk (RRI) factors for equities, CDS, and bonds from 2004 to 2024. Each RRI factor is constructed as the high-minus-low refinancing-intensity portfolio using NYSE breakpoints and residual pricing measures that have been adjusted for size, book-to-market equity, and, for bonds, Amihud illiquidity. The resulting time-series are standardised to mean zero and unit variance prior to estimation. Lag length is selected using the Bayesian Information Criterion. For each ordered market pair, the table tests the null hypothesis that past values of the causing series do not improve the prediction of the affected series once its own lags and those of the remaining RRI variables are included. Reported are the corresponding F-statistics and p-values from these Granger non-causality tests.

Causing	**Affected**	**F-stat**	**p-value**
RRI Equity	RRI CDS	1.305	0.254
RRI Equity	RRI Bond	8.165	0.004
RRI CDS	RRI Bond	46.060	0.000
RRI CDS	RRI Equity	1.363	0.243
RRI Bond	RRI CDS	4.357	0.037
RRI Bond	RRI Equity	0.482	0.488

Table VIII reports Granger causality tests from the VAR(1) model of RRI in equity, CDS, and bond markets. For each ordered market pair, the null hypothesis is that lagged values of the causing RRI do not improve predictions of the affected series once its own lags and those of the remaining variables are included. Reported are the F-statistics and associated p-values.

The results show strong evidence that CDS refinancing stress Granger-causes bond refinancing stress ($F = 46.060$, $p < 0.01$). This indicates that refinancing related information is incorporated into CDS spreads before it reaches cash bond markets, where price adjustment is slower because of trading frictions and heterogeneous investor demand.

This corresponds to established CDS–bond lead-lag patterns documented by Norden and Weber (2009). Equity refinancing stress also Granger-causes bond refinancing stress ($F = 8.165$, $p < 0.01$), although the magnitude is smaller. Even though equity RRI is weakly persistent, innovations in this series can still reflect rapid equity market reactions to changing assessments of firms' refinancing prospects. These reactions are then incorporated with a delay into bond prices as investors update their views on rollover related default risk.

There is modest feedback from bonds to CDS ($F = 4.357$, $p = 0.037$), which indicates some two-way interaction across credit markets as bond repricing occasionally spills back into CDS spreads. By contrast, there is no significant Granger causality between equity and CDS in either direction ($p > 0.243$), so the data do not support a simple equity $\rightarrow$ CDS $\rightarrow$ bond hierarchy. Instead, the pattern suggests that refinancing related shocks emerge primarily within credit markets and are transmitted most clearly from CDS to bonds, while equities exert a direct but more limited influence on bond market refinancing spreads. This directional structure matters because it shows that refinancing stress arises where refinancing risk is priced most explicitly and only later affects borrowing costs through bond spreads. It therefore links the cross-sectional pricing evidence to how refinancing conditions propagate across credit markets rather than remaining confined to one instrument.

D.2 Impulse responses: Dynamic adjustment of refinancing stress

While Granger tests identify directional predictability, they do not reveal how shocks evolve over time. We therefore compute orthogonalised impulse response functions (IRFs) to trace the magnitude and persistence of refinancing shocks as they propagate across markets.

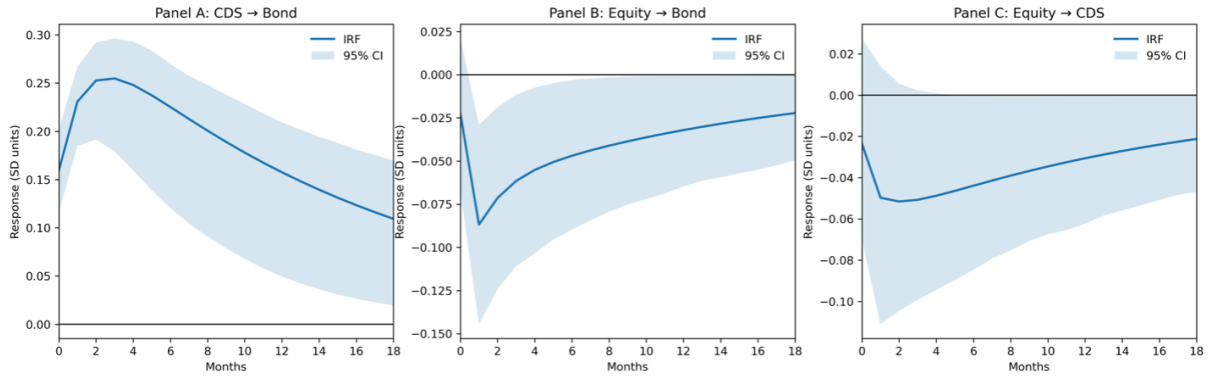


Figure 3. Impulse Responses of Refinancing Stress Across Markets
This figure plots orthogonalised impulse response functions (IRFs) from a three-variable VAR(1) model estimated on monthly standardised residual refinancing risk (RRI) for equities, CDS, and bonds from 2004 to 2024. RRI is constructed as the high-minus-low refinancing intensity (RI) portfolio using NYSE breakpoints and firm-level residuals adjusted for size and book-to-market equity, and for bonds also Amihud illiquidity. All factors are standardised to mean zero and unit variance before estimation. Each panel shows the response of one market's RRI to a one standard deviation shock in another market over an eighteen-month horizon. Panel A displays the reaction of bond RRI to a CDS shock, Panel B shows the response of bond RRI to an equity shock, and Panel C shows the response of CDS RRI to an equity shock. Shaded regions indicate 95 percent confidence intervals based on 1,000 Monte Carlo simulations.

Figure 3 illustrates how refinancing shocks evolve once they occur. Refinancing shocks that originate in CDS markets generate a sizeable and persistent increase in bond-based refinancing spreads. The response rises during the first few months and then recedes, consistent with CDS markets incorporating refinancing related information first. Shocks from equity markets lower bond refinancing spreads, although the effects are small and fade rapidly. Equity valuations may adjust to changes in firms' refinancing prospects, yet this information does not accumulate into a durable credit signal once characteristic driven variation has been removed.

By contrast, CDS refinancing spreads show little response to equity shocks, which indicates that refinancing related information rarely flows from equities into CDS markets. This asymmetry reinforces the view that refinancing stress manifests most clearly in credit instruments and that CDS markets adjust first when refinancing conditions change. Figure A.2 provides the corresponding cumulative impulse responses, which show that the ordering and relative magnitudes of the effects remain unchanged once responses are aggregated over time.

D.3 Variance decomposition: sources of refinancing stress fluctuations

The impulse responses show how refinancing shocks propagate once they occur, but they do not reveal which market drives most of the variation in refinancing stress. To identify the main sources of these fluctuations, we use forecast error variance decompositions (FEVDs).

This approach quantifies how much of each market's future refinancing risk movements can be attributed to shocks that originate in equities, CDS, or bonds.

Table IX
Forecast Error Variance Decomposition of Refinancing Stress

This table reports the 12-month ahead forecast error variance decomposition (FEVD) from the three-variable VAR(1) model estimated on standardised monthly residual refinancing risk (RRI) factors for equities, credit default swaps (CDS), and bonds from 2004 to 2024. Each RRI measure is constructed as the return on a high-minus-low refinancing intensity (RI) portfolio using NYSE breakpoints and residual pricing measures adjusted for size and book-to-market equity, and for bonds also the Amihud illiquidity measure. All factors are standardised prior to estimation. For each affected market, the table reports the share of its 12-month forecast error variance that is explained by orthogonalised shocks originating in equity, CDS, and bond RRI. Rows sum to one. These variance shares indicate the relative importance of each market in driving refinancing stress-related fluctuations over the 12-month horizon.

Affected	Shock RRI Equity	Shock RRI CDS	Shock RRI Bond
RRI Equity	0.992	0.006	0.001
RRI CDS	0.028	0.935	0.037
RRI Bond	0.042	0.721	0.237

Table IX summarises the 12-month forecast error variance decomposition and provides a quantitative view of how refinancing stress originates and evolves across markets. The equity RRI is almost entirely driven by its own shocks, with 99 percent of its future variation explained internally and negligible contributions from CDS or bonds. Once characteristic driven variation is removed, the equity factor does not retain refinancing information in a form that influences other markets, so equity-based innovations do not persist long enough to shape credit risk premia.

By contrast, CDS shocks dominate refinancing dynamics. They explain 94 percent of future movements in the CDS RRI and more than 72 percent of the variation in the bond RRI. Bonds account for a smaller share of their own RRI variation and contribute little to other markets. This pattern mirrors the impulse response results: CDS markets incorporate refinancing stress quickly, while bonds absorb it with delay.

These findings do not imply that equities lack informational content, but they show that equities are not the mechanism through which refinancing-specific shocks propagate. Refinancing stress is tied to funding conditions and liability rollover, which are priced most directly in credit instruments. Equity reactions may occur, yet they do not accumulate into a persistent refinancing signal once characteristics are removed, which limits their relevance for cross-market refinancing spillovers.

The variance decomposition therefore confirms the hierarchical structure revealed in this section. Refinancing stress originates within credit markets, enters CDS spreads first, and

subsequently appears in bond spreads, while equities provide only a transient indication of refinancing pressure. The evolution of refinancing spreads is shaped by the structure of credit instruments and the frictions that govern how funding conditions are priced.

V Robustness

We next evaluate whether the core empirical patterns persist when alternative credit instruments, sample definitions, and modelling assumptions are introduced. The purpose is not to revisit the baseline estimates but to assess whether the pricing of refinancing stress and its transmission remain observable once the empirical setting is altered.

Table X
Robustness of refinancing intensity Pricing

This table reports robustness checks of the pricing of refinancing intensity (RI) in credit default swap (CDS) and bond markets. All reported coefficients come from the full-specification regressions, which include the complete set of controls covering firm characteristics, credit rating, maturity, and liquidity. For each alternative specification, the table shows the time-series average of the monthly Fama-MacBeth regression slope on RI, along with Newey-West t-statistics based on three lags. CDS spreads are expressed in basis points. Bond spreads are defined relative to maturity-matched U.S. Treasury yields from the H.15 release. The baseline uses 5-year CDS contracts and bonds with two to ten years of remaining maturity. To test sensitivity to the choice of credit risk measurement, CDS regressions are re-estimated using 3-year and 7-year tenors. To assess bond-market robustness, the bond sample is extended to the full universe of traded maturities ranging from one month to 30 years. The CDS sample spans between the years 2004-2024, and the bond sample 2002-2024. State dependence is examined by estimating the regressions separately for crisis and non-crisis periods. Crisis windows include July 2007 to June 2009, August 2011 to December 2012, and March to June 2020. All remaining months form the noncrisis sample.

Robustness specification	CDS (RI coeff., t-stat)	Bonds (RI coeff., t-stat)
Baseline	27.204 (6.79)	13.560 (1.46)
3-year CDS tenor	20.386 (4.74)	
7-year CDS tenor	31.938 (6.71)	
Full bond maturity sample		11.938 (1.36)
Crisis periods only	38.865 (3.40)	28.614 (0.99)
Non-crisis periods only	24.743 (6.30)	11.836 (1.28)

Table X reports how the pricing of refinancing intensity (RI) responds to alternative credit risk measures, sample definitions and market conditions. Re-estimating the credit default swap (CDS) regressions with 3-year and 7-year contracts yields coefficients that remain positive and highly significant. Their magnitudes increase at longer maturities. This shows that the CDS spread associated with RI is not tied to the five year benchmark. Extending the bond analysis to the full TRACE universe produces coefficients that remain small and insignificant. This confirms that the weak pricing of RI in bonds is not a consequence of the two to ten year maturity restriction. The table also shows that refinancing pressure becomes more pronounced during periods of financial stress. The CDS coefficient almost doubles in crisis windows. The corresponding bond estimates increase in magnitude but remain statistically indistinguishable from zero. Taken together, the results demonstrate that RI is consistently reflected in CDS spreads, while bond spreads do not display a robust refinancing premium across alternative specifications or market environments. Full regression outputs for these robustness tests are reported in Tables A.VI to A.VIII.

A second set of tests examines whether the findings depend on the empirical framework. Friewald, Nagel and Wagner (2022) use triple sorted portfolios based on RI, firm size and leverage to capture rollover exposure without imposing a regression structure, and this approach is replicated here. Table A.IX shows that firms with higher RI continue to exhibit higher CDS spreads once they are sorted by these characteristics. This is consistent with the baseline evidence. The corresponding bond differential turns negative, reinforcing the earlier result that RI is not reliably priced in bond spreads. Once characteristic driven variation is removed, the bond High-Low spread becomes positive but remains small. This indicates that any refinancing signal in bonds is considerably weaker than in CDS spreads. The pricing pattern therefore persists outside the regression setting and does not hinge on the functional form of the baseline model.

Additional diagnostics confirm the stability of the main VAR results. Re estimating the VAR on a reduced system that includes only CDS and bond residual refinancing risk (RRI) factors with one lag, as reported in Table A.X., yields impulse responses that continue to show that shocks to CDS refinancing stress generate a sizeable and persistent increase in bond refinancing spreads. Figure A.3 illustrates this pattern and confirms that the dominant direction of propagation runs from CDS to bonds. The reduced VAR also uncovers a modest response of CDS spreads to bond shocks, an interaction that was not visible in the three variable specification. The principal transmission channel nevertheless remains intact. This shows that the dynamic role of CDS markets in pricing refinancing conditions does not depend on the inclusion of equity RRI.

Finally, the Toda and Yamamoto (1995) procedure is applied to verify that the causal inferences are not sensitive to assumptions about the order of integration or pre testing for stationarity in the RRI series. Lag selection follows the same criterion used in the baseline three variable VAR, and Appendix Table A.V confirms that one lag is appropriate for

this specification. Appendix Table A.XI reports the corresponding causality tests and shows that the Toda Yamamoto results align with the baseline Granger evidence. Both approaches yield the same directional structure. Refinancing stress originates in CDS markets and subsequently affects bond markets. Equity-based refinancing stress exerts only a limited influence that operates through bonds and does not predict CDS dynamics.

Across all robustness exercises, no alternative specification produces a materially different hierarchy of markets or pricing patterns.

VI Conclusion

This paper set out to examine whether refinancing intensity (RI), defined as the share of debt maturing within three years, is reflected in credit default swap (CDS) spreads and corporate bond spreads, and whether refinancing stress propagate across markets. The motivation comes from the observation that funding disruptions often coincide with sharp increases in both CDS spreads and bond spreads, as seen during the COVID-19 shock and earlier episodes of market stress. These periods show that the timing of debt rollover, rather than aggregate leverage alone, can amplify firms' exposure to adverse financing conditions and shape the cost at which they access credit.

Our empirical evidence shows that RI is priced in CDS markets once firm characteristics are controlled for, yet it carries no robust pricing effect in corporate bond spreads. CDS spreads increase for firms with more concentrated near-term maturities even after adjusting for leverage, size and profitability. Bond spreads, by contrast, remain shaped by the scale of total indebtedness. The economic magnitudes confirm that RI is a secondary determinant of CDS spreads. Its effect is modest relative to leverage and book-to-market, but sufficiently persistent to merit attention. RI does not predict short horizon changes in either CDS spreads or bond spreads. This suggests that credit markets incorporate rollover exposure contemporaneously rather than anticipating it. RI therefore behaves like a static characteristic in cross-sectional pricing rather than a forward-looking indicator of spread dynamics.

The construction of residual refinancing risk (RRI) factors sharpens this distinction. Once size, value and, for bonds, liquidity premia are removed, firms with high RI display consistently higher residual CDS spreads but only weakly higher residual bond spreads. The equity based residual factor contains no persistent refinancing signal. The credit market residuals allow us to examine how refinancing stress evolves across instruments. Shocks originate in CDS markets, where refinancing conditions are priced most directly, and later transmit to bond markets, where trading frictions slow adjustment. Equity markets contribute little to the propagation of refinancing related shocks once characteristic driven variation has been removed. This hierarchy indicates that refinancing stress behaves as a pricing force specific to credit markets rather than a broad risk factor visible across

asset classes.

Future work could explore whether RI becomes more salient in credit markets with different liquidity structures or regulatory environments, and whether stronger interaction with firms' liquidity buffers alters the pricing of RI. Such extensions would clarify whether the patterns observed here are general or specific to the U.S. credit market setting and the period studied.

These findings give rise to concrete implications for firms and investors. The structure of debt maturities determines how exposed firms become when funding conditions shift, and refinancing pressure materialises only when credit markets reflect higher protection premia, rather than in anticipation of such revisions. Since neither CDS spreads nor bond spreads embed refinancing risk ahead of stress, firms cannot rely on price signals that support orderly adjustment of maturity profiles. The sequence in which refinancing stress appears across credit instruments reinforces this constraint. CDS markets register refinancing strain first, and this pressure later diffuses into bond valuations. As a result, the information set available to managers compresses precisely when refinancing becomes more expensive. Firms that rely on short-term liabilities must therefore smooth maturities and maintain liquidity buffers well before conditions deteriorate, because once stress propagates through credit markets, refinancing premia rise quickly and the opportunity to reshape debt structures diminishes at the moment flexibility is most valuable.

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VII Appendix

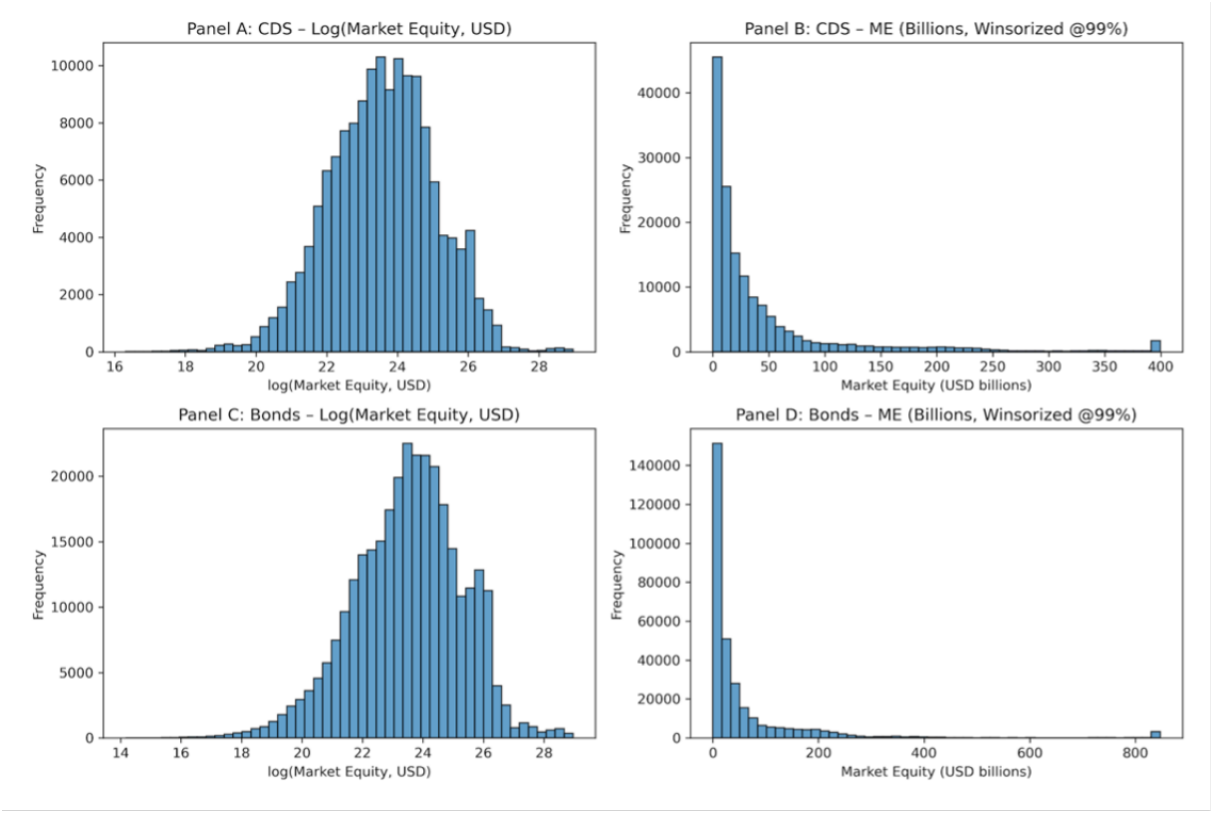


Figure A.1. Distribution of Market Equity
This figure illustrates the distribution of firm size across the credit default swap (CDS), CDS-equity and bond-equity samples. Panels A and C display the natural logarithm of market equity in U.S. dollars, while Panels B and D show market equity in billions of U.S. dollars, winsorised at the 99th percentile to reduce the influence of extreme values. The distributions are right-skewed, indicating that both datasets are dominated by large, publicly traded firms. As a result, log-market equity is used in all subsequent empirical analysis to mitigate the impact of firm size skewness.

Table A.I
Summary Statistics for the Merged CDS-Bond-Equity Panel

This table reports means and standard deviations for key variables in the merged CDS-bond-equity panel, which forms the dataset used to construct residual refinancing risk (RRI) factors and in the joint VAR analysis. Variables include refinancing intensity (RI), credit default swap (CDS) spreads, and bond spreads (in basis points), excess equity returns, firm size measured as the natural logarithm of market equity (log ME), book-to-market equity (BM), profitability (ROA), and the Amihud illiquidity measure for bonds (scaled by 10^6). The panel contains 118,651 firm-month observations across 273 firms between the years 2004-2024.

Variable	Mean	Std. Dev.
RI	0.238	0.153
CDS spread	122.786	176.671
Bond spread	170.619	193.071
Excess return (%)	1.085	9.750
Log ME	23.794	1.435
BM	0.502	0.550
ROA	0.053	0.065
Amihud	0.050	0.138
Observations	118,651	
Firms	273	

Table A.II
Monthly Cross-Sectional Residual Regressions

This table reports results from monthly cross-sectional ordinary least squares (OLS) regressions used to remove the effect of standard firm characteristics from credit default swap (CDS) spreads, bond spreads, and equity excess returns, over the period 2004-2024. Each month, cross-sectional OLS regressions are estimated of CDS spreads, bond spreads, or equity excess returns on natural logarithm of market equity (Log ME), and book-to-market equity (BM). For bonds, the Amihud illiquidity measure is also included. This mirrors the first step of a Fama-MacBeth (1973) procedure: coefficients are estimated separately each month, averaged across time, and Newey-West (1987) t-statistics are computed from the time-series of monthly coefficients. The resulting residuals capture the portion of spreads or returns unexplained by size, value, or liquidity. The residual standard deviation reports the time-series average of the cross-sectional standard deviation of residuals, indicating how much variation remains unexplained after controlling for firm characteristics.

Variable	CDS coeff.	CDS t	Bond coeff.	Bond t	Equity coeff.	Equity t
Intercept	1285.249	18.68	1670.153	14.16	2.208	0.74
Log ME	-51.146	-17.72	-64.951	-13.58	-0.021	-0.18
BM	72.010	11.57	55.541	9.00	-1.283	-5.77
Amihud			-64.330	-5.50		
Adjusted R^2	0.351		0.529		0.088	
Residual standard deviation	119.372		93.936		7.360	
Months	241		241		241	

Table A.III
Cross-Sectional Regressions on the Full Equity Sample

This table reports Fama-MacBeth (1973) cross-sectional regressions of monthly equity excess returns on refinancing intensity (RI) and firm characteristics over the period 2004-2024. The regressions are estimated using the full equity sample, which includes all firms with available CRSP or Compustat data before any bond or credit default swap (CDS) merging. The dependent variable is the firm's monthly excess return in percent. The main independent variable is RI and control variables include the natural logarithm of market equity (Log ME) and the book-to-market equity (BM). The regressions are estimated monthly, and the table reports the time-series average of the cross-sectional coefficients with Newey-West (1987) t-statistics. The final rows show the average cross-sectional R^2 and the number of estimation months.

Variable	Coefficient	t-statistic
Intercept	−4.716	−2.95
RI	0.635	4.54
Log ME	0.293	4.95
BM	−1.029	−10.89
Average R^2	0.031	
Months	240	

Table A.IV
Stationarity of Residual Refinancing Risk Factors

This table reports stationarity diagnostics for monthly residual refinancing risk in equity, credit default swap (CDS), and bond markets from 2004 to 2024. For each market, firm-level returns or spreads are first residualised using cross-sectional regressions on the natural logarithm of market equity and book-to-market equity, and for bonds also the Amihud illiquidity measure. Firms are then sorted into NYSE-based refinancing intensity (RI) terciles, and RRI is defined as the difference between the average residual in the High and Low terciles each month. To test for stationarity in levels, the table reports Augmented Dickey-Fuller (ADF) test statistics and p-values (null: unit root) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) statistics and p-values (null: stationarity). Sample means, standard deviations (SD), and first-order autocorrelations AR(1) are also shown. Lag lengths are selected automatically (autolag = "AIC" for ADF and nlags = "auto" for KPSS).

Factor	ADF statistic	ADF p-value	KPSS statistic	KPSS p-value	Mean	SD	AR(1)
RRI Equity	−14.982	0.000	0.054	0.100	−0.277	2.303	0.027
RRI CDS	−2.944	0.041	0.908	0.010	13.309	35.788	0.926
RRI Bond	−3.624	0.005	0.687	0.015	3.442	38.207	0.924

Table A.V
Lag Length Selection for VAR Model

This table reports the Bayesian Information Criterion (BIC) values for a vector autoregression (VAR) estimated on the standardised monthly residual refinancing risk (RRI) factors for equity, credit default swap (CDS), and bond markets. The sample spans 2004 to 2024, and all series are transformed to z-scores prior to estimation. For lag lengths p=1 to 6, the table presents the BIC for an unrestricted VAR estimated with p lags. Lower BIC values indicate better model fit penalised for complexity. The lag order used in the baseline specification corresponds to the value of p that minimises the BIC.

Lag (p)	BIC
1	−4.086
2	−3.992
3	−3.910
4	−3.815
5	−3.714
6	−3.565

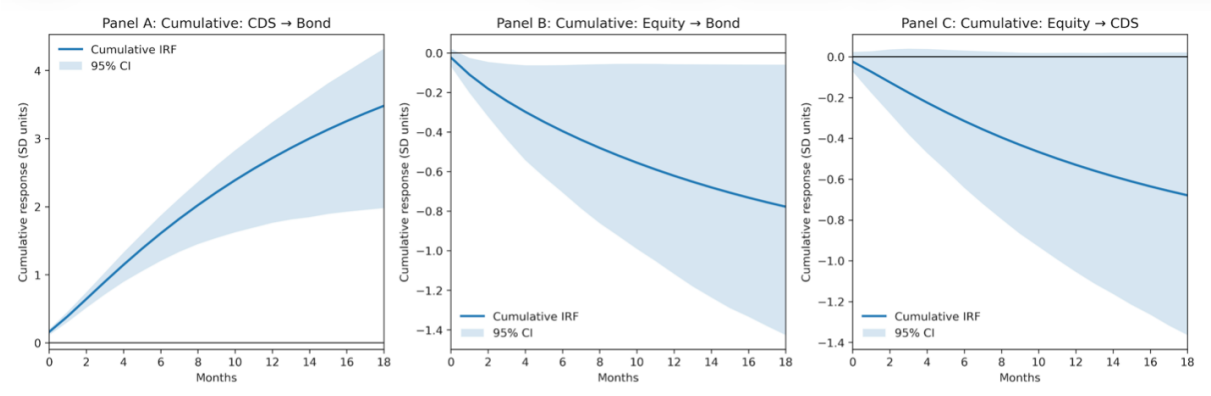


Figure A.2. Cumulative Impulse Responses of Refinancing Stress Across Markets

This figure presents cumulative impulse-response functions (IRFs) from a three-variable VAR model with one lag. The model is estimated on standardised monthly residual refinancing risk (RRI) in the equity, credit default swap (CDS), and bond markets from 2004 to 2024. All factors are transformed into z-scores before estimation. Shocks are orthogonalised using a Cholesky decomposition with the ordering (Equity, CDS, Bond). Each panel shows the cumulative response of one market's RRI to a one-standard-deviation shock in another market over an 18-month horizon. Panel A reports the cumulative response of bond RRI to a CDS shock, Panel B shows the response of bond RRI to an equity shock, and Panel C shows the response of CDS RRI to an equity shock. Shaded regions indicate 95 percent confidence intervals based on 1,000 Monte Carlo simulations.

Table A.VI
Refinancing Intensity and CDS Spreads: Alternative Tenors

This table reports Fama-MacBeth (1973) cross-sectional regressions of credit default swap (CDS) spreads on refinancing intensity (RI) and firm characteristics using 3-year and 7-year contracts. The dependent variable is the CDS spread in basis points. Control variables include leverage (LEV), the natural logarithm of market equity (Log ME), return on assets (ROA), and book-to-market equity (BM). For each tenor, four specifications are estimated monthly: RI only; RI with LEV; RI with LEV and Log ME; and a full model including ROA and BM. The table reports time-series averages of the slope coefficients, with Newey-West (1987) t-statistics (three lags) in parentheses. The last two rows report the average cross-sectional R^2 and the number of estimation months. CDS tenors are identified by Markit codes 36 (3-year) and 84 (7-year). The sample spans 241 monthly cross-sections from 2004 to 2024. CDS spreads are winsorised at the 1st and 99th percentiles within each calendar year.

	CDS 3Y				CDS 7Y			
Variable	1	2	3	4	1	2	3	4
Constant	109.112 (13.92)	7.188 (1.58)	1097.855 (13.39)	722.498 (15.25)	166.122 (24.74)	27.711 (5.55)	1458.369 (21.78)	1027.316 (24.07)
RI	-4.829 (-0.56)	17.014 (2.22)	18.404 (3.68)	20.386 (4.74)	-3.406 (-0.32)	23.771 (2.55)	30.587 (5.54)	31.938 (6.71)
LEV		329.804 (9.98)	185.114 (11.24)	200.692 (11.53)		443.882 (14.17)	268.011 (16.39)	282.325 (16.68)
Log ME			-45.161 (-13.13)	-30.600 (-15.24)			-59.190 (-21.11)	-42.397 (-24.17)
ROA				-130.373 (-3.85)				-187.061 (-4.43)
BM				64.068 (11.32)				77.306 (12.79)
Average R^2	0.007	0.104	0.258	0.345	0.007	0.131	0.336	0.412
Months	241	241	241	241	241	241	241	241

Table A.VII
Refinancing Intensity and Corporate Bond Spreads: Full TRACE Universe

This table reports Fama-MacBeth (1973) cross-sectional regressions of corporate bond spreads on refinancing intensity (RI) using the full TRACE bond universe without imposing a maturity restriction. Bond spreads are measured relative to U.S. Treasury yields matched by remaining maturity, using H.15 benchmark rates from one month to 30 years. Control variables are leverage (LEV), the natural logarithm of market equity (Log ME), return on assets (ROA), and book-to-market equity (BM). Additional bond-level controls in later specifications include an investment-grade indicator, remaining maturity, coupon rate, and the Amihud illiquidity measure (scaled by 10^6). Five specifications are estimated each month. The table reports time-series averages of the monthly coefficients with Newey-West (1987) t-statistics (three lags) in parentheses. Bond spreads and the liquidity measure are winsorised annually at the 1st and 99th percentiles. The sample consists of 270 monthly cross-sections from 2002 to 2024. The final rows report the average cross-sectional R^2 and the number of estimation months.

Variable	1	2	3	4	5
Intercept	221.378 (16.19)	54.284 (8.21)	1743.932 (13.79)	1147.250 (14.00)	1067.861 (13.23)
RI	-88.463 (-6.48)	-72.410 (-5.30)	-2.311 (-0.18)	-2.740 (-0.28)	11.938 (1.36)
LEV		527.276 (10.44)	212.385 (11.41)	173.532 (13.99)	171.735 (13.61)
Log ME			-69.100 (-13.00)	-42.434 (-13.67)	-41.091 (-13.49)
ROA				-265.007 (-8.61)	-246.265 (-8.27)
BM				71.262 (18.40)	72.301 (17.84)
Investment-grade dummy				-60.869 (-6.90)	-76.442 (-10.53)
Remaining maturity					2.371 (7.67)
Coupon rate					5.031 (5.54)
Amihud					32.249 (13.66)
Average R^2	0.015	0.136	0.413	0.533	0.599
Months	270	270	270	270	270

Table A.VIII
Refinancing Intensity and Credit Spreads in Crisis vs Non-Crisis Periods

This table reports Fama-MacBeth (1973) cross-sectional regressions of credit spreads on refinancing intensity (RI) estimated separately during crisis and non-crisis periods. The CDS sample spans between the years 2004-2024, and the bond sample 2002-2024. Crisis months are defined as July 2007 to June 2009, August 2011 to December 2012, and March 2020 to June 2020. Non-crisis months include all remaining observations. Panel A uses credit default swap (CDS) spreads as the dependent variable. Panel B uses corporate bond spreads over maturity-matched U.S. Treasury yields. Firm-level controls include leverage (LEV), the natural logarithm of market equity (Log ME), return on assets (ROA), and book-to-market equity (BM). Bond regressions additionally include an investment-grade indicator, remaining maturity, coupon rate, and the Amihud illiquidity measure (scaled by 10^6). The Amihud measure is winsorised at the 1st and 99th percentiles within each calendar year; accounting variables are not winsorised. For each subsample, four specifications are estimated monthly. The table reports time-series averages of the slope coefficients and Newey-West (1987) heteroskedasticity- and autocorrelation-consistent t-statistics (three lags) in parentheses. The final rows report the average cross-sectional R^2 and the number of monthly regressions.

Panel A. CDS spreads

Variable	Crisis (1)	Crisis (2)	Crisis (3)	Crisis (4)	Non-Crisis (1)	Non-Crisis (2)	Non-Crisis (3)	Non-Crisis (4)
Intercept	236.520 (12.72)	12.313 (1.19)	2067.592 (9.06)	1192.129 (7.53)	123.125 (28.63)	12.444 (2.88)	1118.507 (24.98)	824.980 (25.63)
RI	-23.861 (-0.87)	28.838 (1.20)	30.116 (2.29)	38.865 (3.40)	-0.053 (-0.01)	21.157 (2.72)	28.443 (6.59)	24.743 (6.30)
LEV		775.444 (7.82)	419.091 (8.32)	464.337 (8.31)		344.578 (15.27)	227.301 (16.53)	230.271 (19.05)
Log ME			-85.653 (-8.76)	-51.455 (-8.19)			-45.688 (-24.63)	-34.213 (-25.72)
ROA				-107.040 (-0.91)				-180.960 (-4.82)
BM				122.131 (10.21)				60.554 (9.79)
Average R^2	0.006	0.151	0.309	0.406	0.006	0.127	0.327	0.398
Months	42	42	42	42	199	199	199	199

Panel B. Bond spreads

Variable	Crisis (1)	Crisis (2)	Crisis (3)	Crisis (4)	Non-Crisis (1)	Non-Crisis (2)	Non-Crisis (3)	Non-Crisis (4)
Intercept	433.439 (7.63)	109.332 (6.17)	3279.610 (6.71)	2291.545 (5.98)	208.357 (18.55)	41.919 (6.21)	1778.101 (16.45)	993.366 (19.63)
RI	-216.574 (-7.89)	-177.739 (-6.48)	21.337 (0.61)	28.614 (0.99)	-111.161 (-5.99)	-84.030 (-4.65)	7.979 (0.59)	11.836 (1.28)
LEV		1065.062 (6.23)	341.197 (6.37)	276.004 (8.31)		486.491 (11.66)	169.592 (13.86)	145.941 (15.27)
Log ME			-131.835 (-6.52)	-87.393 (-5.87)			-71.358 (-15.34)	-39.214 (-20.98)
ROA				-286.815 (-4.12)				-254.404 (-7.43)
BM				82.183 (12.19)				72.324 (14.78)
Investment-grade dummy				-113.903 (-10.63)				-71.970 (-9.03)
Remaining maturity				-0.360 (-0.23)				3.666 (3.24)
Coupon rate				1.678 (3.02)				6.739 (5.50)
Amihud				9.174 (1.31)				20.419 (2.89)
Average R^2	0.024	0.221	0.567	0.682	0.020	0.142	0.482	0.643
Months	42	42	42	42	228	228	228	228

Table A.IX
Comparison of Triple-Sorted Refinancing Intensity Portfolios and Residual Refinancing Risk Portfolios

This table compares two portfolio approaches used to capture refinancing risk. Both methods sort firms each month into refinancing intensity (RI) terciles using NYSE breakpoints. Panel A reports characteristics of triple-sorted portfolios constructed on RI, firm size (Log ME), and leverage (LEV), following the approach of Friewald, Nagler and Wagner (2022). For each RI group, the table shows average credit default swap (CDS) spreads, bond spreads, equity excess returns, firm size, leverage, and bond illiquidity. The high-minus-low spread provides the portfolio-based measure of refinancing risk implied by the original Friewald et al. (2022) method. Panel B presents the portfolios used in this thesis. Here, CDS spreads, bond spreads, and equity returns are first residualised each month using cross-sectional regressions on the natural logarithm of market equity, and book-to-market equity (BM), and for bonds also the Amihud illiquidity measure (scaled by 10^6). These residuals are then averaged within RI terciles. The high-minus-low row yields the residual refinancing risk (RRI) factor that forms the basis of the time-series analysis.

Panel A. Triple-Sorted RI Portfolios

Group	RI	CDS spread (bp)	Bond spread (bp)	Excess return	Log ME	LEV	Amihud
High	0.426	135.407	184.440	0.009	23.486	0.303	0.067
Low	0.071	132.851	196.013	0.010	23.355	0.308	0.064
Mid	0.213	117.908	175.704	0.010	23.611	0.309	0.062
H-L	0.355	2.556	-11.573	-0.001	0.131	-0.005	0.003

Panel B. Residual RRI Portfolios

Group	RI	Residual CDS	Residual bond	Residual equity	Log ME	BM	Amihud
Low	0.077	-5.389	-1.259	0.101	23.242	0.521	0.062
Mid	0.210	-2.011	-0.243	0.082	23.748	0.529	0.054
High	0.410	7.710	1.953	-0.168	23.511	0.501	0.062
H-L	0.333	13.100	3.212	-0.269	0.270	-0.021	0.000

Table A.X
Lag Selection for the CDS–Bond VAR (BIC)

This table reports Bayesian Information Criterion (BIC) values used to select the optimal lag length for a reduced two-variable vector autoregression estimated on standardised monthly residual refinancing risk (RRI) factors in the credit default swap (CDS) and bond markets. Both factors are converted to z-scores before estimation. For lag orders p = 1 to 6, the VAR is estimated with p lags and the corresponding BIC is recorded. Lower BIC values indicate a preferred balance between statistical fit and model parsimony. The lag order with the lowest BIC is selected as the baseline specification for the reduced CDS-Bond VAR used to generate the robustness impulse-response functions in Figure A.3.

Lag order	BIC
1	-4.174
2	-4.121
3	-4.125
4	-4.103
5	-4.118
6	-4.054

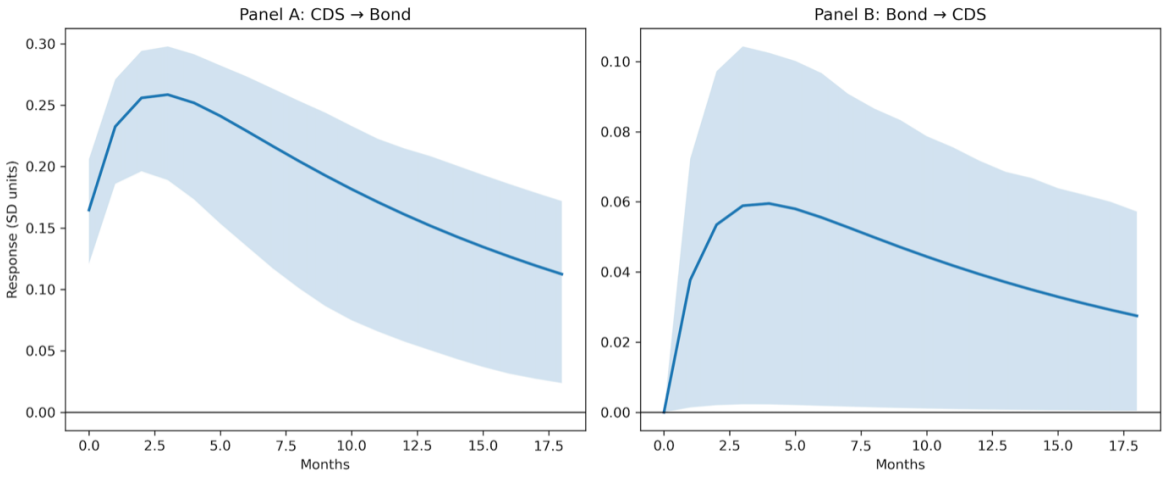


Figure A.3. Impulse Responses between CDS and Bond Refinancing Stress. This figure shows orthogonalised impulse-response functions obtained from a bivariate VAR estimated on standardised monthly residual refinancing risk (RRI) in the credit default swap (CDS) and bond markets. The VAR includes one lag, selected using the Bayesian Information Criterion, and is estimated over the period 2004 to 2024. Both factors are constructed as high-minus-low refinancing-intensity portfolio returns and are standardised to have zero mean and unit variance before estimation. The left panel reports the response of bond RRI to a one standard deviation shock in the CDS factor. The right panel shows the corresponding response of CDS RRI to a bond shock. Responses are traced over an eighteen-month horizon and expressed in standard-deviation units. Shaded areas represent 95 percent confidence intervals based on 1,000 Monte Carlo simulations.

Table A.XI
Causality of Residual Refinancing Risk: Granger vs. Toda–Yamamoto

This table compares two causality frameworks applied to the residual refinancing risk (RRI) factors in the equity, credit default swap (CDS), and bond markets. Each factor is constructed as the high-minus-low refinancing intensity portfolio return after adjusting spreads or returns for firm size and book-to-market equity, and for bonds also the Amihud illiquidity measure. All factors are standardised before estimation. Panel A reports Granger causality tests from a three-variable VAR(1) in levels. For each ordered market pair, the table presents F-statistics and p-values for the null hypothesis that lagged values of the causing factor do not improve predictions of the affected factor. Panel B reports the Toda and Yamamoto modified Wald tests based on the same VAR lag structure augmented by one additional lag to accommodate the integration properties of the factors. For each ordered pair, the table reports chi-square statistics and p-values for the corresponding null hypotheses.

Panel A: Granger Causality

Causing	Affected	F-statistic	p-value
RRI Equity	RRI CDS	1.305	0.254
RRI Equity	RRI Bond	8.165	0.004
RRI CDS	RRI Bond	46.060	0.000
RRI CDS	RRI Equity	1.363	0.243
RRI Bond	RRI CDS	4.357	0.037
RRI Bond	RRI Equity	0.482	0.488

Panel B: Toda–Yamamoto Causality

Causing	Affected	Chi-Square	p-value
RRI Equity	RRI CDS	1.305	0.253
RRI Equity	RRI Bond	8.165	0.004
RRI CDS	RRI Bond	46.060	0.000
RRI CDS	RRI Equity	1.363	0.243
RRI Bond	RRI CDS	4.357	0.037
RRI Bond	RRI Equity	0.482	0.488

AI Appendix

We used AI tools, including ChatGPT and Grammarly, solely to assist with Python implementation and language editing during the preparation of this paper. All empirical analyses, interpretations, and conclusions are entirely our own.