DEBT MATURITY, FIRM LIQUDITY, AND EQUITY RETURNS

EUROPEAN EVIDENCE

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Debt Maturity, Firm Liquidity, and Equity Returns: European Evidence

Abstract:

This paper provides evidence that European firms that frequently refinance outstanding debt exhibit higher equity returns, but this premium is conditional on firm size and liquidity. We find that small firms that frequently rollover debt with a stable liquidity position have higher returns, whereas those with weaker liquidity face lower returns. The refinancing premium is consistent with greater exposure to rollover risk, a key risk for which equityholders demand compensation. Even so, refinancing when liquidity is constrained amplifies the risk of financial distress, reflected in a return discount rather than a premium. Our results suggest that corporate asset pricing should consider not only the maturity structure of debt but also its joint interplay with liquidity position and firm size.

Keywords:

Debt maturity, Maturity mismatch, Liquidity, Equity returns, Asset pricing, Capital structure

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I. Introduction

The 2023 collapse of Silicon Valley Bank reignited concerns over *maturity mismatches*, where firms finance illiquid long-term assets with short-term debt. This showcased that, despite overall solvency, mismatches can pressure a firm's liquidity position and trigger financial distress (Jha, Akhtar, and Rana, 2025). While often framed as a bank-specific risk, similar mismatches exist in nonfinancial sectors. From a corporate finance perspective, a shorter debt maturity structure can offer lower financing costs and greater flexibility. Even so, it also exposes firms to rollover risk, the risk associated with refinancing their outstanding debt. As short-term debt requires more frequent refinancing, firms become sensitive to shifts in credit market conditions. In response, investors may demand compensation in the form of higher returns. Friewald, Nagler, and Wagner (2022) document that U.S. firms with higher *refinancing intensity*, the share of short-term debt to total debt, have higher average stock returns. They argue that this premium is driven by greater exposure to rollover risk, while distress risk remains low.

In this paper, we extend the work by Friewald et al. (2022) in two ways. First, we broaden the empirical setting by focusing on publicly listed European firms. Second, we examine how a firm's liquidity position, proxied by maturity mismatch, conditions the pricing of refinancing risk in equity markets. Specifically, we explore two central research questions:

1. Do firms with higher refinancing intensity earn higher expected returns due to rollover risk exposure?

2. Is this premium conditional on firms' liquidity position?

When a firm cannot refinance maturing debt or generate sufficient near-term cash flows, it may be forced into default. In such cases, creditors assume control, and shareholders may inherit little to no residual value. Equity markets are typically sensitive to this dynamic. In a distressed state with an elevated default probability, investors tend to discount firm value (Campbell, Hilscher, and Szilagyi, 2008). While previous research suggests that high refinancing intensity is associated with low distress risk, firms may be more vulnerable to distress when simultaneously constrained by a pressured liquidity position, complicating debt refinancing. As a result, the interaction between debt maturity structure and a firm's liquidity position is likely to play a central role in determining how rollover risk is priced. Refinancing intensity may command a risk premium only when firms have sufficient liquidity. Otherwise, it may cause heightened distress risk and be penalized accordingly.

To investigate these questions, we construct a dataset of publicly traded nonfinancial firms listed on major European stock exchanges from 1993 to 2025. Following existing literature, we measure two key aspects of debt characteristics. First, we measure refinancing intensity, capturing exposure to rollover risk. Second, we measure maturity mismatch, the degree to which a firm's short-term debt finances long-term assets, indicative of a pressured liquidity position. We examine how these two dimensions affect equity returns independently and jointly.

Additionally, we consider the role of firm size and market conditions in shaping these effects. Petersen and Rajan (1994) show that access to financing increases with better lender relationships. Larger firms, having been in the market longer, are more likely to have established such ties with creditors, granting them more stable access to credit. This can help reduce the distress risks typically linked to maturity mismatches. Cornett, McNutt, Strahan, and Tehranian (2011) show that credit supply decreased during the 2007-2009 financial crisis, suggesting that access to financing dries up during crisis periods. To account for these variations, we analyze subsamples based on firm size and market volatility. This allows us to assess how access to credit shapes the relationship between debt maturity and equity returns.

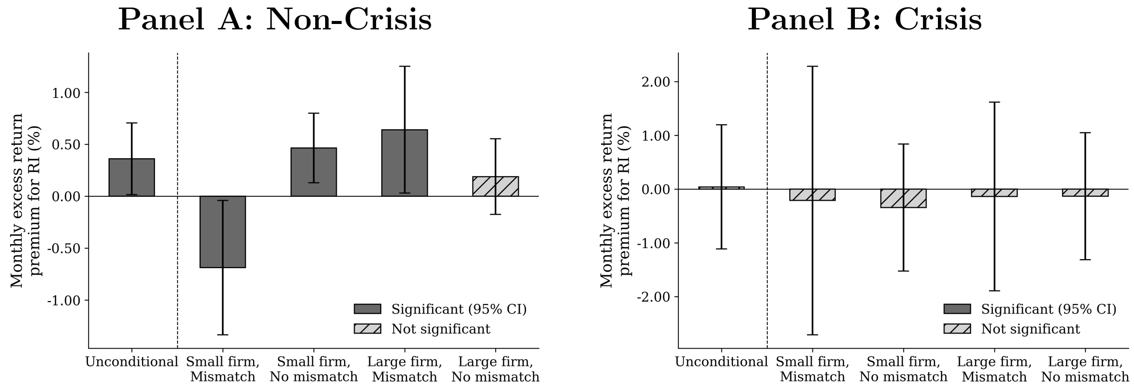

Figure 1. Return Spreads for Refinancing Intensity During Non-Crisis and Crisis Periods. This figure presents the average monthly high-minus-low excess return spreads for refinancing intensity (RI) based on the All-LEV dataset. Results are shown separately for non-crisis (Panel A) and crisis periods (Panel B), defined as months when the EURO STOXX 50 Volatility Index exceeds 30, on average. Each bar represents the return differential between high and low RI portfolios, formed using a $3 \times 3 \times 2 \times 2$ independent sort on leverage (LEV), RI, maturity mismatch (MM), and market capitalization ($MCAP$). We define high and low RI portfolios as the top and bottom 20% each month. We classify firms as having a maturity mismatch if $MM > 0$, and group firms into small and large based on median $MCAP$. The leftmost bar shows the RI premium for the full sample, while the remaining bars show spreads by maturity mismatch and firm size. Error bars represent 95% confidence intervals using robust standard errors.

Our main finding is that European firms with higher refinancing intensity have higher equity returns, consistent with a priced premium for exposure to rollover risk. Even so, the relationship between equity returns and debt maturity depends on the underlying liquidity position, influenced by whether sufficient liquid assets support near-term obligations, and firm size. We show this in Figure 1. Panel A shows that firms with high refinancing intensity only earn higher returns when not facing a maturity mismatch, and when the firm is large enough to ensure stable access to credit markets. In contrast, small firms with high refinancing intensity and a maturity mismatch earn lower returns, consistent with the market imposing a discount for financial distress risk. Moreover, Panel B shows that during periods of heightened market stress, the pricing of debt characteristics disappears, suggesting that macroeconomic uncertainty triumphs over firm-specific balance sheet information.

Our results contribute to the literature in two ways. First, we show that short-term debt generally commands a premium, consistent with increased exposure to rollover risk, extending previous literature to a European setting. Second, we demonstrate that the pricing of debt maturity in equity markets depends on context. This highlights the importance of jointly considering refinancing intensity, maturity mismatch, and firm size when assessing risk premia, providing a new perspective to the literature. Together, these findings deepen our understanding of how debt maturity interacts with firm characteristics to influence equity returns, with implications for asset pricing and corporate finance.

The remainder of the paper is structured as follows: Section II introduces the key theoretical concepts, reviews the related literature, and positions our contribution thereafter. Section III describes the data collection, variable construction, filtering, and sample characteristics. Section IV outlines the empirical methodology and presents our main results, including controls for size and market uncertainty. Section V presents the results from the robustness test, and Section VI concludes our findings and discusses their broader implications.

II. Theoretical Background and Literature Review

A. Fundamental concepts

We begin by outlining key concepts relevant to the pricing of debt maturity in equity markets.

The choice between short-term and long-term debt plays a key role in shaping financial risk and operational flexibility, reflecting opposing economic forces. These trade-offs shape a firm's overall risk profile and influence the return equity investors require. Importantly, they drive systematic and idiosyncratic risk differently. As a firm's exposure to systematic (market) risk increases, investors demand higher expected returns, a relationship formalized by Sharpe (1964) through the Capital Asset Pricing Model (CAPM). Fama and French (2015) extend this framework with the five-factor model (FF5), capturing additional dimensions of systematic risk, including size, value, profitability, and investment. In contrast, idiosyncratic risk, being firm-specific and diversifiable, should not command a risk premium in expected returns.

Short-term debt offers greater adaptability, enabling firms to adjust capital structures in response to evolving conditions. Dangl and Zechner (2021) show that short-term debt improves responsiveness to shifts in operational needs. Additionally, Anginer, Demirguc-Kunt, Simsir, and Tepe (2022) argue that shorter maturities strengthen monitoring, mitigating agency costs through regular creditor oversight. While these mechanisms can reduce firm-specific risk, He and Xiong (2012) emphasize that frequent refinancing also increases exposure to rollover risk, and thereby exposure to systematic risk.

Conversely, long-term debt reduces rollover risk but limits responsiveness to shocks and may exacerbate debt overhang, where existing debt obligations discourage new, value-creating investments, a concern raised by Myers (1977). Short-term debt amplifies systematic, priced risk, whereas long-term debt increases idiosyncratic, non-priced risk.

B. Related Literature

The role of leverage in explaining equity returns in the U.S. has been widely debated, with contradicting evidence. Fama and French (1992) show that leverage adds little explanatory power to cross-sectional return models once size and book-to-market are accounted for. Building on this, Penman, Richardson, and Tuna (2007) decompose the book-to-market ratio into an enterprise and leverage component and find that financial leverage is negatively associated with stock returns. In contrast, Ippolito, Steri, and Tebaldi (2017) introduce a trade-off model where firms adjust towards a target leverage, where equity returns depend on whether firms are above or below their target leverage. Taken together, the literature provides an ambiguous explanation of how financial risk from leverage is reflected in equity prices. In this paper, we depart from the focus on leverage and instead examine debt maturity structure.

Recent studies offer mixed evidence on how debt maturity influences equity returns in the U.S. Chaderina, Weiss, and Zechner (2022) find that firms with long-term debt earn higher equity returns, attributing this to more countercyclical leverage profiles and greater exposure to persistent market risk. In contrast, Friewald et al. (2022) show that the maturity premium associated with long-term debt diminishes once leverage is accounted for. Instead, they find a return premium for firms with short-term debt, consistent with the pricing of rollover risk. These findings suggest that while debt maturity impacts equity returns, the interaction with other balance sheet characteristics, such as leverage, appears impactful. Building on this literature, we examine the pricing of debt maturity in a European context and investigate how this relationship depends on firm-level liquidity, proxied by maturity mismatch.

Extensive literature examines the relationship between equity returns and financial distress risk. Vassalou and Xing (2004) employ a Merton-style model to estimate firm-level default probabilities and document a positive association between expected default risk and subsequent equity returns, suggesting that distress may be a priced systematic factor under the size and value effects. Supporting this view, Chan and Chen (1991) argue that small, financially constrained firms drive the size effect. However, most literature challenges these views, where firms with higher bankruptcy risk earn lower, not higher, returns. Using the Ohlson O-score and Altman Z-score models, Dichev (1998) measures bankruptcy risk and shows that high-distress stocks systematically underperform low-distress stocks, contradicting the notion that distress risk is positively priced. Campbell et al. (2008) reinforce this view using a failure prediction model. They find that financially distressed firms, despite their higher volatility and systematic risk exposure, deliver anomalously low returns. We further contribute to the literature on distress risk by evaluating whether a pressured liquidity position affects the pricing of debt maturity in equity markets.

More recent work examines the role of maturity mismatch in shaping equity returns. Qiu, Bai, and Chen (2024) analyze Chinese firms and show that an asset-liability maturity mismatch is associated with lower abnormal returns. They attribute this pattern to investors being more concerned about liquidity shortfalls and elevated distress risk. Their findings provide empirical support for using maturity mismatch as a proxy for liquidity pressure. While not the focus of our study, we expand on this discussion by looking at the pricing of maturity mismatches in Europe.

Literature has also tried to explain the persistent underperformance of firms with high distress risk in the U.S. Gao, Parsons, and Shen (2018) find that the negative return is most pronounced among small-cap firms in developed markets, attributing this to mispricing for smaller firms. In contrast, Griffin and Lemmon (2002) propose that the underperformance of distressed firms, particularly those with low book-to-market ratios, reflects market mispricing. They argue that investors overvalue these "distressed growth" firms, which underperform as expectations reverse. Friewald et al. (2022) provide a different perspective, disentangling the effects of leverage and debt maturity on distress risk. Their model shows that higher leverage increases default probability and lowers credit risk premium. At the same time, refinancing intensity leads to lower default probability and a higher credit risk premium. Although their model underscores debt maturities' role in shaping distress risk and equity returns, they do not consider the interaction with firm-level liquidity positions. We extend their analysis by examining how a firm's liquidity position affects the pricing of debt maturity in equity markets.

Although prior research has examined the pricing of debt maturity in equity markets, the role of a firm's liquidity position in shaping the relationship remains unexplored. To address this gap, we introduce a conditional framework that captures the interaction between debt maturity, liquidity position, and firm size. In addition, we contribute by extending the U.S.-centric research of debt maturity to a European setting.

III. Data

We comprise a sample of nonfinancial firms listed on major European stock exchanges: AIM, ATSE, BDM, BIT, BME, BRSE, BST, CPSE, DB, DUSE, ENXTAM, ENXTBR, ENXTLS, ENXTPA, HLSE, HMSE, HNSE, ISE, LSE, MUN, NGM, OB, OFEX, OM, OTCNO, SWX, WBAG, and XTRA. We retrieve firm-level monthly returns, stock exchanges, and accounting data from Capital IQ and monthly Fama-French factors from the Kenneth French Data Library. Additionally, to proxy periods of financial crisis, we collect the daily volatility index of European stocks, the EURO STOXX 50 Volatility Index, from STOXX and compute monthly averages. Following Fidelity International's (n.d.) definition, we classify months with an average index exceeding 30 as crisis periods.

Following Friewald et al. (2022), we match each firm's accounting data to its stock returns using a six-month reporting lag. For example, financial statements dated December 2020 are matched to returns beginning in July 2021. This lag ensures that market valuations reflect reported accounting information. As a result, while our return sample spans January 1993 to January 2025, the accounting data concludes with the latest annual reports available as of July 2024.

Furthermore, we fix each firm's market capitalization, $MCAP$, at its first observed value of the respective year and hold this value constant throughout the year. This prevents our financial metrics from being influenced by intra-year fluctuations in market capitalization, providing a consistent basis for calculating variables like market leverage, LEV, and refinancing intensity, RI. Fama and French (1992) employ a similar approach, using market equity from December of the previous year to compute BE/ME.

We exclude firms in the financial sector (SIC codes 6000-6999) from our sample. Financial firms' distinct balance sheet structures and regulatory requirements hinder comparability with non-financial firms (Fama and French, 1992). We further exclude observations with non-positive or missing values for market capitalization, book equity, long-term liabilities, total debt, total assets, or long-term assets to ensure that the debt characteristics we examine are defined. To estimate β, we regress each firm's monthly stock excess returns against the market risk premium, MRP, over 60 months preceding January 2025, following the CAPM. To ensure robustness in the β-estimation, we require a minimum of 24 months of return data for each firm to ensure robustness in the estimations. We apply these filtering criteria to further ensure data quality and consistency between observations.

Capital IQ provides comprehensive balance sheet data on firms' debt maturity structures, detailing various debt components. Specifically, using information on total debt and long-term debt maturing within one, two, and three years, we construct our key leverage measures. Following Friewald et al. (2022), we define LEV as the ratio of total debt to the sum of total debt and $MCAP$,

$$LEV = \frac{TotalDebt}{TotalDebt + MCAP},$$

and refinancing intensity, RI, as the proportion of short-term refinancing needs, represented by the sum of long-term debt maturing within the next three years, relative to total debt,

$$RI = \frac{LTDebtDue1Yr + LTDebtDue2Yr + LTDebtDue3Yr}{TotalDebt}.$$

To ensure RI is defined, we exclude observations with $LEV < 0$. Furthermore, as this study focuses on the returns associated with varying degrees of RI, we exclude observations with $RI \leq 0$. Finally, consistent with Friewald et al. (2022), we classify observations with $LEV < 0.05$ as almost-zero leverage, AZL. To examine potential differences arising from these observations, we split the dataset into two groups: All-LEV, which includes all observations, and All-but-AZL, which excludes firms classified as AZL.

To investigate the effect of debt maturity mismatch, we follow Qiu et al. (2024) by defining maturity mismatch, MM, as

$$MM = \frac{LTAssets - LTLiabilities - Equity}{LTAssets}.$$

This metric indicates the extent to which short-term funds finance a firm's long-term assets: higher values suggest a greater mismatch, whereas negative or low values denote that long-term financing sufficiently covers long-term assets. MM is a continuous variable bounded above by 1, taking values in the interval $MM \in (-\infty, 1]$.

Before summarizing our data, we compute *Excess Return* for each observation as the monthly return less the risk-free interest rate, r_f. Finally, we filter extreme outliers among key variables from our dataset: *Excess Return*, *RI*, return on equity (*ROE*), operating profitability (*OP*), book-to-market (*B/M*), investment-to-assets (*I/A*), and *MM*. This step prevents extreme values from distorting the analysis.

The complete sample of levered firms (All-LEV) includes 209,766 observations across 1,931 unique firms, whereas the subset excluding firms with almost-zero leverage (All-but-AZL) contains 188,535 observations across 1,854 unique firms.

Table I

Summary Statistics

This table presents the means and standard deviations (σ) for *Excess Return*, market leverage (*LEV*), refinancing intensity (*RI*), maturity mismatch (*MM*), beta (β), and market capitalization (*MCAP*). *Excess Return* is in percentages. We present summary statistics for the full sample of all levered firms (All-LEV) and the subsample excluding firms with a leverage ratio below 5% (All-but-AZL). We base the statistics on monthly data for non-financial firms listed on major European stock exchanges between January 1993 and January 2025. We also report the number of observations and unique firms for each dataset.

	All-LEV		All-but-AZL	
	Mean	σ	Mean	σ
Excess Return [in %]	0.15	10.22	0.15	10.24
LEV	0.29	0.20	0.31	0.19
RI	0.49	0.24	0.47	0.23
MM	-0.37	0.53	-0.32	0.48
β	1.02	0.41	1.02	0.42
MCAP [in $1bn]	8.35	24.46	8.28	24.09
Observations	209,766		188,535	
Firms	1,931		1,854	

Table I presents means and standard deviations for *Excess Return*, debt characteristics, β, and *MCAP* across the full All-LEV sample and the All-but-AZL sample. There are close similarities between the two samples. The average monthly *Excess Return* is 0.15% in both samples, with a standard deviation of 10.22% in the full sample and 10.24% in the All-but-AZL sample, indicating both show variation in stock performance. *LEV* averages 0.29 in the full sample and 0.31 in the All-but-AZL sample, with corresponding standard deviations of 0.20 and 0.19. *RI* has a mean of 0.49 in the full sample and 0.47 in the All-but-AZL sample, with standard deviations of 0.24 and 0.23, respectively. *MM* exhibits a larger shift. The average increases from -0.37 in the full sample to -0.32 in the All-but-AZL sample, while the standard deviation decreases from 0.53 to 0.48. Notably, the average firm in our sample does not exhibit a maturity mismatch. The mean β is 1.02 in both samples, with a standard deviation of 0.42 in the full sample and 0.41 in the All-but-AZL sample. *MCAP* averages 8.35 billion USD in the full sample and 8.28 billion USD in the All-but-AZL sample, with standard deviations of 24.46 and 24.09 billion USD, respectively. Moreover, presented in Table A.I, the book-to-market ratio, operating profitability, investment-to-assets, and return on equity display nearly identical averages across the two samples.

Table II
Correlation Matrices

This table presents the correlation between market leverage (*LEV*), refinancing intensity (*RI*), maturity mismatch (*MM*), and market capitalization (*MCAP*). Panel A reports the findings for the full sample of all levered firms (All-LEV) and Panel B reports the findings for the subsample excluding firms with a leverage ratio below 5% (All-but-AZL). We base the statistics on monthly data for non-financial firms listed on major European stock exchanges between January 1993 and January 2025.

Panel A: Correlation Matrix (All-LEV)				
	LEV	RI	MM	MCAP
LEV	1.00	-0.10	0.29	-0.10
RI	-0.10	1.00	-0.09	-0.13
MM	0.29	-0.09	1.00	0.12
MCAP [in $1bn]	-0.10	-0.13	0.12	1.00
Panel B: Correlation Matrix (All-but-AZL)				
	LEV	RI	MM	MCAP
LEV	1.00	-0.05	0.25	-0.11
RI	-0.05	1.00	-0.08	-0.14
MM	0.25	-0.08	1.00	0.14
MCAP [in $1bn]	-0.11	-0.14	0.14	1.00

We present correlation matrices for *LEV*, *RI*, *MM*, and *MCAP* in Table II. Panel A and Panel B report these correlations for the All-LEV and All-but-AZL samples, respectively. Again, there are close similarities between the two samples.

In both panels, *LEV* and *MM* exhibit a moderate positive correlation, 0.29 in the All-LEV sample and 0.25 in the All-but-AZL sample. Correlations between *RI* and other variables are weak across both samples. *RI* correlates with *LEV* at -0.10 in the All-LEV sample and -0.05 in the All-but-AZL sample, and shows a slightly negative correlation with *MCAP* in both datasets. The correlation between *RI* and *MM* remains small across both samples, -0.09 in the All-LEV sample to -0.08 in the All-but-AZL sample. *MCAP* exhibits weak negative correlation with leverage, around -0.10 in both samples, and a slightly positive correlation with maturity mismatch, 0.12 in the All-LEV sample to 0.14 in the All-but-AZL sample.

The summary statistics and our correlation matrices for the two datasets reveal very similar distributions and relationships across all key variables. This suggests that including firms with near-zero leverage does not materially alter the overall patterns in the data. Given the strong similarities and to preserve the full sample size, we proceed with the complete All-LEV dataset for the remainder of the analysis.

The distribution of our data over time shows higher concentration in recent years, due to data availability in Capital IQ (see Figure A.1). Following Vassalou and Xing (2004), we require a minimum number of monthly observations. Setting this threshold mitigates the risk of our results being driven by a small number of firms. This requirement leads to different sample start dates across the methods in our empirical analysis. However, the variations are relatively small, with start dates ranging from July 1998 to October 2001.

A further concern is survivorship bias. The Capital IQ database may underrepresent firms that ceased to exist or have delisted during the sample period, distorting the results (Carpenter and Lynch, 1999). However, given the size of our dataset and an average beta above one, we consider the sample broadly representative of the wider equity market, reducing concerns over survivorship bias.

We rely on established and widely used sources. Capital IQ is a widely used commercial database for global financial, accounting, and market data. While data availability and quality can vary across countries and firm sizes, we filter our data accordingly to mitigate such concerns. The Kenneth French Data Library is a reputable source for asset pricing factors, including the Fama-French three- and five-factor models. A known limitation is that non-U.S. factors, including those for Europe, are constructed as regional aggregates. To address this, we restrict our sample to firms listed on the major European exchanges that underlie the construction of these factors. Our proxy for market-wide financial stress is based on the EURO STOXX 50 Volatility Index, published by STOXX Ltd., which is majority owned by Deutsche Börse Group. Overall, given their widespread use and strong academic reputation, we consider these data sources reliable for our purposes, while taking appropriate measures to mitigate potential problems and ensure the robustness of our analysis.

IV. Empirical Analysis

We examine the relationship between debt maturity, maturity mismatch, and equity returns in four stages. First, we run cross-sectional regressions to assess the individual and joint associations of debt maturity and maturity mismatch with equity returns. Second, we form portfolios sorted on high versus low levels of debt maturity and maturity mismatch, and we conduct spanning regressions against standard risk factors to evaluate whether the return spreads reflect systematic risk exposure. Third, we perform conditional analyses to isolate the interaction effect between refinancing intensity and maturity mismatch on equity returns. Specifically, we examine return spreads for one variable (e.g., refinancing intensity) conditional on fixed levels of other variables, such as maturity mismatch and firm size. Finally, we examine how the relationship varies between non-crisis and crisis periods by dividing the sample into two subsamples and rerunning both the unconditional and conditional regressions.

A. Cross-sectional regressions

We begin our empirical analysis with cross-sectional Fama and MacBeth (1973) regressions to estimate how leverage (LEV), refinancing intensity (RI), and maturity mismatch (MM) relate to monthly excess returns. Specifically, we regress firm-level excess returns on these variables and then average over time. This approach lets us isolate the effect of each characteristic, holding others constant, as well as observe interactions between them. We run both ordinary least squares (OLS) and weighted least squares (WLS) specifications. The WLS, weighting firms by $MCAP$, reveals whether small firms drive any effects observed.

All regressions use heteroskedasticity- and autocorrelation-consistent (HAC) standard errors following Newey and West (1987), with the optimal truncation lag determined according to Andrews (1991). Given that the data availability is more concentrated towards the latter part of our dataset, we require a minimum of 50 firms per month. As a result, our sample period starts in July 2000.

Table III

Cross-Sectional Regression on Excess Returns

This table presents Fama and MacBeth (1973) cross-sectional regressions on monthly excess returns for leverage (LEV), refinancing intensity (RI), and maturity mismatch (MM). Columns (i)-(iii) and (iv)-(vii) show univariate and multivariate regressions, respectively. We report robust t-statistics along with coefficients. Panel A presents the results for the ordinary least squares regressions, while Panel B reports the results for the weighted least squares regressions, weighted by market capitalization ($MCAP$). We base both panels on the full sample of all levered firms (All-LEV). We require a minimum of 50 firms per month, resulting in an effective sample start date of July 2000.

Panel A: Ordinary Least Squares (OLS)							
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
LEV	-0.41			-0.40	-0.25		-0.25
	[-1.13]			[-1.07]	[-0.67]		[0.64]
RI		0.36		0.32		0.32	0.29
		[2.31]		[1.97]		[2.08]	[1.83]
MM			-0.28		-0.25	-0.27	-0.24
			[-3.42]		[-2.90]	[-3.32]	[-2.80]
Panel B: Weighted Least Squares (WLS)							
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
LEV	-0.52			-0.54	-0.43		-0.47
	[-1.14]			[-1.18]	[-0.90]		[-0.98]
RI		0.44		0.45		0.40	0.45
		[1.72]		[1.78]		[1.64]	[1.83]
MM			-0.46		-0.40	-0.44	-0.38
			[-2.82]		[-2.27]	[-2.78]	[-2.22]

Table III reports the Fama-MacBeth coefficient estimates for LEV, RI, and MM under various model specifications. Specifications (i)-(iii) report univariate regressions for excess returns, each on (LEV, RI, and MM). Specifications (iv)-(vii) show multivariate regressions for excess returns to assess joint explanatory power across these variables. Panel A presents the OLS estimations, while Panel B presents the WLS estimations.

LEV is not significantly associated with excess returns in any specification. This implies that leverage alone fails to explain cross-sectional return variation, aligning with the findings of Friewald et al. (2022) in their U.S. sample. In contrast, our findings indicate that RI and MM exhibit statistically significant associations with excess returns. In specification (ii), RI is significant and positively related to excess returns, with an estimated premium of 0.36% (t-statistic=2.31) and 0.44% (t-statistic=1.72) per month across OLS and WLS regressions, indicating that higher refinancing intensity coincides with higher excess returns. We also find a significant and negative relationship between MM and excess returns across all specifications in both panels. In specification (iii), MM is associated with a discount of -0.28% (t-statistic=-3.42) in OLS and -0.46% (t-statistic=-2.82) in WLS per month, indicating lower excess returns for firms with higher maturity mismatch. The weaker significance in the WLS estimates, for both refinancing intensity and amtruity mismatch, suggests that these relationships are more pronounced among smaller firms.

In the multivariate OLS regression (vii), the coefficient for RI drops to marginal significance (t-statistic=1.83), once both LEV and MM are included. Similarly, in the WLS regressions, RI loses significance in specification (vi) when MM is included (t-statistic=1.64). These results suggest that the explanatory power of RI is not fully independent. Instead, it appears to overlap with other debt characteristics, particularly maturity mismatch, which may capture part of the return variation previously attributed to refinancing intensity in the univariate specifications. This underscores the importance of jointly considering multiple aspects of firms when assessing how equity markets price debt maturity.

Overall, our results align with those of earlier studies. We find that firms with higher refinancing intensity earn higher excess returns, consistent with the rollover risk premium documented by Friewald et al. (2022). In contrast, firms with higher maturity mismatch exhibit lower returns, in line with the liquidity risk penalty reported by Qiu et al. (2024). While leverage may not influence equity returns, maturity mismatch and refinancing intensity appear to influence variation in equity pricing jointly. Next, we consider that the relationship with excess return varies across firms with high and low refinancing intensity or maturity mismatch levels.

B. Portfolio sorting

We proceed with portfolio sorting to examine how equity returns differ between high and low levels of each debt characteristic. Each month, we sort firms into portfolios and compute the average returns. Following Friewald et al. (2022), we implement an independent $3 \times 3 \times 2 \times 2$ sort based on leverage (LEV), refinancing intensity (RI), maturity mismatch (MM), and market capitalization ($MCAP$). For LEV and RI, we classify firms into high and low groups using empirical breakpoints: the top 20 percent form the high group, and the bottom 20 percent form the low group. For $MCAP$, we split firms into large and small groups based on the monthly median. For MM, we assign firms to the high group if $MM > 0$ and to the low group if $MM \leq 0$, reflecting whether a maturity mismatch exists. This sorting procedure creates $3 \times 3 \times 2 \times 2 = 36$ portfolios.

The inclusion of LEV in the portfolio sorting ensures comparability with prior studies, particularly Friewald et al. (2022), and an adequate spread in the sorting variables. However, since leverage is not central to our research question and shows limited explanatory power, we do not emphasize it in subsequent portfolio-based analysis.

Table IV

Portfolio Summary Statistics

This table reports the mean values for leverage (LEV), refinancing intensity (RI), maturity mismatch (MM), market capitalization ($MCAP$), beta (β), and equally (EW) and value-weighted (VW) excess returns across high and low buckets of LEV, RI, and MM. We form these portfolio buckets through an independent $3 \times 3 \times 2 \times 2$ sort on LEV, RI, MM, and $MCAP$. We define high and low RI and LEV portfolios as the top and bottom 20% each month. Maturity mismatch is high if $MM > 0$ and low if $MM \leq 0$. Finally, we classify firms into high and low $MCAP$ buckets based on the monthly median. The sample includes all levered firms (All-LEV).

	RI		MM		LEV	
	Low	High	Low	High	Low	High
LEV	0.30	0.24	0.26	0.38	0.05	0.59
RI	0.18	0.84	0.49	0.46	0.55	0.45
MM	-0.31	-0.44	-0.51	0.16	-0.62	-0.16
MCAP [in $1bn]	11.18	4.06	7.48	11.45	10.08	5.21
β	0.96	1.03	1.03	0.95	1.04	0.96
Excess Return [EW] [in %]	0.30	0.50	0.40	0.08	0.47	0.21
Excess Return [VW] [in %]	0.28	0.58	0.42	0.01	0.43	0.17

Table IV reports the summary statistics and return spreads across the constructed portfolios. The portfolio distributions confirm that the sorting procedure creates meaningful spreads in the intended variables, allowing us to disentangle the effect associated with MM and RI. For example, the spread in RI among the portfolios sorted on MM and LEV is 0.03 and 0.10, respectively. Meanwhile, this spread for the portfolios sorted on RI is 0.66. Table A.II reports portfolio statistics for portfolios sorted on high and low $MCAP$. These portfolios exhibit a pronounced difference in firm size, with an average market cap spread of $15.83 billion, confirming that each sorting dimension is well-defined.

Portfolio averages differ across LEV, RI, and MM. We find that the mean portfolio β is positively related to RI, but negatively associated with both LEV and MM, suggesting that a higher RI is associated with higher market risk, whereas higher LEV and MM reduce market risk. While no portfolio is dominated by small firms, we do observe variation in $MCAP$ across portfolios, particularly for RI, suggesting that the relation between refinancing intensity and equity returns may be impacted by firm size. This further supports the inclusion of firm size as a conditioning variable in our subsequent analysis.

We present equally weighted and value-weighted portfolio excess returns in the last two rows of Table IV. Consistent with our earlier findings and those of Friewald et al. (2022), we observe a positive return premium for refinancing intensity for both high-minus-low equally weighted and value-weighted excess returns, at 0.20% and 0.30%, respectively. In contrast, we find negative return spreads for maturity mismatch, with high-minus-low excess returns of -0.32% for equally weighted and -0.41% for value-weighted excess returns.

The portfolio sorting results align with the findings from our cross-sectional regressions and prior literature. Investors reward firms with high refinancing intensity and penalize those with a maturity mismatch across European firms. The premium for refinancing intensity and the discount for maturity mismatch are further supported by the observed differences in β across portfolios; firms with high *RI* exhibit higher β, while those with high *MM* exhibit lower β. This is supported by Friewald et al. (2022), who argue that the premium for *RI* relates to additional market risk exposure. However, Qiu et al. (2024) attribute the discount for *MM* to distress risks, rather than lower market risk exposure.

C. Portfolio spanning regressions

Next, we examine whether refinancing intensity and maturity mismatch compensate equityholders for bearing systematic risk by conducting spanning regressions. Specifically, we assess whether exposures to established risk factors explain high-minus-low return spreads.

We let $r_t^{EW}(G)$ and $r_t^{VW}(G)$ denote the equally weighted and value-weighted excess returns at time t for portfolio group G, where G is defined by sorting criteria on one or more characteristics. For any characteristic $X \in \{\mathrm{LEV}, \mathrm{RI}, \mathrm{MM}, \mathrm{MCAP}\}$, we define the return spread between the high and low groups at time t as:

$$\begin{aligned} R_{X,t}^{EW} &= r_t^{EW}(X = \text{high}) - r_t^{EW}(X = \text{low}), \\ R_{X,t}^{VW} &= r_t^{VW}(X = \text{high}) - r_t^{VW}(X = \text{low}). \end{aligned} \tag{1}$$

We begin by testing whether the high-minus-low return spreads are significantly different from zero using specification (i), which regresses each spread series $R_{X,t}$ on a constant. This corresponds to a one-sample t-test of the mean return. To evaluate whether the spreads reflect compensation for systematic risk, we estimate two additional specifications: (ii) a CAPM regression including the market risk premium (*MRP*), and (iii) a Fama and French (2015) FF5 model including *MRP*, size (*SMB*), value (*HML*), profitability (*RMW*), and investment (*CMA*).

To ensure sufficient firm representation in each portfolio, we relax the data availability requirement to at least 10 firms per portfolio per month. This, opposed to 50 minimum in the cross-sectional regressions, represents the proportionate decrease in size of the data sample for high and low sorts of *LEV* and *RI*. Consequently, our samples' start dates now range between July 1998 and July 2000.

Table V

Spanning Regressions on Excess Returns

This table presents spanning regressions on high-minus-low return spreads for refinancing intensity (RI) and maturity mismatch (MM) on excess returns. We form high and low portfolio buckets through an independent $3 \times 3 \times 2 \times 2$ sort on leverage (LEV), RI, MM, and market capitalization $MCAP$. We define high and low RI and LEV portfolios as the top and bottom 20% each month. Maturity mismatch is high if $MM > 0$ and low if $MM \leq 0$. Finally, we classify firms into high and low $MCAP$ buckets based on the monthly median. We calculate return spreads as the difference in returns for high and low RI portfolios (R_{RI}), and MM portfolios (R_{MM}). Panel A reports coefficients for equally weighted returns, and Panel B for value-weighted returns, weighted by $MCAP$. In specifications (i) and (iv), we regress returns on a constant to test whether the mean return spread differs significantly from zero. Specifications (ii) and (v) include the CAPM market risk premium (MRP), and specifications (iii) and (vi) include the Fama-French five factors: MRP, size (SMB), value (HML), profitability (RMW), and investment (CMA). We report robust t-statistics along with coefficients. The spanning regressions cover the full sample of all levered firms (All-LEV). We require a minimum of 10 firms per month, resulting in an effective sample start date between July 1998 and July 2001, depending on the subgroup analyzed.

Panel A: Equally-Weighted

	R_{RI}^{EW}			R_{MM}^{EW}		
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Intercept	0.20	0.21	0.09	-0.38	-0.34	-0.38
	[1.82]	[1.79]	[1.10]	[-4.11]	[-3.89]	[-4.26]
R_{MRP}		-0.01	-0.03		-0.08	-0.06
		[-0.56]	[-1.41]		[-4.31]	[-3.65]
R_{SMB}			0.19			-0.11
			[4.11]			[-1.79]
R_{HML}			0.19			-0.00
			[2.98]			[-0.01]
R_{RMW}			0.16			0.10
			[1.86]			[1.34]
R_{CMA}			-0.13			0.11
			[-1.96]			[1.36]

Panel B: Value-Weighted

	R_{RI}^{VW}			R_{MM}^{VW}		
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Intercept	0.31	0.22	0.24	-0.42	-0.38	-0.23
	[1.74]	[1.34]	[1.43]	[-2.32]	[-2.08]	[-1.31]
R_{MRP}		0.21	0.14		-0.08	-0.07
		[6.35]	[4.07]		[-1.89]	[-1.79]
R_{SMB}			-0.05			-0.22
			[-0.48]			[-2.38]
R_{HML}			0.28			-0.26
			[2.64]			[-2.83]
R_{RMW}			0.07			-0.20
			[0.64]			[-1.64]
R_{CMA}			-0.51			0.09
			[-3.62]			[0.60]

Table V reports results from spanning regressions of the high-minus-low return spreads for RI, R_{RI}. In specification (i), the average return spread is positive and marginally statistically significant, 0.20% (t-statistic=1.82) per month for R_{RI}^{EW} and 0.31% (t-statistic=1.74) for R_{RI}^{VW}. These results suggest a refinancing premium, particularly among larger firms.

In the CAPM specification (ii), the intercept for R_{RI}^{EW} remains marginally significant (t-statistic=1.79), with no significant loading on the market factors (t-statistic=-0.56). In contrast, R_{RI}^{VW} loads positively on the market factor (t-statistic=6.35) with no significant intercept (t-statistic=1.34). This suggests that, for large firms, the refinancing premium is consistent with exposure to market risk, whereas for smaller firms it is not.

The FF5 specification (iii) provides further insight. R_{RI}^{EW} exhibits significant positive loadings on size (t-statistic=4.11) and value (t-statistic=2.98) factors, and marginally on profitability (t-statistic=1.86) and investment (t-statistic=-1.96), with an insignificant intercept (t-statistic=1.10). R_{RI}^{VW} exhibits significant loadings on market (t-statistic=4.07), value (t-statistic=2.64), and investment (t-statistic=-3.62) factors, again with no residual intercept (t-statistic=1.43). These findings indicate that the premium associated with refinancing intensity is fully explained by systematic risk exposures. Their elevated risk exposures justify a return premium that is consistent with compensation for systematic risk exposure.

For R_{RI}^{VW}, our results overlap with those of Friewald et al. (2022), where we find a significant loading on the market risk factor, attributable to heightened rollover risk that arises with high refinancing intensity. However, we note different loadings on the other risk factors driving the premium. Moreover, R_{RI}^{EW} shows no significant loading on the market risk factor. Instead, value and profitability factors drive the risk premium. Additionally, the premium for R_{RI}^{VW} is larger than R_{RI}^{EW}, indicating that the effect of RI is larger when larger companies receive more weight. Again, this suggests that firm size plays an important role in how refinancing intensity relates to excess returns.

The average return spread between high and low MM firms, R_{MM} is negative and statistically significant in specification (iv), at -0.38% (t-statistic=-4.11) per month for R_{MM}^{EW} and -0.42% (t-statistic=-2.32) for R_{MM}^{VW}. This indicates that firms with greater mismatches earn lower returns on average, consistent with previous work by Qiu et al. (2024). In line with the broader literature on distress risk, these results support the use of maturity mismatch as a proxy for firms' underlying liquidity pressure.

In the CAPM specification (v), both return spreads exhibit significant negative loadings on the market factor, albeit R_{RI}^{VW} is marginally significant (t-statistic=-1.89). However, the intercepts remain significant (t-statistic between -3.89 and -2.08), indicating that market risk explains part, but not all, of the return spread.

In the FF5 specification (vi), R_{MM}^{EW} exhibits a significantly negative loading on the market factor (t-statistic=-3.65) and marginally significant loading on size (t-statistic=-1.79). The intercept remains significant (t-statistic=-4.26), indicating that systematic risk factors fail to explain the full variations in return spreads. By contrast, R_{MM}^{VW} is fully explained by systematic risk exposure as it loads negatively on size (t-statistic=-2.38) and value (t-statistic=-2.83), with an insignificant intercept (t-statistic=-1.31). These results suggest that the discount for maturity mismatch reflects reduced systematic risk among firms with high maturity mismatch. This interpretation aligns with our earlier observation from the portfolio summary statistics, where firms with high maturity mismatch displayed lower average market betas. However, when we do not weight by firm size, the discount is driven by a significant non-systematic component. As Qiu et al. (2024) observed, this discount can be attributed to firm-specific distress risk stemming from maturity mismatches. Smaller firms have poorer access to credit markets, and therefore, the liquidity pressures from maturity mismatches become more pronounced.

European firms with higher levels of short-term debt are associated with higher expected returns, with a compounded annual premium of approximately 3.70%. Systematic risk factors fully explain this premium, but factor loadings differ by firm size. When larger firms receive more weight, we note that the premium is driven by rollover risk. However, our results indicate that both the magnitude and statistical significance of the refinancing premium differ between European and U.S. firms, suggesting that geographical differences may impact our analysis. This underscores a note of caution in generalising regional findings globally, which is a potential limitation in applying our findings outside of Europe.

Next, we examine the interaction between *RI* and *MM*, and the subsequent impact on equity returns, dividing the analysis between small and large firms to account for differences in firm size. This approach allows us to disentangle the observed return spreads and gain deeper insights into the underlying drivers of the *RI* premium and the *MM* discount.

D. Interaction effects

To further examine the effects of debt characteristics on equity returns, we analyze the interaction between refinancing intensity (RI) and maturity mismatch (MM) through a set of conditional spanning regressions. In particular, we assess whether the high-minus-low return spreads for (RI) and (MM) differ while segmenting the sample by firm size, and high and low values of the other variable. We distinguish between small, $MCAP$ = low, and large, $MCAP$ = high firms. This approach builds on the results from Panel B of Table V and allows us to explore how the pricing of debt characteristics varies with firms' liquidity positions, debt maturity structures, and size.

We estimate three regression specifications for each conditional spread. (i & iv) are regression implementations of a one-sample t-test to test whether the average spreads differ from zero. To evaluate whether the spreads reflect compensation for systematic risk, we estimate additional specifications: (ii & v) are CAPM regressions, and (iii & vi) are FF5 models. We use value-weighted returns throughout, and each conditional spread is the difference in average returns between firms with high versus low values of each characteristic, holding the conditioning variables constant. To do this, we simply extend equation (1) to account for additional criteria. For example, the return spread for maturity mismatch, conditional on high refinancing intensity and small firm size, is given as:

$$R^{VW}_{MM,t|RI=\text{high},\,MCAP=\text{low}} = r^{VW}_t(MM = \text{high},\ RI = \text{high},\ MCAP = \text{low}) - r^{VW}_t(MM = \text{low},\ RI = \text{high},\ MCAP = \text{low}).$$

We require a minimum of three observations per month, as our stricter sample criteria further limit the number of observations in our dataset. Requiring more observations would reduce the number of monthly returns available, making the results less reliable. Consequently, our samples' start dates now range between July 1999 and October 2001.

Table VI

Conditional Spanning Regressions on Excess Returns

This table presents conditional spanning regressions on value-weighted high-minus-low return spreads for constructed portfolios of firms. We form high and low portfolio buckets through an independent $3 \times 3 \times 2 \times 2$ sort on leverage (LEV), refinancing intensity (RI), maturity mismatch (MM), and market capitalization ($MCAP$). We define high and low RI and LEV portfolios as the top and bottom 20% each month. Maturity mismatch is high if $MM > 0$ and low if $MM \leq 0$. Finally, we classify firms into high and low $MCAP$ buckets based on the monthly median. We calculate return spreads as the average difference in returns for high and low RI portfolios R^{VW}_{RI}, holding MM and $MCAP$ constant at either high or low levels. Similarly, we calculate the return spread for MM, R^{VW}_{MM}, holding RI and $MCAP$ constant at either high or low levels. In specifications (i) and (iv), we regress returns on a constant to test whether the mean return spread differs significantly from zero. Specifications (ii) and (v) include the CAPM market risk premium (MRP), and specifications (iii) and (vi) include the Fama-French five factors: MRP, size (SMB), value (HML), profitability (RMW), and investment (CMA). We report robust t-statistics along with coefficients. The spanning regressions cover the full sample of all levered firms (All-LEV). We require a minimum of three firms per month, resulting in an effective sample start date between July 1999 and October 2001, depending on the subgroup analyzed.

	$\mathrm{R}^{VW}_{RI\|MM=high,MCAP=low}$			$\mathrm{R}^{VW}_{RI\|MM=high,MCAP=high}$		
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Intercept	-0.59	-0.62	-0.56	0.45	0.31	0.58
	[-1.80]	[-1.85]	[-1.58]	[1.49]	[1.12]	[1.90]
R_{MRP}		0.06	0.01		0.28	0.15
		[0.95]	[0.07]		[4.49]	[1.93]
R_{SMB}			0.11			0.16
			[0.73]			[1.26]
R_{HML}			0.16			0.10
			[0.63]			[0.50]
R_{RMW}			-0.22			-0.53
			[-0.83]			[-2.54]
R_{CMA}			-0.06			-0.78
			[-0.16]			[-3.27]

Continued

Table VI (continued)

	$R^{VW}_{RI\|MM=low,MCAP=low}$			$R^{VW}_{RI\|MM=low,MCAP=high}$		
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Intercept	0.40	0.43	0.28	0.15	0.06	0.13
	[2.52]	[2.62]	[1.60]	[0.80]	[0.34]	[0.68]
R_{MRP}		-0.06	-0.03		0.22	0.17
		[-1.82]	[-0.96]		[5.51]	[4.56]
R_{SMB}			0.20			-0.11
			[2.32]			[-0.96]
R_{HML}			0.06			0.15
			[0.57]			[1.46]
R_{RMW}			0.31			0.05
			[1.94]			[0.31]
R_{CMA}			0.02			-0.44
			[0.13]			[-2.59]

	$R^{VW}_{MM\|RI=high,MCAP=low}$			$R^{VW}_{MM\|RI=high,MCAP=high}$		
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Intercept	-0.77	-0.78	-0.64	0.06	0.10	0.17
	[-2.79]	[-2.81]	[-2.19]	[0.28]	[0.42]	[0.67]
R_{MRP}		0.01	0.03		-0.07	-0.13
		[0.12]	[0.52]		[-1.17]	[-1.73]
R_{SMB}			-0.06			0.17
			[-0.34]			[1.27]
R_{HML}			-0.32			0.09
			[-1.48]			[0.51]
R_{RMW}			-0.53			-0.26
			[-2.02]			[-1.27]
R_{CMA}			0.41			-0.21
			[1.35]			[-0.83]

	$R^{VW}_{MM\|RI=low,MCAP=low}$			$R^{VW}_{MM\|RI=low,MCAP=high}$		
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Intercept	0.31	0.35	0.28	-0.24	-0.19	-0.29
	[1.23]	[1.37]	[1.04]	[-1.18]	[-0.91]	[-1.33]
R_{MRP}		-0.11	-0.02		-0.11	-0.08
		[-2.41]	[-0.44]		[-2.30]	[-1.76]
R_{SMB}			0.02			-0.15
			[0.11]			[-1.07]
R_{HML}			-0.28			0.11
			[-1.84]			[0.89]
R_{RMW}			0.17			0.28
			[0.78]			[1.72]
R_{CMA}			0.37			0.11
			[1.77]			[0.57]

Table VI presents the results from our spanning regressions on conditional portfolio returns. Refinancing intensity is conditional on firms' maturity structure and size. $R^{VW}_{RI|MM=\text{high},MCAP=\text{low}}$ exhibits a marginally significant discount of -0.59% (t-statistic=-1.80) in specification (i). In the CAPM regression (ii), we note an insignificant loading on market risk (t-statistic=0.95) and a marginally significant intercept (t-statistic=-1.85), indicating that the discount is not explained by market risk. In the FF5 regression (iii), we find insignificant loadings across all systematic risk factors and the intercept. While we observe a significant discount, the insignificance of the intercept and factor loadings in specification (iii) suggests that we cannot attribute the discount to either systematic or idiosyncratic risk. Although the source of the discount remains ambiguous, the results from specification (i) imply that there is a discount for refinancing intensity when small firms have a maturity mismatch.

Short-term debt increases refinancing frequency, and when firms simultaneously carry a maturity mismatch, this compounding of liquidity pressure appears to trigger investor concerns. Rather than being rewarded for actively managing debt, these firms are viewed as financially fragile. Consequently, we can conclude that higher refinancing intensity does not uniformly correlate with higher equity returns, as suggested by Friewald et al. (2022), our cross-sectional regression (R_{RI}), and our spanning regressions (R^{EW}_{RI} and R^{VW}_{RI}) in Tables IV and V.

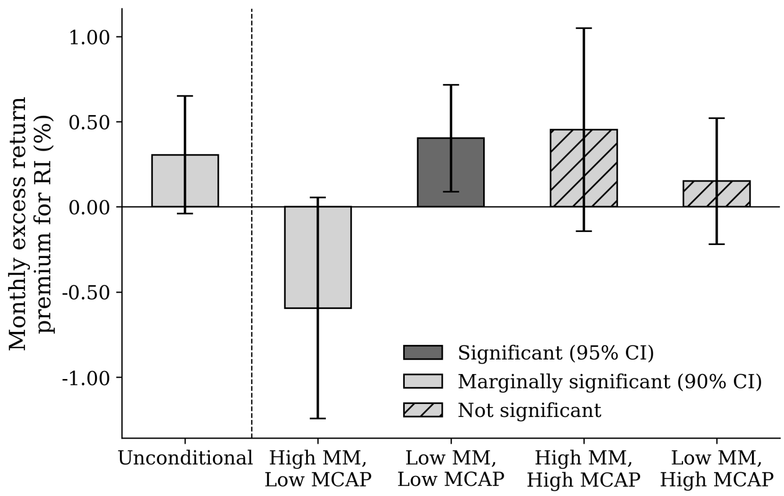

Figure 2. Return Spreads for Refinancing Intensity. This figure presents the average monthly high-minus-low excess return spreads for refinancing intensity (RI) based on the All-LEV dataset. Each bar represents the return differential between high and low RI portfolios, formed using a $3 \times 3 \times 2 \times 2$ independent sort on leverage (LEV), RI, maturity mismatch (MM), and market capitalization ($MCAP$). We define high and low RI and LEV portfolios as the top and bottom 20% each month. Maturity mismatch is high if $MM > 0$ and low if $MM \leq 0$. Finally, we classify firms into high and low $MCAP$ buckets based on the monthly median. We calculate return spreads as the average difference in returns for high and low RI portfolios, holding MM and $MCAP$ constant at either high or low levels. The leftmost bar shows the RI premium for the full sample, while the remaining bars show spreads by maturity mismatch and firm size. Error bars represent 95% confidence intervals using robust standard errors. For our calculations, we require a minimum of three firms per month, resulting in an effective sample start date between July 1999 and October 2001, depending on the subgroup analyzed.

These findings are further reinforced by $R^{VW}_{RI|MM=\text{low},MCAP=\text{low}}$ where we observe a significant premium, with an estimate of 0.40% (t-statistic=2.52) in specification (i). This premium is larger and statistically more significant than the 0.31% (t-statistic=1.74) premium reported in the unconditional regression in Figure 2, indicating that small firms without a pressured liquidity position earn a more pronounced return premium for high refinancing intensity. In the CAPM regression (ii), we note a marginally significant loading on market risk (t-statistic=-1.82) with a significant intercept (t-statistic=2.62), indicating that the premium is not explained by market risk. In the FF5 regression (iii), we note a significant loading on size (t-statistic=2.32), a marginally significant loading on profitability (t-statistic=1.94), and an insignificant intercept (t-statistic=1.60), indicating that the premium reflects compensation for exposure to systematic risk.

For large firms, we find no statistically significant relationship between refinancing intensity and equity returns, regardless of maturity mismatch. Although we cannot completely rule out the presence of an effect, the results indicate that a relationship is likely weaker. This suggests that smaller firms without a maturity mismatch drive the unconditional refinancing premium. These findings indicate that the pricing of refinancing intensity is not consistent across firms, but rather depends on a firm's liquidity position and size. Specifically, small firms appear to only benefit from higher refinancing activity when their maturity structures align.

While our analysis focuses on how distress risk impacts the pricing of debt maturity, running conditional spanning regressions on R^{VW}_{MM} reveals that the interaction between refinancing intensity and maturity mismatch goes both ways. We observe a statistically significant discount of -0.77% (t-statistic=-2.79) per month for $R^{VW}_{MM|RI=\text{high},MCAP=\text{low}}$ in specification (i). The CAPM specification (ii) fails to explain the return differential as the market risk factor is insignificant, but the intercept remains significant (t-statistic=-2.81). In the FF5 specification (iii), $R^{VW}_{MM|RI=\text{high},MCAP=\text{low}}$ exhibits a significant negative loading on the profitability factor (t-statistic=-2.02). At the same time, the intercept (t-statistic=-2.19) remains significant, indicating that standard risk exposures do not fully account for the observed discount.

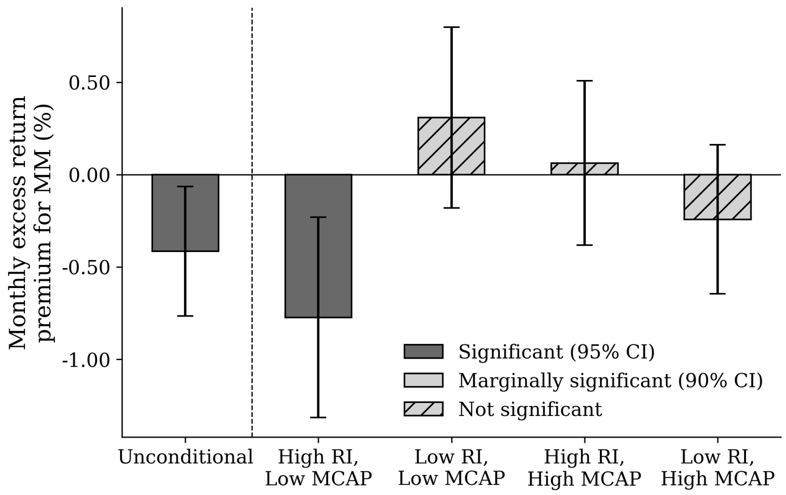

Figure 3. Return Spreads for Maturity Mismatch. This figure presents the average monthly high-minus-low excess return spreads for maturity mismatch (MM) based on the All-LEV dataset. Each bar represents the return differential between high and low MM portfolios, formed using a $3 \times 3 \times 2 \times 2$ independent sort on leverage (LEV), refinancing intensity (RI), MM, and market capitalization ($MCAP$). We define high and low RI and LEV portfolios as the top and bottom 20% each month. Maturity mismatch is high if $MM > 0$ and low if $MM \leq 0$. Finally, we classify firms into high and low $MCAP$ buckets based on the monthly median. We calculate return spreads as the average difference in returns for high and low MM portfolios, holding RI and $MCAP$ constant at either high or low levels. The leftmost bar shows the MM premium for the full sample, while the remaining bars show spreads by refinancing intensity and firm size. Error bars represent 95% confidence intervals using robust standard errors. For our calculations, we require a minimum of three firms per month, resulting in an effective sample start date between July 1999 and October 2001, depending on the subgroup analyzed.

Among small firms with high refinancing intensity, a maturity mismatch is associated with significantly lower equity returns, not explained by exposures to systematic risk. As seen in Figure 3, the return discount in this group is both larger and statistically more significant than the -0.42% (t-statistic=-2.32) unconditional discount for R^{VW}_{MM}. The combination of frequent refinancing and maturity mismatch appears to heighten small firms' financial vulnerability, leading investors to penalize them further. We interpret this discount as compensation for elevated distress risk, in line with the literature. Since smaller firms generally face more limited access to financing, the liquidity strain from rolling over short-term debt under mismatched maturities is particularly severe.

Consequently, higher levels of short-term debt amplify default risk for firms already facing liquidity pressure. This provides a new perspective to Friewald et al. (2022), who argue that refinancing intensity does not exacerbate distress risk. Furthermore, we find no significant relationship between maturity mismatch and equity returns among large firms, regardless of their level of refinancing intensity; nor do we find such a relationship among small firms with low refinancing intensity. These results suggest that smaller firms with a pressured liquidity position who frequently refinance debt drive the unconditional discount observed. This aligns with the findings of Gao et al. (2018), who document that small firms primarily drive the negative relationship between default probability and equity returns.

Our findings indicate that the return premium associated with refinancing intensity is not uniform across firms. Instead, it is conditional on both firm size and liquidity position. Small firms earn a refinancing-intensity premium only if they can manage the accompanying pressure it puts on their liquidity. If managed, this premium is 4.90% per year, compared to -6.90% with a maturity mismatch. Investors distinguish between rollover risk, which reflects exposure to broader market conditions, and distress risk caused by frequently rolling over debt in an already pressured position. Moreover, while maturity mismatch is generally penalized by investors, the magnitude of this effect varies with firm size and debt maturity structure. These results underscore the importance of jointly evaluating debt maturity, liquidity position, and firm size, as maturity structure can amplify distress risk and thereby influence how equity markets price rollover risk.

E. Periods of crisis and non-crisis

To examine whether equityholders price debt maturity differently under different market conditions, we extend our empirical analysis by dividing the sample into two subsamples. We use the EUR STOXX 50 Volatility Index to identify periods of financial stress, defining crisis periods as months in which the index exceeds 30. All other months belong to non-crisis periods. We then re-estimate our baseline unconditional and conditional spanning regressions separately for each subsample. This approach allows us to assess whether the previously identified relationships vary under heightened uncertainty and reduced credit availability.

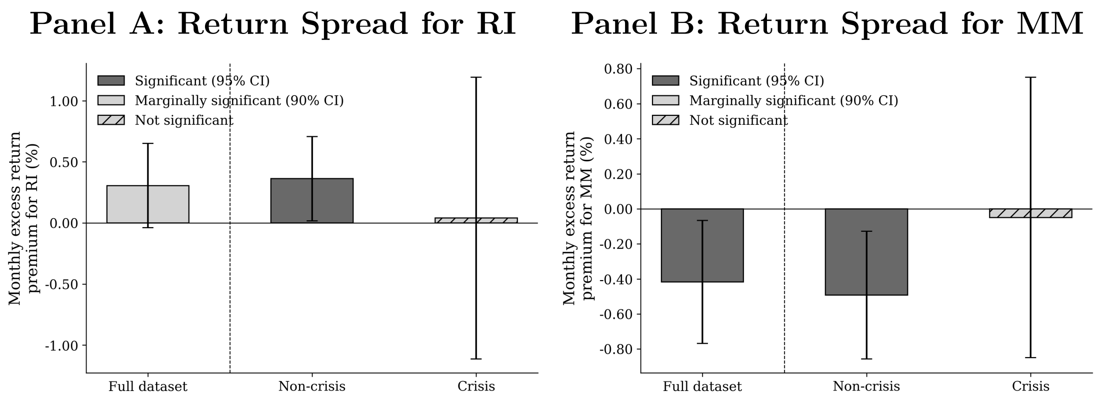

Figure 4. Return Spreads for Refinancing Intensity and Maturity Mismatch Across Different Market Conditions. This figure presents monthly high-minus-low excess return spreads for refinancing intensity (RI) and maturity mismatch (MM) across different subsamples. Each panel presents the excess return spread for a variable, calculated for the full dataset (leftmost bar), non-crisis periods (center bar), and crisis periods (rightmost bar). We define crisis periods as months when the EURO STOXX 50 Volatility Index exceeds 30, on average. Panel A presents the premium for high-minus-low *RI*, and Panel B presents the corresponding discount for *MM*. We calculate return spreads based on portfolios formed through an independent $3 \times 3 \times 2 \times 2$ sort on leverage (LEV), *RI*, *MM*, and market capitalization ($MCAP$). Each month, we sort firms into high and low groups of *MM* based on whether $MM > 0$ or $MM \leq 0$. For *RI*, we use empirical breakpoints: the bottom 20% as low and the top 20% as high. Error bars represent 95% confidence intervals using robust standard errors. We require a minimum of 10 firms per month, resulting in an effective sample start date between July 1998 and July 2001, depending on the subgroup analyzed.

Figure 4 presents the unconditional return spreads for the full dataset, non-crisis periods, and crisis periods. We present full results for our unconditional spanning regressions during non-crisis and crisis periods in Table A.III and Table A.IV, respectively. The key findings in our full sample persist and even strengthen in the non-crisis subsample, where both the magnitudes and statistical significance increase. During non-crisis, firms with high refinancing intensity exhibit a monthly excess return premium of 0.36% (t-statistic=2.06), while those with high maturity mismatch exhibit a discount of -0.49% (t-statistic=-2.64) per month. This suggests that investors reward firms with higher refinancing activity and penalize those with high maturity mismatch, but only in non-crisis periods.

During periods of crisis, none of the estimated return spreads remain statistically significant. Investors tend to reallocate portfolios toward safer asset classes, such as bonds, in a flight-to-quality response (Papadamou, Fassas, Kenourgios, and Dimitriou, 2021). As a result, firm-level balance sheet characteristics, including maturity structures and debt maturity, receive less attention. Consequently, the reduced access to financing during periods of crisis has limited impact, as broader market conditions are more prominent.

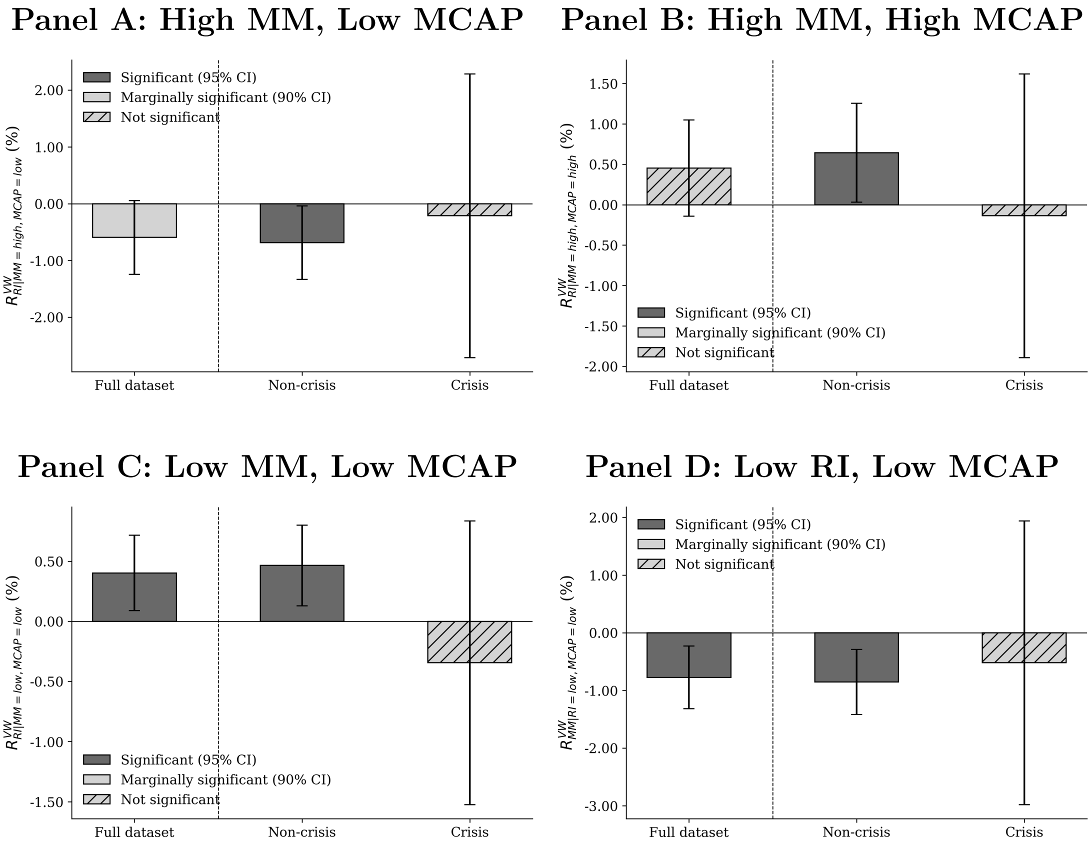

Figure 5. Conditional Return Spreads Across Different Market Conditions. This figure presents monthly high-minus-low excess return spreads for refinancing intensity (RI) and maturity mismatch (MM) conditioned by different portfolio characteristics. Each panel presents the excess return spread for a variable, calculated for the full dataset (leftmost bar), non-crisis periods (center bar), and crisis periods (rightmost bar). We define crisis periods as months when the EURO STOXX 50 Volatility Index exceeds 30, on average. Panel A presents the excess return spread for RI among firms with high MM and low market capitalization ($MCAP$). Similarly, Panel B presents the same spread among firms with high MM and high $MCAP$. Again, Panel C shows the same spread among firms with low MM and low $MCAP$. Finally, Panel D presents the return spread for high-minus-low MM among firms with low RI and low $MCAP$. We calculate return spreads on portfolios formed through an independent $3 \times 3 \times 2 \times 2$ sort on leverage (LEV), RI, MM, and $MCAP$. Each month, we sort firms into high and low groups of MM based on whether $MM > 0$ or $MM \leq 0$. For RI, we use empirical breakpoints: the bottom 20% as low and the top 20% as high. Error bars represent 95% confidence intervals using robust standard errors. We require a minimum of three firms per month, resulting in an effective sample start date between July 1999 and October 2001, depending on the subgroup analyzed.

Figure 5 presents the conditional return spreads for the full dataset, non-crisis periods, and crisis periods. We present full results for our conditional spanning regressions during non-crisis and crisis periods in Table A.V and Table A.VI, respectively. Again, our key findings in the full sample are even stronger in the non-crisis subsample, with the magnitudes and statistical significances of the return spreads increasing. During crisis periods, none of the estimated return spreads remain statistically significant, suggesting that the pricing of debt maturity by equityholders weakens during periods of crisis.

In contrast to our findings in the full sample, during non-crisis periods we find a significant premium (t-statistic=2.06) for $R^{VW}_{RI|MM=\text{high},MCAP=\text{high}}$. This suggests that, during stable times, equity investors do not penalize large firms with high refinancing intensity and a maturity mismatch. This contrasts with smaller firms, which are penalized in the same situation. Larger firms tend to have better access to credit markets, allowing them to manage rollover risk more effectively. As a result, equity investors may perceive these firms as less vulnerable to financial distress. Instead, they exhibit a premium for bearing rollover risk. Consistently, this premium is fully explained by systematic risk exposure, with a significant loading on the market risk premium (t-statistic=2.91), as shown in specification (vi) of Table A.V. These findings highlight the role of credit access and firm size in shaping how equity markets price debt maturity.

Overall, the pricing of debt maturity in equity markets is contingent on the prevailing market conditions. Specifically, during periods of financial stress, investors appear to disregard debt maturity and liquidity position altogether, regardless of firm size. In contrast, during non-crisis periods, the effects identified in our main analysis become more pronounced, suggesting that crisis periods distort the consistent pricing of debt maturity and maturity mismatch, both jointly and independently, observed over longer time horizons.

V. Robustness

To assess the robustness of our main results, we perform a series of sensitivity analyses along three dimensions. First, we test for sample period dependence by restricting the dataset to the most recent 20 and 15-year windows. Second, we examine the impact of varying portfolio breakpoints for refinancing intensity (RI), adjusting the high and low thresholds from the baseline 20% to 25% and 15%. Third, we substitute our baseline maturity mismatch measure with the inverse current ratio, following Li (2024), who demonstrates that the current ratio captures firm-level liquidity risk. The inverse current ratio is calculated as short-term liabilities divided by short-term assets, where higher values indicate an inferior liquidity position.

Table VII
Robustness tests

This table presents robustness tests for the key return premia identified in our main analysis. Each column represents the average high-minus-low return spread, along with robust t-statistics. We show return spreads for refinancing intensity (*RI*) and maturity mismatch (*MM*), as well as conditional return spreads: *MM* conditional on high *RI* and low market capitalization (*MCAP*); *RI* conditional on high *MM* and low *MCAP*; and *RI* conditional on low *MM* and low *MCAP*. We assess robustness along three dimensions. First, we restrict the sample to the most recent 20- and 15-year periods to test time sensitivity. Second, we adjust portfolio breakpoints for *RI*, from 20% (baseline) to 25% and 15%. Third, we substitute maturity mismatch with the inverse current ratio as an alternative proxy for a pressured liquidity position. Our baseline results represent the key findings from our primary analysis using the full All-LEV dataset.

	Unconditional		**Conditional**		
	R^{VW}_{RI}	R^{VW}_{MM}	$R_{\text{MM}\|\text{RI}=high,\ MCAP=low}$	$R_{\text{RI}\|\text{MM}=high,\ MCAP=low}$	$R_{\text{RI}\|\text{MM}=low,\ MCAP=low}$
Baseline	**0.31**	**-0.42**	**-0.77**	**-0.59**	**0.40**
	[1.74]	**[-2.32]**	**[-2.79]**	**[-1.80]**	**[2.52]**
Data Length					
20 years	0.34	-0.20	-0.86	-0.92	0.46
	[1.74]	[-1.46]	[-3.01]	[-2.71]	[3.06]
15 years	0.29	-0.13	-0.34	-0.44	0.39
	[1.38]	[-0.89]	[-1.29]	[-1.24]	[2.52]
Cutoff					
Top 15%	0.40	-0.42	-0.67	-0.44	0.51
	[2.22]	[-2.32]	[-2.10]	[-1.23]	[2.62]
Top 25%	0.21	-0.42	-0.77	-0.50	0.35
	[1.14]	[-2.32]	[-3.32]	[-1.69]	[2.46]
MM Definition					
1 / Current Ratio	0.28	-0.50	-0.58	-0.62	0.33
	[1.60]	[-2.37]	[-1.86]	[-1.46]	[1.95]

Table VII presents the findings from our robustness exercise. When shortening the sample period, the value-weighted premium for *RI* and the discount for *MM* identified in the baseline unconditional regressions lose statistical significance. In contrast, the conditional return patterns, emphasizing the joint role of *RI*, *MM*, and firm size, remain broadly stable over the 20-year horizon, though less so over 15 years. These results suggest that the unconditional return spreads are sensitive to sample length, whereas the conditional relationships exhibit greater persistence. Nonetheless, the sensitivity of both unconditional and conditional estimates over shorter periods represents a limitation of our study, restricting the generalizability of our findings.

We next assess the sensitivity of our sorting procedure by varying the empirical breakpoints for *RI*. We observe minor variation in return differentials using the 15th and 25th percentiles instead of the 20% baseline. However, the main findings remain consistent, suggesting that the specific choice of cutoff does not drive the results and that the sorting procedure yields reliable estimates.

Finally, we evaluate the robustness of our definition of maturity mismatch as a proxy for a pressured liquidity position. We use the inverse current ratio as an alternative to our baseline measure, with high mismatch defined as values exceeding one and low mismatch as values at or below one. This revised threshold reflects a change from our original cutoff (above zero) and aligns more closely with established indicators of short-term liquidity pressure. While the direction of estimated coefficients remains consistent across specifications, the conditional return spreads among *RI*, *MM*, and firm size weaken under the alternative proxy. Moreover, we no longer find evidence of an unconditional *RI* premium.

Overall, our robustness tests indicate that the main results are relatively stable across variations in portfolio sorting methodology. However, their sensitivity to the sample period and the weakening of both unconditional and conditional effects under an alternative liquidity proxy highlight important limitations. These results suggest that the interaction between refinancing intensity, maturity mismatch, and firm size is economically meaningful, but its strength and generalizability are sensitive to empirical design choices. Notably, the only relationship that consistently holds across all robustness tests is that small firms with high refinancing intensity and low maturity mismatch earn a return premium.

VI. Conclusion

This paper examines the role of debt maturity in shaping equity returns, with particular attention to its interaction with firm-specific liquidity and size. Specifically, we investigate whether European firms with a higher reliance on short-term debt exhibit systematically higher equity returns, unconditionally and conditional on the degree of maturity mismatch between assets and liabilities, and firm size. We further explore whether the pricing of these relationships varies across crisis and non-crisis periods to assess the influence of market stress.

Our empirical analysis indicates that European firms with higher levels of short-term debt tend to earn higher equity returns, consistent with investors requiring compensation for exposure to systematic risk, which we attribute to rollover risk. We document an annualized excess return premium of 3.70% for firms with high refinancing intensity relative to their low-exposure counterparts.

However, this premium is not uniform across firms. The pricing of refinancing intensity is conditional on both liquidity position and firm size. Firms earn a premium for short-term debt only when exhibiting a matched maturity structure. In the presence of a maturity mismatch, higher short-term debt instead amplifies financial distress risk, reflected in a return discount rather than a premium. Importantly, this relationship is influenced by firm size, as only small firms are penalized. In contrast, large firms that frequently rollover debt with comparable liquidity profiles continue to earn a premium in non-crisis periods. This suggests that rollover risk is only priced when firms have good credit market access. These findings highlight that firm-level financials and market conditions shape the pricing of debt maturity in equity markets.

Furthermore, this interaction appears sensitive to market uncertainty. During periods of crisis, we find no significant relationship. This is consistent with flight-to-quality behavior by market participants, where broader market trends overshadow firm-specific characteristics. These periods distort the otherwise consistent pricing of debt maturity and maturity mismatch, both jointly and independently, observed in non-crisis periods. As such, empirical analysis of how balance sheet structure influences equity returns is likely more informative when conducted in non-crisis environments.

While our findings point to an economically meaningful relationship between refinancing intensity, maturity mismatch, firm size, and equity returns, several limitations constrain the generalizability of our results. First, our robustness exercise shows sensitivity to time periods and definitions of maturity mismatch. Second, debt characteristics appear to be priced differently across geographies, reflecting market variations. Finally, we only show correlation, not causality. Extending our conclusions, especially beyond the context of listed European firms, should be done cautiously. Future research could address the limitations in our paper by examining how the pricing of debt maturity varies across geographies and time periods. Additionally, future studies could use natural experiments to find a potential causality between debt maturity and equity returns.

Practically, our findings have important implications for both firms and equity investors. For corporate managers, the results highlight that capital structure decisions, specifically those concerning debt maturity and maturity alignment, influence investors' perceptions of the firm. Small companies that rely on short-term debt should be mindful that, in the absence of sufficient liquidity buffers or matched asset-liability profiles, they may be subject to lower valuations as investors adjust for perceived distress risk. By identifying firms that effectively manage their liquidity and distinguishing them from those more vulnerable to refinancing pressures, investors can better understand the pricing of balance sheet risk in the cross-section of returns.

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VII. Appendix

Table A.I

Summary Statistics of Additional Variables

This table presents means and standard deviations (σ) for book-to-market ratio (B/M), operating profitability (OP), investment-to-asset ratio (I/A), and return on equity (ROE). We present summary statistics for the full sample of all levered firms (ALL-LEV) and for the subsample excluding firms with a leverage ratio below 5% (All-but-AZL). The statistics are based on monthly data for non-financial firms listed on major European stock exchanges over the period from January 1993 to January 2025.

	All-LEV		All-but-AZL	
	Mean	σ	Mean	σ
B/M	0.75	0.56	0.78	0.57
OP	0.07	0.06	0.06	0.06
I/A	0.05	0.15	0.05	0.15
ROE	0.10	0.14	0.10	0.14
Observations	209,766		188,535	
Firms	1,931		1,854	

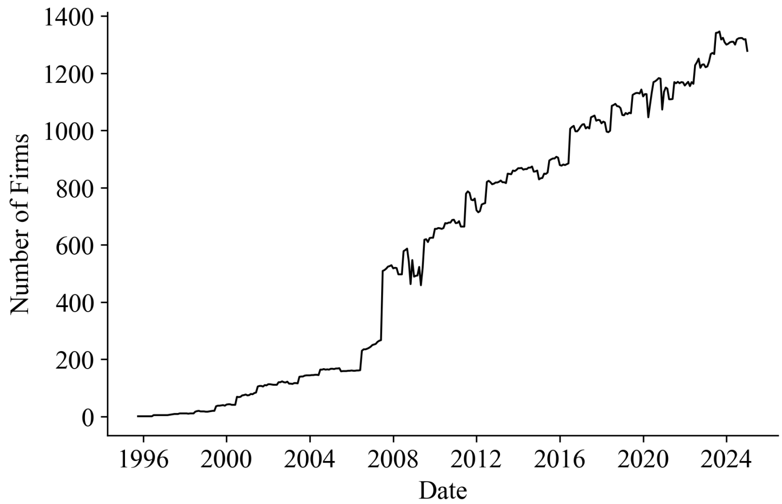

Figure A.1. Number of Firms Per Month. This figure presents the number of firms per month in the All-LEV dataset.

Table A.II
Portfolio Statistics for MCAP

This table reports the mean values for leverage (*LEV*), refinancing intensity (*RI*), maturity mismatch (*MM*), market capitalization (*MCAP*), beta (β), and equally (EW) and value-weighted (VW) excess returns across high and low buckets of *MCAP*. We form portfolio buckets through an independent $3 \times 3 \times 2 \times 2$ sort on *LEV*, *RI*, *MM*, and *MCAP*. Firms are classified into high and low *MCAP* buckets based on the monthly median. The sample includes all levered firms (All-LEV).

	MCAP	
	Low	High
LEV	0.31	0.26
RI	0.53	0.44
MM	-0.45	-0.28
MCAP [in $1bn]	0.42	16.25
β	0.94	1.10
Excess Return [EW] [in %]	0.28	0.33
Excess Return [VW] [in %]	0.40	0.21

Table A.III

Spanning Regressions on Excess Returns During Non-Crisis Periods

This table presents spanning regressions of high-minus-low return spreads for refinancing intensity (RI) and maturity mismatch (MM) during non-crisis periods. We form high and low portfolio buckets through an independent $3 \times 3 \times 2 \times 2$ sort on leverage (LEV), RI, MM, and market capitalization $MCAP$. High and low RI and LEV portfolios are defined as the top and bottom 20% each month. Maturity mismatch is classified as high if $MM > 0$ and low if $MM \leq 0$. Finally, firms are classified into high and low $MCAP$ buckets based on the monthly median. We calculate return spreads as the difference in returns for high and low RI portfolios (R_{RI}), and MM portfolios (R_{MM}). Panel A reports coefficients for equally weighted returns, and Panel B for value-weighted returns, weighted by $MCAP$. In specifications (i) and (iv), we regress returns on a constant to test whether the mean return spread differs significantly from zero. Specifications (ii) and (v) include the CAPM market risk premium (MRP), and specifications (iii) and (vi) include the Fama-French five factors: MRP, size (SMB), value (HML), profitability (RMW), and investment (CMA). We report robust t-statistics along with coefficients. The spanning regressions cover the full sample of all levered firms (All-LEV). We require a minimum of 10 firms per month, resulting in an effective sample start date between July 1998 and July 2001.

Panel A: Equally-Weighted

	R_{RI}^{EW}			R_{MM}^{EW}		
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Intercept	0.23	0.25	0.16	-0.40	-0.36	-0.36
	[2.17]	[2.16]	[1.81]	[-4.35]	[-3.69]	[-3.69]
R_{MRP}		-0.02	-0.03		-0.04	-0.02
		[-1.02]	[-1.34]		[-1.84]	[-1.31]
R_{SMB}			0.21			-0.17
			[3.64]			[-3.19]
R_{HML}			0.11			-0.05
			[1.38]			[-0.78]
R_{RMW}			0.08			0.03
			[0.82]			[0.38]
R_{CMA}			-0.04			0.11
			[-0.51]			[1.15]

Panel B: Value-Weighted

	R_{RI}^{VW}			R_{MM}^{VW}		
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Intercept	0.36	0.16	0.18	-0.49	-0.46	-0.26
	[2.06]	[0.93]	[1.01]	[-2.64]	[-2.14]	[-1.37]
R_{MRP}		0.21	0.15		-0.03	-0.03
		[4.97]	[3.29]		[-0.46]	[-0.52]
R_{SMB}			-0.00			-0.27
			[-0.01]			[-2.08]
R_{HML}			0.28			-0.31
			[2.13]			[-3.57]
R_{RMW}			0.07			-0.23
			[0.55]			[-1.36]
R_{CMA}			-0.56			0.07
			[-3.07]			[0.34]

Table A.IV
Spanning Regressions on Excess Returns During Crisis Periods

This table presents spanning regressions of high-minus-low return spreads for refinancing intensity (RI) and maturity mismatch (MM) during crisis periods. We form high and low portfolio buckets through an independent $3 \times 3 \times 2 \times 2$ sort on leverage (LEV), RI, MM, and market capitalization $MCAP$. High and low RI and LEV portfolios are defined as the top and bottom 20% each month. Maturity mismatch is classified as high if $MM > 0$ and low if $MM \leq 0$. Finally, firms are classified into high and low $MCAP$ buckets based on the monthly median. We calculate return spreads as the difference in returns for high and low RI portfolios (R_{RI}), and MM portfolios (R_{MM}). Panel A reports coefficients for equally weighted returns, and Panel B for value-weighted returns, weighted by $MCAP$. In specifications (i) and (iv), we regress returns on a constant to test whether the mean return spread differs significantly from zero. Specifications (ii) and (v) include the CAPM market risk premium (MRP), and specifications (iii) and (vi) include the Fama-French five factors: MRP, size (SMB), value (HML), profitability (RMW), and investment (CMA). We report robust t-statistics along with coefficients. The spanning regressions cover the full sample of all levered firms (All-LEV). We require a minimum of 10 firms per month, resulting in an effective sample start date between July 1998 and July 2001.

Panel A: Equally-Weighted

	R^{EW}_{RI}			R^{EW}_{MM}		
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Intercept	-0.07	-0.14	-0.41	-0.23	-0.72	-0.72
	[-0.20]	[-0.42]	[-1.12]	[-0.76]	[-2.91]	[-2.73]
R_{MRP}		-0.02	-0.01		-0.17	-0.16
		[-0.52]	[-0.32]		[-4.57]	[-2.92]
R_{SMB}			0.11			-0.03
			[1.27]			[-0.17]
R_{HML}			0.17			0.18
			[1.30]			[1.49]
R_{RMW}			0.42			0.19
			[2.95]			[1.27]
R_{CMA}			-0.20	-		0.05
			[-1.12]			[0.28]

Panel B: Value-Weighted

	R^{EW}_{RI}			R^{EW}_{MM}		
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Intercept	0.04	0.89	0.92	-0.05	-0.56	-0.20
	[0.07]	[2.18]	[2.28]	[-0.12]	[-1.29]	[-0.48]
R_{MRP}		0.29	0.17		-0.17	-0.23
		[5.52]	[2.54]		[-3.46]	[-2.92]
R_{SMB}			-0.15			-0.11
			[-1.28]			[-0.74]
R_{HML}			0.49			0.01
			[3.93]			[0.04]
R_{RMW}			0.10			-0.45
			[0.43]			[-2.11]
R_{CMA}			-0.55			0.08
			[-2.55]			[0.30]

Table A.V

Conditional Spanning Regressions on Excess Returns During Non-Crisis Periods

This table presents conditional spanning regressions on value-weighted high-minus-low return spreads for constructed portfolios during non-crisis periods. We form high and low portfolio buckets through an independent $3 \times 3 \times 2 \times 2$ sort on leverage (LEV), refinancing intensity (RI), maturity mismatch (MM), and market capitalization ($MCAP$). High and low RI and LEV portfolios are defined as the top and bottom 20% each month. Maturity mismatch is classified as high if $MM > 0$ and low if $MM \leq 0$. Finally, firms are classified into high and low $MCAP$ buckets based on the monthly median. We calculate return spreads as the average difference in returns for high and low RI portfolios R^{VW}_{RI}, holding MM and $MCAP$ constant at either high or low levels. Similarly, we calculate the return spread for MM, R^{VW}_{MM}, holding RI and $MCAP$ constant at either high or low levels. In specifications (i) and (iv), we regress returns on a constant to test whether the mean return spread differs significantly from zero. Specifications (ii) and (v) include the CAPM market risk premium (MRP), and specifications (iii) and (vi) include the Fama-French five factors: MRP, size (SMB), value (HML), profitability (RMW), and investment (CMA). We report robust t-statistics along with coefficients. The spanning regressions cover the full sample of all levered firms (All-LEV). We require a minimum of three firms per month, resulting in an effective sample start date between July 1999 and October 2001, depending on the subgroup analyzed.

	$R^{VW}_{RI\|MM=high,MCAP=low}$			$R^{VW}_{RI\|MM=high,MCAP=high}$		
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Intercept	-0.69	-0.70	-0.73	0.64	0.27	0.42
	[-2.08]	[-2.07]	[-1.97]	[2.06]	[0.94]	[1.32]
R_{MRP}		0.01	-0.05		0.32	0.24
		[0.20]	[-0.61]		[3.83]	[2.91]
R_{SMB}			0.16			0.29
			[0.84]			[1.74]
R_{HML}			0.33			0.18
			[1.14]			[0.70]
R_{RMW}			-0.02			-0.25
			[-0.06]			[-1.06]
R_{CMA}			-0.35			-0.90
			[-0.96]			[-3.09]
	$R^{VW}_{RI\|MM=low,MCAP=low}$			$R^{VW}_{RI\|MM=low,MCAP=high}$		
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Intercept	0.47	0.50	0.39	0.19	-0.03	0.10
	[2.73]	[2.85]	[0.39]	[1.02]	[-0.18]	[0.52]
R_{MRP}		-0.04	-0.01		0.23	0.17
		[-1.03]	[-0.29]		[4.01]	[3.22]
R_{SMB}			0.24			-0.11
			[2.62]			[-0.74]
R_{HML}			-0.04			0.14
			[-0.31]			[1.08]
R_{RMW}			0.23			-0.07
			[1.57]			[-0.41]
R_{CMA}			0.17			-0.56
			[0.98]			[-2.97]

Continued

Table A.V (continued)

	$R^{VW}_{MM\|RI=high,MCAP=low}$			$R^{VW}_{MM\|RI=high,MCAP=high}$		
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Intercept	-0.85	-0.83	-0.84	0.04	0.01	0.03
	[-2.97]	[-2.83]	[-2.68]	[0.16]	[0.06]	[0.11]
R_{MRP}		-0.03	-0.03		0.02	0.00
		[-0.60]	[-0.68]		[0.27]	[0.06]
R_{SMB}			0.12			0.16
			[0.68]			[1-26]
R_{HML}			0.06			0.02
			[0.32]			[0.08]
R_{RMW}			-0.03			-0.12
			[-0.11]			[-0.53]
R_{CMA}			0.02			-0.10
			[0.07]			[-0.34]

	$R^{VW}_{MM\|RI=low,MCAP=low}$			$R^{VW}_{MM\|RI=low,MCAP=high}$		
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Intercept	0.47	0.54	0.40	-0.38	-0.32	-0.32
	[1.72]	[1.94]	[1.35]	[-1.60]	[-1.35]	[-1.29]
R_{MRP}		-0.07	0.00		-0.05	-0.05
		[-1.07]	[0.03]		[-0.88]	[-0.88]
R_{SMB}			0.17			-0.24
			[1.14]			[1.75]
R_{HML}			-0.17			-0.04
			[-0.84]			[-0.03]
R_{RMW}			0.42			0.01
			[1.59]			[0.03]
R_{CMA}			0.43			0.17
			[1.89]			[0.63]

Table A.VI
Conditional Spanning Regressions on Excess Returns During Crisis Periods

This table presents conditional spanning regressions on value-weighted high-minus-low return spreads for constructed portfolios during crisis periods. We form high and low portfolio buckets through an independent $3 \times 3 \times 2 \times 2$ sort on leverage (LEV), refinancing intensity (RI), maturity mismatch (MM), and market capitalization ($MCAP$). High and low RI and LEV portfolios are defined as the top and bottom 20% each month. Maturity mismatch is classified as high if $MM > 0$ and low if $MM \leq 0$. Finally, firms are classified into high and low $MCAP$ buckets based on the monthly median. We calculate return spreads as the average difference in returns for high and low RI portfolios R_{RI}^{VW}, holding MM and $MCAP$ constant at either high or low levels. Similarly, we calculate the return spread for MM, R_{MM}^{VW}, holding RI and $MCAP$ constant at either high or low levels. In specifications (i) and (iv), we regress returns on a constant to test whether the mean return spread differs significantly from zero. Specifications (ii) and (v) include the CAPM market risk premium (*MRP*), and specifications (iii) and (vi) include the Fama-French five factors: *MRP*, size (*SMB*), value (*HML*), profitability (*RMW*), and investment (*CMA*). We report robust t-statistics along with coefficients. The spanning regressions cover the full sample of all levered firms (All-LEV). We require a minimum of three firms per month, resulting in an effective sample start date between July 1999 and October 2001, depending on the subgroup analyzed.

	$R^{VW}_{RI\|MM=high,MCAP=low}$			$R^{VW}_{RI\|MM=high,MCAP=high}$		
	(i)	(ii)	(iii)	(i)	(ii)	(iii)
Intercept	-0.21	-0.45	0.18	-0.14	0.64	1.48
	[-0.17]	[0.30]	[0.16]	[-0.15]	[0.83]	[2.00]
R_{MRP}		-0.08	0.07		0.23	-0.18
		[-0.54]	[0.31]		[2.81]	[-1.22]
R_{SMB}			0.35			-0.02
			[0.82]			-0.06[]
R_{HML}			-0.50			0.61
			[-1.16]			[1.81]
R_{RMW}			-0.63			-1.33
			[-1.00]			[-3.17]
R_{CMA}			1.15			-1.13
			[1.69]			[-2.59]
	$R^{VW}_{RI\|MM=low,MCAP=low}$			$R^{VW}_{RI\|MM=low,MCAP=high}$		
	(i)	(ii)	(iii)	(i)	(ii)	(iii)
Intercept	-0.34	-0.79	-1.43	-0.13	0.71	0.57
	[-0.57]	[-1.10]	[-1.97]	[-0.22]	[1.43]	[1.13]
R_{MRP}		-0.15	-0.04		0.29	0.28
		[-1.69]	[-0.41]		[5.17]	[3.69]
R_{SMB}			-0.04			-0.19
			[-0.17]			[-1.22]
R_{HML}			0.01			0.35
			[0.06]			[2.39]
R_{RMW}			1.00			0.44
			[3.41]			[1.30]
R_{CMA}			-0.14			-0.22
			[-0.52]			[-0.81]

Continued

Table A.VI (continued)

	$R^{VW}_{MM\|RI=high,MCAP=low}$			$R^{VW}_{MM\|RI=high,MCAP=high}$		
	(i)	(ii)	(iii)	(i)	(ii)	(iii)
Intercept	-0.52	-0.79	0.04	0.04	-0.82	-0.26
	[-0.42]	[-0.54]	[0.05]	[0.06]	[-1.09]	[-0.39]
R_{MRP}		-0.09	0.16		-0.30	-0.60
		[-0.67]	[1.07]		[-5.32]	[-7.14]
R_{SMB}			0.15			0.18
			[0.52]			[0.73]
R_{HML}			-1.14			0.49
			[-4.20]			[1.82]
R_{RMW}			-1.35			-0.99
			[-3.04]			[-2.49]
R_{CMA}			1.71			-0.73
			[3.94]			[-2.10]

	$R^{VW}_{MM\|RI=low,MCAP=low}$			$R^{VW}_{MM\|RI=low,MCAP=high}$		
	(i)	(ii)	(iii)	(i)	(ii)	(iii)
Intercept	-0.80	-1.46	-1.90	-0.07	-0.82	-1.10
	[-0.87]	[-1.53]	[-2.11]	[-0.14]	[-1.64]	[-2.19]
R_{MRP}		-0.20	-0.08		-0.22	-0.15
		[-2.56]	[-0.62]		[-2.99]	[-1.76]
R_{SMB}			-0.35			-0.00
			[-1.04]			[-0.00]
R_{HML}			-0.27			0.25
			[-1.18]			[0.91]
R_{RMW}			0.49			0.74
			[1.07]			[2.15]
R_{CMA}			0.06			0.13
			[0.16]			[0.62]

AI Appendix

Recognition:
While preparing this paper, we made use of the AI tools ChatGPT and Grammarly for assistance with Python coding and grammar. However, all analyses, interpretations, and conclusions are solely our own.