Effect of Rollover Risk on Default Risk: Evidence from Bank Financing

Chih-Wei Wang[1], Wan-Chien Chiu[2*], and Juan Ignacio Peña[3]

Abstract

We study the effect of rollover risk on the risk of default using a comprehensive database of U.S. industrial firms during 1986–2013. Dependence on bank financing is the key driver of the impact of rollover risk on default risk. Default risk and rollover risk present a significant positive relation in firms dependent on bank financing. In contrast, rollover risk is uncorrelated with default probability in the case of firms that do not rely on bank financing. Our measure of rollover risk is the amount of long-term debt maturing in one year, weighted by total assets. In the case of a firm that depends on bank financing, an increase of one standard deviation in this measure leads to a significant increase of 3.2% in its default probability within one year. Other drivers affecting the interaction between rollover risk and default risk are whether a firm suffers from declining profitability and has poor credit. Additionally, rollover risk's impact on default probability is stronger during periods when credit market conditions are tighter.

JEL classification: G00; G18; G21; G32; G33

Keywords: Rollover risk, default risk, debt maturity, bank dependence

[1] Department of Finance, National Sun Yat-sen University, 70. Lianhai Rd., Kaohsiung, 804 Taiwan; e-mail chwang@mail.nsysu.edu.tw.

[2] Accounting and Finance, Adam Smith Business School, University of Glasgow, Glasgow G12 8QQ, United Kingdom; e-mail Wan-Chien.Chiu@glasgow.ac.uk.

[3] Department of Business Administration, Universidad Carlos III de Madrid, Calle Madrid 126, 28903 Getafe, Madrid, Spain; e-mail ypenya@eco.uc3m.es.

*Corresponding author: Email: Wan-Chien.Chiu@glasgow.ac.uk; Phone: +44 01413306317

Acknowledges

We thank José Antonio Clemente-Almendros at the XXII Finance Forum in Zaragoza (Spain), Claus Schmitt at the 18th SGF in Zurich (Switzerland), Baheo Kim at the 2015 Asian FMA in Seoul (South Korea), and participants at the 2015 FEBS in Nantes (France) and the above listed conferences for useful comments. Chih-Wei acknowledges financial funding from MOST 105-2410-H-110-015. This research is partially supported by the College of Management, National Sun Yat-sen University, TAIWAN under grant CMNSYSU-SRS-2016-04.

1. Introduction

Rollover (refinancing) risk arises when a firm's debt is close to maturity but the firm wants to refinance it. During the financial crisis of 2007–2009, rollover risk exacerbated default risk because liquidity deteriorated in debt markets. This lack of liquidity negatively affected the main channel used by firms needing to refinance their maturing debt. He and Xiong (2012) theorize that this interaction between rollover risk and default risk, where rollover risk sharpens conflicts of interest between shareholders and debt holders because shareholders have to bear refinancing costs, making equity holders declare the firm insolvent earlier, thus increasing the default probability.

Empirical evidence about the effect of rollover risk over default risk is in its early stages.[1] This paper empirically examines rollover risk using a comprehensive dataset of industrial firms in the U.S. market from 1986 to 2013. We thus provide new evidence on this issue by exploring whether a firm's financing structure drives this risk. Our key finding is that rollover risk increases the default probability of firms that depend on bank financing. This increase is greater if they suffer from declining profitability and poor credit quality. Moreover, crises in credit market boost the effect.[2] In contrast, we do not find significant evidence of this rollover risk effect

[1] To the best of our knowledge, only two published articles (Gopalan, Song, and Yerramilli, 2014; Valenzuela, 2015) document that firms that experience large increases in rollover risk are likely to suffer a strong deterioration in their credit quality. The work of Chen, Xu, and Yang (2012) and Hu (2010) also relates to this topic.

[2] The literature argues that firms that depend on bank financing are different from firms that enjoy wider financing choices, because bank-dependent firms tend to face more difficulties with long-term borrowing, have lower debt capacity, and suffer greater liquidity risk (e.g., Mian and Santos, 2011). In turn, we hypothesize that the impact of rollover risk on increasing default risk is stronger for bank-dependent firms than for non-bank-dependent firms. This is the central hypothesis in this paper and it is illustrated thoroughly in Section 2.2.

(RRE) for firms that do not rely on bank financing. The risk is not significant, even when such firms have weak fundamentals or credit markets are in crisis.

Our sample contains all publicly traded industrial firms in the U.S. market from 1986 to 2013. We employ a panel data regression. We measure default risk using the expected default frequency based on the Merton's (1974) model. Our measure of rollover risk is the amount of the firm's long-term debt outstanding at the end of year $t-1$, due for repayment in year t, weighted by total assets. This measure is attractive because it is usually uncorrelated with the firm's current risk characteristics. Therefore, we avoid possible endogeneity problems that could arise with other commonly used proxies for rollover risk (e.g., proportion of short-term debt in total debt; see Harford *et al*., 2014).

Our evidence suggests that rollover risk is significant for bank-dependent (BD) firms, because such firms suffer from significant increases in default rates when rollover risk increases, even after we control for a comprehensive list of default risk factors, firm fixed effects, and year fixed effects. However, rollover risk is not significant in the case of firms that do not depend on bank financing, suggesting that the source of financing (banks or other sources) is the factor determining the impact of rollover risk.

Rollover risk is not only statistically significant but also economically substantial. For a BD firm, a one standard deviation increase in the rollover risk measure leads to a significant 3.2% increase in the default probability during the next year.

To gain more insight about the effect of rollover risk on the default probability, we examine several factors that could influence this effect. We find that, for BD firms, RRE is particularly stronger among those with declining profitability and poor credit quality. Moreover, tighter credit markets amplify the effect. In contrast, the RRE for non-BD firms is not significant, even under these amplification forces, suggesting that a firm's dependence on bank financing plays a dominant role in driving the impact of rollover risk on default.

For BD firms, a one standard deviation increase in the rollover risk measure *increases* the default probability by 7.6% when firms also experience declining profitability, but *decreases* it by 2.7% when firms become profitable. The default probability *increases* from 3.5% to 5.2% when firms suffer from poor credit. In contrast, the default probability *decreases* from 2.8% to 11.1% when firms enjoy good credit. During periods of stress in credit markets, the default probability increases from 6.4% to 14.4%. However, under normal market circumstances, the default probability increases by only 1%.

We present several robustness tests. First, in the baseline analysis, we classify a firm as BD when it has no ratings (Chava and Purnanandam, 2011). We realize that this bank dependence identification strategy is open to criticism. For example, a firm could not be rated because it chose to not ask for a rating, irrespective of whether it relies on financing from banks or from other sources. Therefore, we adopt an alternative identification scheme by examining a firm's actual dependence on bank loans relative to its total assets. Second, we use the ratio of debt maturing in more than three years to total debt as an alternative measure of rollover risk. Third, we use stock returns volatility as an alternative default risk measure and repeat the baseline regressions. Overall, the results from these robustness tests largely support our baseline findings.

This study adds to the literature in several ways. First, we contribute to the literature on both debt maturity and credit risk by empirically validating the theoretical prediction that rollover risk arising from a firm's debt maturity structure increases the firm's overall credit risk (e.g., Morris and Shin, 2009; He and Xiong, 2012).

Second, we complement empirical studies on the RRE by showing that the level of dependence on bank financing largely drives the rollover risk channel, in which BD firms experience a significant increase in default probability because of their exposure to rollover risk. Moreover, our findings suggest that, if BD firms can properly manage their debt maturity structure, this strategy could help mitigate the likelihood of bankruptcy.

Furthermore, we find that rated firms do not suffer additional default risk arising from rolling over debt. This result is inconsistent with the findings of Gopalan *et al*. (2014). One possible explanation for this disagreement could be that we assess default risk based on Merton's (1974) model, which provides a continuous, absolute measure of default risk that changes over the course of the credit cycle, reflecting changes in the level of default risk. However, Gopalan *et al*. use credit ratings as a proxy for default risk, which can only reflect relative rankings of credit risk across firms at each time (see the discussion by Hovakimian, Kayhan, and Titman, 2012).

Finally yet importantly, this article also contributes to the bank dependence literature by highlighting adverse consequences of relying on bank financing (e.g., Chava and Purnanandam, 2011). Our evidence suggests that bank dependence exposes firms to higher default risk because of the additional impact of rollover risk.

The remainder of this article proceeds as follows: We present related literature and our hypotheses in Section 2. Section 3 describes the main variables and the data. Section 4 discusses the empirical results. Section 5 documents robustness tests. Section 6 concludes with a discussion of the results and suggestions for further research.

2. Literature Review and Hypothesis Development

This section outlines both theoretical and empirical research into the effect of rollover risk on default risk and discusses the potential impact of reliance on bank financing.

2.1 RRE on Default Risk

2.1.1 Theoretical Background

Recent studies propose theoretical models in which rollover (refinancing) risk increases default risk. Morris and Shin (2009) incorporate insights from the bank-run literature (Diamond and Dybvig, 1983) into a stylized model and examine the interaction, showing that a negative fundamental shock can increase the probability of short-term debt holders deciding not to refinance, which then increases the bank's default probability. He and Xiong (2012) apply Myers's (1977) notions to Leland and Toft's (1996) model and find that, when debt market liquidity deteriorates, firms face rollover losses if they issue new bonds to replace maturing bonds. To avoid default, equity holders must bear rollover losses. The intrinsic conflict of interest between debt and equity holders could force equity holders to choose a higher fundamental firm value as a default barrier. In the presence of refinancing risk, a firm has a lower probability of survival. Forte and Peña (2011) also investigate the long-run effects of refinancing and find that debt refinancing increases default risk and induces systematic rating downgrades, unless some minimum level of firm value growth occurs. Deviations from this growth path imply asymmetric results: Lower firm value growth generates downgrades and higher firm value growth generates upgrades. However, downgrades tend to be greater in absolute terms.

A key implication of these theoretical contributions is that the amount of firm debt that matures in the short term increases the firm's overall default probability, beyond traditional default risk factors, causing the RRE we define herein.

2.1.2 Empirical Evidence

Recent empirical evidence indicates the existence of an RRE. Gopalan *et al*. (2014) find that firms with greater exposure to rollover risk have poorer credit ratings. The RRE is also stronger among firms with speculative-grade ratings and declining profitability, as well as during economic recessions. According to Chen *et al*. (2012), a bigger drop in the maturity of debt led to larger increases in credit spreads during the 2007–2009 crisis. This maturity effect on credit spreads is more pronounced for firms with high leverage or high systematic risk. Valenzuela (2015) finds that debt market illiquidity increases firms' corporate bond spreads through rollover risk in the international context. Our first hypothesis follows directly from these theoretical predictions and empirical evidence.

H1: *Firms with high exposure to rollover risk suffer higher default risk than firms without such exposure.*

Empirical studies that use particular proxies for default risk usually study a restricted sample that does not cover all firms. For example, they use credit ratings, corporate bond spreads, or credit default swap spreads, limiting samples to large or less risky firms. We argue though that it is important to study all firms, especially those that have not been widely considered thus far. In particular, unrated firms, which represent a rather large proportion of U.S. firms, are ignored in previous studies. Due to these considerations, we employ a general default risk measure and study a comprehensive sample, which should lead to more robust conclusions.

2.2 Bank Financing Dependence on the RRE

The RRE is notable with regard to the potential role of alternative financing sources. To address this insufficiently explored issue, we particularly investigate whether reliance on bank borrowing drives the RRE.

Carey *et al*. (1993) show that BD firms are more likely to have trouble finding long-term debt financing, because bank debts have shorter average maturities than publicly traded debt. Lemmon and Zender (2010) also note that unrated firms (typically classified as BD firms) tend to exhibit lower debt capacity, possess a lower collateral value of assets, and suffer from higher borrowing costs due to financial distress. These factors suggest unrated firms are potentially more exposed to rollover risk. Finally, Barclay and Smith (1995) find that a firm's debt maturity correlates negatively with credit risk for unrated firms, but positively for rated firms. Their findings suggest that higher short-term debt (i.e., higher rollover risk) could thus lead to higher credit risk for BD firms, compared with firms that do not rely on bank borrowing. Thus, our second hypothesis is as follows.

H2: *The RRE is stronger for BD firms than for firms that do not depend on bank borrowing.*

3. Variables and Data

3.1 Variables

This section explains the measure we used to proxy for default risk, the construction of rollover risk as our main explanatory variable, and the characteristics of the control variables we employ in the corresponding regression.

3.1.1 Default Risk Variable

To examine the RRE for all levered firms and obtain as large a sample as possible, we cannot use some common proxies for default risk. That is, we need default risk measures that are flexible enough to quantify default risk for firms across the entire market. We compute the expected default frequency (*EDF*), based on Merton's (1974) model, as the baseline measure of default risk; it has been widely used to indicate default risk for non-financial corporations (Bharath and Shumway, 2008; Chava and Purnanandam, 2010; Hovakimian *et al*., 2012). We adopt Moody's well-known KMV approach to measure *EDF*, defined as

$$EDF = N\left(-\left(\frac{\log\left(V/B\right)+\left(\mu-\sigma_V^2/2\right)T}{\sigma_V\sqrt{T}}\right)\right), \tag{1}$$

where $N(.)$ is the cumulative distribution function for a standard normal distribution, V is a firm's total asset value, B represents a firm's face value of debt, σ_V is the volatility of the firm's asset return, μ offers an estimate of the expected long-run return of a firm's asset return, and T indicates the maturity of a firm's debt. The *EDF* measure is a statistical prediction of default over some specified time horizon; we calculate the one-year default probability. In addition, we implement an estimate based on a one-year rolling window, updated monthly, to obtain time-series *EDF* data. We explain the details of the estimation procedure in Appendix A.

Using *EDF* provides several advantages. Unlike credit ratings, which measure the relative probability of default at a fixed number of discrete levels, *EDF* is a continuous, absolute measure that changes over the course of the credit cycle (Hovakimian *et al*., 2012).[3] When the aim is to capture the time-series dimension of default risk, *EDF* is a more appropriate measure of default risk than credit ratings.[4] Furthermore, computing *EDF* only requires stock price and accounting information, both of which are publicly available, so we can measure the default risk for many firms, rather than just a restricted group. Finally, *EDF* measures the likelihood of a firm defaulting in the future, rather than the past, which is the spirit of the RRE.

Alternatively, for a robustness check, we use stock volatility as the default risk measure. We present a detailed discussion in Section 5.3. Overall, both default risk measures (i.e., *EDF* and stock volatility) support our two hypotheses.

3.1.2 Rollover Risk Variable

We use the proportion of long-term debt that matures every year to gauge the impact of rollover risk by following several recent papers (e.g., Almeida *et al*., 2012; Gopalan *et al*., 2014). Long-term debt payable during the year essentially captures rollover risk because debt matures near time and also depends on the firm's previous long-term debt maturity decisions but is less correlated with the firm's current risk

---

[3] Hovakimian *et al*. (2012) posit that ratings reflect the relative rankings of credit risk at each point in time, without reference to an explicit time horizon. Although credit ratings provide an ordinal ranking of default risk across firms, depending on the business cycle, mappings between ratings and short-run default probabilities may change.

[4] Gopalan *et al*. (2014) use credit ratings and, as far as we know, we are the first study using *EDF* to examine the RRE.

characteristics or credit quality. This measure is thus largely free of the potential endogeneity that affects other measures of refinancing risk (e.g., short-term debt).

The rollover risk variable is defined as $(LT)_{-1,t-1}$: the amount of a firm's long-term debt outstanding at the end of year t – 1 due for repayment in year t (i.e., Compustat item *dd1* in year t – 1), weighted by the book value of total assets. A positive value of $(LT)_{-1,t-1}$ implies that a firm's exposure to rollover risk increases in year t.

3.1.3 Control Variables

We control for several relevant firm characteristics that could affect a firm's default risk in our empirical model: (1) *Cash*, the ratio of cash holdings to total assets; (2) *MTB*, the ratio of the market value of total assets to the book value of total assets; (3) *Idiovol*, measured using the standard deviation of excess equity returns; (4) *Tangibility*; (5) *Size*, measured using the logarithm of total assets; (6) *R&D*, the ratio of research and development expenditures to the book value of total assets; (7) *Tax*, the ratio of tax expenditures to the book value of total assets; (8) *Profitability*, the ratio of operating income to sales; (9) *Leverage*, the ratio of total debt to total assets; and (10) *IntCov*, interest coverage. These variables are commonly adopted in the literature on determinants of default risk (e.g., Gopalan *et al*., 2014). Appendix B provides detailed definitions, constructions, and economic rationales for these variables.

3.2 Data

We investigate public firms in the U.S. market from 1986 to 2013.[5] Financial statement data are from Compustat and the stock return data are from the Center for Research Security Prices (CRSP). We exclude financial firms (standard industrial classification [SIC] codes 6000–6999), utilities (SIC codes 4900–4999), and quasi-public firms (SIC codes over 8999), whose capital structure decisions can be subject to regulation. In addition, we include only those firms whose total debt represents at least 5% of their assets (Chen *et al.*, 2012), to avoid inappropriately contrasting firms that can issue long-term debt with ones that cannot. To minimize the effects of outliers on the results, all variables are winsorized at the 1st and 99th percentiles (e.g., values exceeding the 99th percentile are set equal to the 99th percentile). The final sample size featured comprises 67,609 firm–year observations, representing 10,479 firms.

To investigate whether the RRE is stronger for BD firms, we first need to identify borrowers that depend on their lenders. We use Standard & Poor's long-term issuer-level rating, extracted from the Compustat database, to identify a firm as either a BD firm or a non-BD firm. The prior literature similarly uses rating information to discriminate between BD and non-BD firms (e.g., Chava and Purnanandam, 2011), because firms that do not have ratings likely lack access to public debt markets and depend on bank loan borrowing.[6] Our final sample contains 45,529 firm–year

---

[5] We use 1986 as the initial year because the Compustat database started to cover credit ratings that year. Furthermore, our sample includes all firms during this period; thus, there is no survivorship bias.

[6] We also use the ratio of a firm's bank debt to total assets as an alternative proxy for bank dependence. Since the bank debt information is covered only rather comprehensively since 2002, we treat this analysis as evidence of robustness and provide the results in the robustness section (i.e., Section 5.1).

observations for BD firms (approximately 67% of the full sample) and 22,080 firm–year observations for non-BD firms (approximately 33% of the full sample).

Table 1 presents the summary statistics for the variables, including $(LT)_{-1,t-1}$, *EDF*, and the firm characteristics used as regressors in our empirical model. In terms of the full sample (Panel A), the mean *EDF* is about 0.117 and its median is 0.001, indicating that its distribution is very right skewed and almost half of the firms are less likely to default, according to the very low median value. The mean (median) for $(LT)_{-1,t-1}$ is 0.029 (0.012); an interquartile range of 0.032 implies wide variation in this debt maturity measure across firms.

We also present the firm characteristics for BD and non-BD subsamples separately in Panel B. Regarding our key variable $(LT)_{-1,t-1}$, we find average levels of 0.034 for BD firms and 0.018 for non-BD firms. The median value shows a similar pattern, namely, 0.015 for BD firms and 0.008 for non-BD firms, suggesting that BD firms experience greater rollover risk. The *EDF* measure is approximately 13.7% for BD firms and 7.7% for non-BD firms, indicating that BD firms are generally more likely to default.[7] As for the alternative default risk measure of *StockVol*, BD firms experienced greater stock volatility (0.7) than non-BD firms (0.4), consistent with the expectation that firms depend on bank financing, have restricted to access other funding sources, and are more likely to default. Furthermore, BD firms tend to be smaller and less profitable and have lower asset tangibility, tax rates, leverage, and interest coverage; in contrast, they have higher cash holdings, market-to-book ratios, idiosyncratic volatility, and R&D expenditures. These differences are statistically

[7] Hovakimian *et al*. (2012) find that the average one-year default probability is about 5% for unrated firms and 1.6% for rated firms—lower than in our sample. A possible explanation of this difference is that our sample covers three years (2009, 2010, 2011) that do not appear in their sample and that are particularly turbulent, which likely leads to higher default probabilities.

significant at the 1% level (except for *MTB*) and generally consistent with our expectations and the literature.[8] Because of the difference among these variables between BD firms and non-BD firms, it is important to control for them in our regression analysis.

[Insert Table 1 Here]

3.3 Correlation Matrix

Table 2 shows the correlation matrix of the variables. The correlation between $(LT)_{-1,t-1}$ and *EDF* is 0.16 in the full sample (Panel A) and 0.016 in the subsample of BD firms (Panel B), but only 0.1 in the case of non-BD firms (Panel C). This preliminary result is consistent with our prediction that higher rollover risk would lead to higher default risk and this influence is stronger for firms that depend on bank financing. The signs of the correlations between *EDF* and the other factors are also as generally expected; that is, *Cash*, *MTB*, *Tangibility*, *Size*, *Tax*, *Profitability*, and *IntCov* are negatively related to *EDF*, whereas *Idiovol* and *Leverage* are positively related to it.

[Insert Table 2 Here]

[8] Chava and Purnanandam (2011) show that BD firms have lower leverage and profitability but greater default risk, market to book, and equity volatility. Hovakimian *et al*. (2012) find similar results and also show that BD firms have lower tangibility, size, and taxes. Santos and Winton (2008) find that BD firms have lower leverage and spend more on R&D.

4. Empirical Results

We present the results in four sections, focusing on (1) the results of testing the effect of rollover risk on default risk in the baseline case, (2) the test of the hypothesis that bank borrowing dependence strengthens the RRE, and (3) the extent to which RRE is amplified by micro-level forces and (4) stressed credit markets.

4.1 Baseline Results

We employ a fixed effect regression to examine whether rollover risk increases the default risk at the firm level, that is,

$$EDF_{i,t} = \alpha + \beta (LT)_{-1\,i,t-1} + \gamma \mathbf{X_{i,t-1}} + \text{Firm FE} + \text{Year FE} + \varepsilon_{i,t}\,. \qquad (2)$$

where the dependent variable, $EDF_{i,t}$, represents firm *i*'s expected default frequency during year *t*. The key independent variable, $(LT)_{-1,t-1}$, denotes the amount of a firm's long-term debt outstanding at the end of year $t-1$ due for repayment in year *t*, scaled by the book value of total assets. Thus, a larger value of $(LT)_{-1,t-1}$ implies that a firm's exposure to rollover risk increased during year *t*.

We control for many firm characteristics ($\mathbf{X_{i,t-1}}$) that could affect the firm's default risk, as detailed in Section 3.1.3. Furthermore, we include year fixed effects to control for any macroeconomic variables and firm fixed effects to control for unobservable factors across firms that also affect default risk. Standard errors are robust to heteroskedasticity and autocorrelation, clustered at the firm level.

Table 3 presents the baseline results. Column (1) reports the estimators without control variables and shows that the estimated coefficient of $(LT)_{-1,t-1}$ is positive and significantly different from zero at the 1% significance level, consistent with H1. The coefficient of 0.202 implies that a one standard deviation increase in $(LT)_{-1,t-1}$ leads to an 11.4% increase in default rates.[9] Thus, the effect of rollover risk on default risk is not only statistically but also economically significant.

Next, we control for other default risk factors to examine whether the RRE is still present. To reduce concerns of multicollinearity, we run a set of regressions in which we carefully choose control variables based on their correlations (see Table 2). In particular, Columns (2) to (4) of Table 3 report the results of regressions that include controls with correlations between each other below 0.3, 0.4, and 0.5, respectively, and Column (5) presents the estimators on the specification with all the control variables.[10] The estimated coefficient of $(LT)_{-1,t-1}$ retains a statistical significance of at least 5% across all regressions. The economic impact is also substantial. The result in the case of controlling all the control variables (Column (5)) demonstrates that the coefficient of 0.058 implies that a one standard deviation increase in $(LT)_{-1,t-1}$ leads to a 3.3% increase in default rates.

Regarding the influence of the control variables, the results are largely consistent with our expectations: *Cash*, *MTB*, *Tangibility*, *Tax*, and *Profitability* are significantly negatively related to *EDF*, whereas *Idiovol*, *R&D*, and *Leverage* are significantly positively related to it. The coefficients of *IntCov* and *Size* are positive and significant, which seems bizarre (see Column (5) of Table 3). However, the Pearson correlations

---

[9] We compute economic impact as follows. We multiply one standard deviation of $(LT)_{-1,t-1}$ (0.066, as shown in Table 1) with the estimated coefficient of $(LT)_{-1,t-1}$ (0.202 in this case) and then divide this figure by the unconditional mean value of *EDF* (0.117, as shown in Table 1). In other words, $0.202 \times 0.066 = 0.0133$ and $0.0133/0.117 = 11.395\%$.

[10] We also perform variance inflation factor tests on all model specifications in Table 3 to check the multicollinearity problem. The variance inflation factor statistics are all below two, indicating no multicollinearity problem. We thank a reviewer for pointing this out.

provided in Table 2 show highly *negative* correlations between *EDF* and *IntCov* (–0.18), as well as between *EDF* and *Size* (–0.17), both consistent with expectations.[11]

[Insert Table 3 Here]

4.2 Does dependence on bank financing matter?

H2 argues that bank financing dependence amplifies the impact of rollover risk on increasing default probabilities. We empirically examine this hypothesis in this section. To do so, we run the above baseline regressions on the two subsamples that contain BD and non-BD firms, respectively and we report the results in Table 4.

[Insert Table 4 Here]

Focusing on BD firms, we find the coefficient of $(LT)_{-1,t-1}$ is positive and highly significant across all model specifications with different sets of control variables (see Panel A of Table 4). On the other hand, for non-BD firms, although the coefficient of $(LT)_{-1,t-1}$ is positive, the variable loses its power in determining a firm's default probability once control variables are included (see Panel B). Therefore, our findings support our central hypothesis, that bank dependence is an important driving force in

[11] Furthermore, the coefficient of *IntCov* is negative (as expected) in the regression that excludes explanatory variables with relatively higher correlations among each other (see Column (4)). For further checks, we perform several tests. First, we run regressions in which we remove two independent variables that have rather strong correlations with *IntCov* (tax and profitability) from the regression. The results are given in the Online Appendix, Table OA1 (Columns (1)–(3)), and show that while the coefficient of *IntCov* is positive, it is not statistically significant. Second, we consider the contradicting result for *Size* could be due to firm fixed effects, which largely absorb the influence of *Size* on *EDF*. Therefore we run the regression with random effects instead of fixed effects in the main analysis. We give the results in the Online Appendix, Table OA1 (Columns (4)–(6)). Indeed, we find that the sign of *Size* is negatively related to *EDF* in the regression that includes *Size* as the only control variable. We note that the correlation between *Size* and *Idiovol* is very high (–0.54) and consider the problem of multicollinearity could be driving the regression results. We exclude *Idiovol* from the model and find that *Size* is negatively related to *EDF*. Importantly, the coefficient of our main variable of interest, $(LT)_{-1,t-1}$, is always positive and significant across all these complementary regressions, further supporting the rollover risk hypothesis.

increasing a firm's default risk through the channel in which a firm faces higher refinancing costs when rolling over their maturing loans.

The economic impact is different between BD firms and non-BD firms. For example, a one standard deviation increase in $(LT)_{-1,t-1}$ leads to a 11.2% increase in default rates for BD firms, whereas it is only 6.3% for non-BD firms, for the case of no control variables (Column (1)).[12] After we control for many firm risk characteristics (Column (5) of Table 4), a BD firm, on average, experiences a significant 3.2% increase in default rates for a one standard deviation increase in $(LT)_{-1,t-1}$. On the other hand, a one standard deviation increase in $(LT)_{-1,t-1}$ raises a non-BD firm's default rate by only 0.8%.

Overall, our results suggest that the RRE on increasing default rates has different impacts on firms according to their dependence on bank borrowing. This effect is of material importance for BD firms but not non-BD firms. We should address that the results above constitute evidence on the lower limit of the effect of rollover risk on credit risk. Typically, BD firms use more short-term debt than non-BD firms do.[13] If we consider short-term debt likely to amplify this effect, it can be even stronger for BD firms.

[Insert Table 4 Here]

[12] We compute the economic impacts based on summary statistics for BD and non-BD firms, respectively (see Table 1).

[13] The reason to not use short-term debt measures is the potential for endogeneity. The amount of short-term debt outstanding likely relates to the default risk (e.g., Almeida *et al*., 2012).

4.3 Micro-Level Amplification Forces

To provide more insights on the relation between debt maturity structure and firm default risk, we perform a number of tests on exploring several micro-level amplification forces.

4.3.1 Decline in Profitability

Theory suggests that negative shocks faced by firms could amplify RRE. For example, Diamond (1991) points out that maturing debt exposes a firm to refinancing risk only if the revealed information is negative, which lenders might not refinance—thus forcing a firm into premature liquidation. He and Xiong's (2012) model highlights that negative shock leads to a drop in a firm's liquid reserves and causes it to suffer refinancing losses even more when it is rolling over its short-term debts.

We test this prediction by estimating Equation (2) with two additional variables. The first one is *Decline,* a dummy variable that identifies firms experiencing a decline in profitability during the year compared to the previous year. The second variable is the interaction of $(LT)_{-1,t-1}$ x *Decline.* The main variable of interest is the interaction variable, for which we expect a significant and positive sign, consistent with the theoretical prediction. We separately examine BD and non-BD firms and present the results in Table 5.

Focusing on BD firms, we find the coefficient of the $(LT)_{-1,t-1}$ x *Decline* interaction variable is highly significant and positive (Column (1) of Panel A of Table 5), suggesting rollover risk is associated with a more severe increase in default risk for firms that experience a decline in profitability, consistent with the theory. Interestingly, we find that the coefficient of the standalone variable $(LT)_{-1,t-1}$ is significantly negative, suggesting that maturing debts themselves are not necessary conditions for refinancing risks, but only when firms face negative operating performance.

In terms of economic impacts, we find that a one standard deviation increase in $(LT)_{-1,t-1}$ *increases EDF* by 7.6% when firms face a year-on-year decline in profitability, whereas it *decreases EDF* by 2.7% when firms have a year-on-year increase in profitability.[14]

In contrast, in the case of non-BD firms (Column (1) of Panel B of Table 5), the coefficient of $(LT)_{-1,t-1}$ is not significant. This finding suggests that a firm's dependence on bank financing plays a dominant role in driving the rollover risk hypothesis, whether a firm's profitability declines or not.[15]

[Insert Table 5 Here]

---

[14] The total effect of $(LT)\text{-}1_{,t-1}$ is the summation of the estimated coefficient of $(LT)\text{-}1_{,t-1}$ and the interaction of $(LT)\text{-}1_{,t-1}$ and *Decline*, which gives us –0.048 + 0.183 = 0.135. Thus, the economic impact is computed by multiplying this added coefficient and the standard deviation of $(LT)\text{-}1_{,t-1}$ and then dividing it by the mean of *EDF*, which gives (0.135*0.077)/0.137 = 7.6%. In the case of no decline in profitability (i.e., the *Decline* dummy variable is zero), the economic impact is computed as (–0.048*0.077)/0.137 = –2.7%.

[15] We adopt *Decline* variable following the suggestions in Gopalan *et al*. (2014). However, this *Decline* variable may not fairly capture a shock. For example, the entire industry does not perform well but a firm is still a better performer than the rest of the industry. In order to deal with this issue, we posit an alternative declining profitability indicator, the *Decline_Industry*, which is a dummy variable that identifies firms having year-on-year decline in profitability. This declining magnitude is larger than the industry-level declining magnitude. We replace *Decline_Industry* with *Decline* and rerun the regression in Table 5 (Column 1). The results are consistent with our main findings (see the Online Appendix, Table OA2)

4.3.2 Credit Quality

Theory also suggests that the RRE tends to be stronger for firms with poor credit, because such firms face more difficulties extending the maturity of their debt. For example, Diamond (1991) argues that firms of low credit quality that face greater liquidity risk demand longer-term debt to reduce this risk but cannot find lenders willing to supply it at reasonable cost. Mian and Santos (2011) show that only creditworthy firms can choose to refinance at a lower rate, whereas lower credit quality firms, instead, have minimal access to new capital at a reasonable cost, such that they incur substantial rollover losses.

To test this prediction, we use Altman's (1968) Z-score as a proxy for a firm's credit quality. We first create the dummy variable *Altman_Z-B50* to indicate that firms with Z-score below the median are regarded as having poor credit. We then modify our baseline regression Equation (2) by adding this poor credit dummy and its interaction term with $(LT)_{-1,t-1}$. We are interested in the coefficient of the interaction variable. A positive coefficient of the interaction variable would suggest that the amplification effect of rollover risk on default rates is stronger among firms with worse credit.

In addition to Altman's Z-score, we consider three alternative credit quality proxies: Ohlson's (1980) score, idiosyncratic equity volatility, and leverage. We perform similar tests for each of the credit quality proxies, that is, we construct dummy variables equal to one if the measure in nature has poorer credit. Unlike the Altman Z-score, these variables are positively related to the level of risk and thus the dummy variable assumes a value of one for firms with the variable *above* the median among firms for a given year (i.e., poorer credit) and zero otherwise. These dummies are *Ohlson-A50*, *Idiovol-A50*, and *Leverage-A50*, respectively.[16]

We examine the impact of a firm's credit quality condition on the RRE for BD and non-BD firms separately. The results are reported in Columns (2) to (5) of Table 5, corresponding to the above-mentioned indicators of poor credit. We find that the interaction variable is positive and highly significant for BD firms, suggesting that poor credit indeed amplifies the RRE. In contrast, we find the interaction variable is not significant for non-BD firms. This finding seems to again indicate that bank financing dependence drives the RRE, irrespective of a firm's credit quality.

We examine how much a firm's credit quality would affect the RRE in terms of economic impact. In the case of the BD group, our results show that a one standard deviation increase in $(LT)_{-1,t-1}$, increases *EDF* by between 3.5% and 5.2%, depending on the credit quality proxy.[17]

In contrast, the results based on the standalone $(LT)_{-1,t-1}$ variables (capturing the RRE for firms with better credit) show that a one standard deviation increase in (LT)-$1_{,t-1}$ *decreases EDF* by 2.8% to 11.1%, depending on the credit quality proxy.[18] This finding may be explained by some theoretical arguments. The asset substitution theory suggests that short-term debt can alleviate the asset substitution problem as firms with more short-term debt are subject to frequent renegotiations and scrutiny of

[16] In addition to identifying a firm with poor credit based on the median Altman Z-score and Ohlson score values, we consider other identification schemes adopted in the literature. In particular, we classify a firm as having poor credit when its Altman Z-score is lower than 1.81 (distress zone to default) or lower than 2.99 (gray zone to default) and its Ohlson score is greater than 0.5. The results continue to support our main findings (see the Online Appendix, Table OA3).

[17] In particular, *EDF* increases by 3.8% in the case of *Altman Z-B50*, 3.5% in the case of *Ohlson-A50*, 4.3% in the case of *Idiovol-A50*, and 5.2% in the case of *Leverage -A50*.

[18] In particular, *EDF* decreases by 4.5% in the case of *Altman Z-B50*, 4.3% in the case of *Ohlson-A50*, 2.8% in the case of *Idiovol-A50*, and 11.1% in the case of *Leverage -A50*.

the borrowers (Jensen and Meckling, 1976), resulting in lower firm risk. The asymmetric information theory argues that a low-risk firm exploits more short-term debts (see discussion in Flannery (1986) and Diamond (1991)).

Overall, the results suggest that rollover risk is associated with a more severe increase in default rates for firms that experience declining profitability and have poor credit and this amplification force only appears for firms that depend on banks to obtain funds.

4.4 Credit Market Conditions

He and Xiong's (2012) theoretical model demonstrates that debt market frictions cause rollover risk to deteriorate default risk. Therefore, the RRE is expected be stronger when credit markets conditions are tighter.

To test this prediction, we consider three proxies for a stressed credit market. The first variable is the spread between yields on Baa- and Aaa-rated corporate bonds. This indicator is widely used to represent a default risk or credit risk factor (e.g., Gatev, Schuermann, and Strahan, 2009).[19] We define a dummy variable *Baa-Aaa Spread* that equals one if the spread increases representing stressed credit market and zero otherwise. The second variable is the three-month TED spread, which is the difference between the interest rate on interbank loans and the T-bill rate. We define the dummy variable *TED Spread* as equal to one if the spread increases, indicating a stressed credit market, and zero otherwise.[20] The third variable we define is the dummy variable *Recession,* which identifies years classified by the National Bureau

[19] We obtain data for the yields from the statistical release published by the Federal Reserve Board.

[20] It is well known that spreads contain default premiums (e.g., Valenzuela, 2015). The TED spread is the daily percentage spread between the three-Month London Interbank Offered Rate (based on U.S. dollars) and the three-month Treasury bill rate, as calculated by the Federal Reserve Bank of St. Louis.

of Economic Research (NBER) as recessionary: 1990, 1991, 2001, 2002, 2008, and 2009. Given that credit market conditions are likely to be related to economic conditions, the literature also uses recessions to proxy for distressed credit markets (e.g., Valenzuela, 2015)

To examine this theoretical prediction, we add the interaction term $(LT)_{-1,t-1}$ x *Baa-Aaa Spread* in the baseline regression. Given that the market condition variable only fluctuates over time, we cannot simultaneously control for market conditions and year dummies. Considering that the focus of this article is associated with the interaction between a firm's maturity debt structure and a stressed credit market, we report the results using time dummies, since this approach controls for all factors that simultaneously affect all corporate default risk over time. Nevertheless, we also run specifications that include the market condition dummies and exclude year fixed effects. To save space, we present the results in the Online Appendix.[21] Our main findings remain qualitatively identical, regardless of the specification.

We perform this test for BD and non-BD firms separately and present the results in Table 6. Focusing on BD firms, we find the coefficient of the interaction is positive and highly significant across all stressed credit market measures (see Panel A). Thus, our results are consistent with the theoretical prediction that a stressed credit market is crucial to amplify the rollover risk channel through which a firm's default probability substantially increases due to its exposure to refinancing risk. However, once again, for non-BD firms, the interaction is insignificant across all models.

[21] Table OA4 in the Online Appendix re-estimates the baseline specification including market condition dummies but excluding yearly dummies. This specification thus relies on market conditions, (i.e., *Baa-Aaa Spread*, *TED Spread*, and *Recession*) rather than year dummies. As expected, the results indicate that bad market conditions are positively related to corporate default risk.

The economic impact is substantial for BD firms. A one standard deviation increase in $(LT)_{-1,t-1}$, on average, increases *EDF* by 6.4% to 14.4%[22] in times of a credit crunch, but only by 0.1% to 1% when the credit market is improved.

Overall, the results suggest that the rollover risk associated with more severe default rates is increased in times of stressed credit market for firms that rely on borrowing from banks.[23]

[Insert Table 6 Here]

5. Robustness Tests

We conduct several robustness checks. First, we use an alternative method to identify the level of bank dependence. Second, we use an alternative proxy for rollover risk. Third, we re-examine our central hypotheses by using equity volatility as the alternative default risk measure.

5.1 Alternative Bank Dependence Measure

We conduct additional tests to strengthen our findings from the baseline analysis on bank dependence by using the firm-level debt structure variable information provided in the Capital IQ database to distinguish BD from non-BD firms. Because

---

[22] We compute the economic impact as follows. We use the model specification for recession for BD firms as an example (Column (3), Panel A, of Table 6). We multiply one standard deviation of $(LT)\text{-}1_{,t-1}$ (0.077, as shown in Table 1) with the estimated coefficient of $(LT)\text{-}1_{,t-1}$ (0.002 + 0.255) = 0.257 in this case) and then divide the previously computed number by the unconditional mean value of *EDF* (0.137, as shown in Table 1). That is, $0.257 \times 0.077 = 0.0198$ and $0.0198/0.137 = 14.4\%$.

[23] We repeat the above analysis for the entire sample. The results are similar to those for the BD firms (see Table OA5 of the Online Appendix). This suggests that distinguishing between BD and non-BD firms is particularly important in terms of exploring the rollover risk hypothesis; otherwise, the true RRE for non-BD firms is unlikely to be captured.

coverage by Capital IQ is comprehensive only from 2002 onward, the Capital IQ-based sample spans 2002 to 2013. We further remove observations with missing values in the database of Capital IQ. The sample size is thus reduced to 16,340 firm–year observations, which covers 24% of the firms selected in the main analysis.[24]

We give a new definition for bank dependence based on the bank's debt-to-total assets ratio. In this analysis, the BD group is the one that contains firms with a bank debt-to-total assets ratio in the top 33%, 25%, 20%, or 10% of firms and the non-BD is the group that contains the remainder of the identified BD subjects. The bank debt-to-total assets ratio is measured by using bank debt, the sum of term loans and revolving credit divided by total assets.

Table OA6 of Online Appendix reports the estimation results of Equation (2) after using the Capital IQ-based identification scheme and for the BD and non-BD groups, respectively. We find that the coefficient of $(LT)_{-1,t-1}$ is positive and significant for BD firms across different criteria for the bank debt-to-total asset ratio across the top 33%, 25%, 20%, and 10%, whereas the coefficients are consistently insignificant across all non-BD subsamples. Overall, the Capital IQ-based analysis provides further evidence supporting that the RRE is more pronounced for firms that rely on bank financing.

5.2 Alternative Rollover Risk Variable

Following, for example, Barclay and Smith (1995) and Chen *et al*. (2012), we construct a measure of debt maturity using the long-term debt share, which is the percentage of total debt that matures in more than three years (*ldebt*3*y*). By

[24] For a detailed construction of the Capital IQ-based sample, see Chiu, Peña , and Wang (2015).

construction, *ldebt*3*y* is conversely related to the benchmark measure of $(LT)_{-1,t-1}$. Therefore, if the RRE exists, we should find the estimated coefficient is negative, instead of positive, which indicates that *ldebt*3*y* reduces *EDF*.

We replace $(LT)_{-1,t-1}$ with *ldebt*3*y* and re-examine the regression specifications in Table 3 (control variables included), with the results reported in Columns (1) to (3) of Table OA7 of Online Appendix. The result for the entire sample (Column (1)) shows the negative and significant coefficient of *ldebt*3*y*, which confirms a RRE for default risk. Columns (2) and (3) provide the regression results, with *ldebt*3*y* as the main independent variable for BD and non-BD firms, respectively. The coefficient of *ldebt*3*y* is negative and significant at the 1% level only for BD firms (Column (2)), but it is barely significant for the non-BD firms (Column (3)). In terms of economic impact, we find that a one standard deviation increase in *ldebt*3*y* decreases *EDF* by 2.88% in the case of all firms and by 2.91% for BD firms, but only by 0.43% for non-BD firms. Overall, these results are consistent with our baseline findings using $(LT)_{-1,t-1}$ as the proxy for rollover risk and further support our central hypotheses.

5.3 Alternative Default Risk Measure

We use stock volatility as an alternative default risk measure. We define total stock return volatility as the annualized standard deviation of daily logarithmic returns over the year followed by the firm's last fiscal year-end, denoted *StockVol*. This proxy is used in a number of studies (e.g., Campbell and Taksler, 2003; Bennett *et al*., 2015). Stock volatility is also viewed as a forward-looking default risk measure, like our benchmark default risk proxy of *EDF*. Furthermore, a firm with a higher standard deviation of stock returns is more likely to fall below its default threshold.

We rerun the benchmark analysis by replacing *EDF* with stock volatility and show the results in Table 7. First, we run the regression without including any firm controls but with firm and year fixed effects and, second, the regression with all the controls. We find that the coefficient of $(LT)_{-1,t-1}$ is highly significant and positive in the group of BD firms (Columns (1) and (2)), but insignificant in the group of non-BD firms (Columns (3) and (4)). This finding offers further evidence to support our argument that BD firms experience greater default risk because of their exposure to the risk of rolling over debt.

[Insert Table 7 Here]

We also rerun the analysis related to micro-level amplification forces and credit market conditions. The results are reported in Table 8. For BD firms (Panel A), we find qualitative similar results as those using *EDF* as the default risk proxy in terms of micro-level amplification forces (see Columns (1)–(5)). With respect to credit market conditions, we find a positive but insignificant coefficient for those *LT-stressed credit market* interaction variables. The results indicate that a stressed credit market reinforces a firm's stock volatility but the impact is weaker than in the case using *EDF* as the default risk measure.

For non-BD firms, echoing our main results, the coefficients of the interaction variables are negative in two cases (*TED Spread* and *Recession*) and systematically insignificant in all cases. The results support the idea that bank dependence dominates other possible factors that amplify default risk because of a firm's exposure to rollover risk.

Finally, we observe that the coefficients of the dummies that identify declining profitability (*Decline*), a firm's poor credit (*Altman_Z-B50, Ohlson_S-A50, Idiovol-A50, Leverage-A50*), and stressed credit market indicators (*Baa-Aaa Spread*, *TED Spread*, and *Recession*) have a positive and significant impact in all cases. This is consistent with the analysis in which we use EDF as the default risk measure.[25]

[Insert Table 8 Here]

6. Conclusion

Understanding the economic factors explaining a firm's credit quality is of paramount importance. Merton's (1974) seminal work singled out the firm's debt structure and the value of its assets as two fundamental variables for explaining a firm's credit quality. Following this intuition, we pay particular attention to one aspect of the debt structure, namely, refinancing or rollover risk. Theory stresses its key role, but empirical evidence is still preliminary. Using the most comprehensive database to date, we consider the extent to which rollover risk has a significant impact on default probabilities.

To this end, we examine the impact on default risk that arises from rollover risk in the U.S. market from 1986 to 2013. Our results support the notion that rollover risk is significant, though not for all firms. Firms that depend on banks for their refinancing needs suffer increases in their credit risk caused by rollover risk. This increase is

[25] We also use the Altman Z-score and Ohlson score as alternative default risk proxies. We do not use the Altman Z-score (or Ohlson score) as the benchmark for default risk because this proxy is a historically based measure, that is, it can only reflect the default risk situation of a firm in the past. In contrast, *EDF* (or stock volatility) is a forward-looking measure, which essentially captures the rollover risk that exacerbates the default risk the next year. Therefore, we expect to see a negative (positive) relation between the Altman Z-score (Ohlson score) and (*LT*) - 1 in a *contemporaneous* setting, rather than a lead–lag relation, as examined in the main context. The result is reported in Table OA8 of the Online Appendix. The coefficient of (*LT*) - 1 is negatively (positively) associated with the Altman Z-score (Ohlson score) and highly significant in the case of the entire sample and in the subsample of BD firms, but not in the subsample of non-BD firms. Therefore, the analysis using the Altman Z-score or the Ohlson score as the default risk measure is consistent with the rollover risk hypothesis.

stronger for firms that have declining profitability or poor credit. Moreover, stress in credit markets magnifies the effect of rollover risk on the default probability. However, the default risk of firms that do not depend on bank financing is uncorrelated with rollover risk. Therefore, it is important to account for financing sources when assessing the interaction between rollover risk and default risk, because a firm's borrowing channel largely determines how rollover risk affects default risk.

Evidence suggests credit markets are aware of the possible impact of refinancing risk on credit quality (Gopalan *et al*., 2014). Therefore, an immediate extension of our work would be to investigate the degree to which banks recognize the importance of the RRE, such that they adjust the terms and conditions of loans dedicated to refinancing existing debt. This is left for future research.

Appendix A: Estimating EDF

Moody's KMV model is closely related to the Black–Scholes (1973) model. The basic idea is that equity can be viewed as a call option whose underlying asset is a firm's asset value and whose strike price is equal to the face value of the firm's debt. A firm's market value of assets is assumed to follow a geometric Brownian motion of the form

$$dV = \mu V dt + \sigma_V V dZ, \tag{A1}$$

where V is the total value of a firm, μ indicates the expected continuously compounded return of V, σ_V represents the volatility of a firm's value, and dZ is standard Brownian motion. With these assumptions and a Black–Scholes (1973) model, we can express a firm's market value of equity V_E as a function of its total value,

$$V_E = VN\left(d_1\right) - Be^{-rT} N\left(d_2\right), \tag{A2}$$

where

$$d_1 = \frac{\ln\left(V/B\right) + \left(r + 0.5\sigma_V^2\right)T}{\sigma_V \sqrt{T}}, \quad d_2 = d_1 - \sigma_V \sqrt{T}\ ,$$

B is the face value of a firm's debt, r is the risk-free rate, T is the forecast horizon, and $N(.)$ is the cumulative standard normal distribution.

In our exercise, we compute V_E as the product of a firm's outstanding shares and its current stock price, assume T equals one year, and treat B as debt in current liabilities plus half of the long-term debt, consistent with prior applications. The two remaining variables in the Black–Scholes equation—the total asset value of firm V and the volatility of firm value σ_V—are estimated with an iterative procedure following the method proposed by Vassalou and Xing (2004). Initially, we estimate σ_V as the annualized standard deviation of a firm's asset returns, using daily data about the summation of the market value of equity and the face value of debt over the past year. This method provides an initial estimate of σ_V and, together with the market value of equity and other inputs, Equation (A2) indicates the daily values of V. Using these estimated values of V, we generate new estimates of σ_V with the implied log returns on assets. The new estimate of σ_V enters the next iteration until the difference in values of σ_V across two consecutive iterations is less than 10^{-3}. Then we take the final estimated σ_V and its implied V. We compute the drift μ by calculating the mean value of the log-returns of *V*. With these estimated values, *EDF* can be calculated according to Equation (1).

Appendix B: Variable Definitions

This appendix provides details of the construction of the explanatory variables and their economic backgrounds. The terms in parentheses refer to item names in their corresponding data sources, as shown in the last column.

Variable Name	Variable Definition	Expected Impact on Default Risk	Economic Explanation	Source
Default Risk Measures				
EDF	Expected default frequency measure based on Merton's (1974) model. The detailed construction is described in Section 3.1.1.			Compustat/CRSP
StockVol	Annualized standard deviation of daily log stock returns (*RET*) over the next year of the accounting fiscal year-end (requires at least 20 daily observations over this period).			CRSP
Rollover Risk Variables				
$LT\text{-}1_{,t-1}$	Amount of a firm's long-term debt outstanding at the end of year $t-1$ due for repayment in year t (i.e., *dd1* in year $t-1$), scaled by the book value of total assets (*AT*).	+	Hypothesis 1 illustrates the mechanism through which rollover risk increases default risk. By construction, the larger the $LT\text{-}1_{,t-1}$, the greater the rollover risk.	Compustat
ldebt3y	Ratio of debt that matures in more than 3 years (*DLTT* – *DD2* – *DD3*) to total debt (*DLC* + *DLTT*)	–	Hypothesis 1 illustrates the mechanism through which rollover risk increases default risk. By construction, the larger the *ldebt3y*, the lower the rollover risk.	Compustat
Firm Variables				
Cash	Ratio of the book value of cash and marketable securities (*CHE*) to the book value of total assets (*AT*).	–	It serves as a tool to pay debt obligations.	Compustat
MTB	Ratio of the market value of total assets (*PRCC_F*×*CSHO* + *DLC* + *DLTT* + *PSTK* – *TXDITC*) to the book value of total assets (*AT*).	–	It reflects growth opportunities and should be negatively correlated with default probability, in that it represents additional value (over and above the book value) that debt holders can access in the event of a default.	Compustat
Idiovol	Idiosyncratic risk: standard deviation of daily excess returns relative to the CRSP value-weighted index for	+	A firm's asset value is below the default boundary; the higher the volatility, the greater the	CRSP

	each firm's equity in a year.		uncertainty and therefore the higher the default probability.	
Tangibility	Ratio of the book value of property, plant, and equipment (*PPENT*) to the book value of total assets (*AT*).	–	Tangible assets lose less of a firm’s value in default than intangible assets do.	Compustat
Size	Natural logarithm of the book value of total assets (*AT*).	–	Larger firms are more diversified, which reduces operating risks.	Compustat
R&D	Ratio of research and development expenditures (*XRD*) to the book value of total assets (*AT*). We replace missing values of *XRD* with zeros.	+	It reflects the firm’s brand equity and intellectual capital and is intangible. Intangible assets tend to lose more value than tangible assets in the event of default.	Compustat
Tax	Ratio of tax expenditure (*TXT*) to the book value of total assets (*AT*).	–	Firms with higher tax rates tend to choose more conservative capital structures.	Compustat
Profitability	Ratio of operating income after depreciation (*OIADP*) to total sales (*SALE*).	–	Profitable firms are less likely to default.	Compustat
Leverage	Ratio of total debt (*DLC* + *DLTT*) to total assets (*AT*).	+	Higher leverage implies a greater chance that the firm will file for bankruptcy.	Compustat
IntCov	Interest coverage: the ratio of operating income after depreciation (*OIADP* + *XINT*) to total interest expenditures (*XINT*).	–	The ratio is used to assess how easily a firm pays interests on its outstanding debts. Thus, the higher the ratio, the less burdened by debt expenses and the less likely to default.	Compustat
Other Variables				
Decline	Dummy variable that identifies firms having a decline in *Profitability* during the year as compared to the previous year.	+	A firm with declining profitability is more likely to default.	Compustat
Altman_Z-B50	Dummy variable equal to one for firms with an Altman Z-score below the sample median for a given year. The Altman (1968) Z-score is calculated as Z = 3.3×(earnings before interest and taxes/total assets) + 1.0×(sales/total assets) + 1.4×(retained earnings/total assets) + 1.2×(working capital/total assets) + 0.6×(market value equity/total debt).	+	A firm with a lower Altman Z-score is more likely to default.	Compustat
Ohlson-A50	Dummy variable equal to one for firms with an Ohlson score above the sample median for a given	+	A firm with a higher Ohlson score is more likely to default.	Compustat

	year. Ohlson's (1980) score is calculated as –1.32 – 0.407(log(total assets)) + 6.03(total liabilities/total assets) – 1.43(working capital/total assets) + 0.076(current liabilities/current assets) – 1.72(1 if total liabilities > total assets, 0 otherwise) – 0.521(net income – lagged net income)/(|net income| + |lagged net income|)).			
Idiovol-A50	Dummy variable equal to one for firms with *Idiovol* above the sample median for a given year.	+	A firm with greater idiosyncratic volatility is more likely to default.	CRSP
Leverage-A50	Dummy variable equal to one for firms with *Leverage* above the sample median for a given year.	+	A firm with more debt is more likely to default.	Compustat
Baa-Aaa Spread	Dummy variable that equals 1 if the spread between yields on Baa- and Aaa-rated corporate bonds increases.	+	A stressed credit market increases firms' likelihood of default.	Fed Reserve Bank
TED Spread	Dummy variable that equals 1 if the spread between the interest rate on interbank loans and the T-bill rate increases.	+	A stressed credit market increases firms' likelihood of default.	Fed Reserve Bank
Recession	Dummy variable that identifies years classified by the NBER as recessionary, i.e., 1990, 1991, 2001, 2002, 2008, and 2009.	+	A stressed credit market increases firms' likelihood of default.	Fed Reserve Bank

References

Almeida, H., M. Campello, B. Laranjeira, and S. Weisbenner, 2012, “Corporate Debt Maturity and the Real Effects of the 2007 Credit Crisis.” *Critical Finance Review*, 1, 3–58.

Altman, E. I., 1968, “Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy.” *Journal of Finance*, 23, 589–609.

Barclay, M. J., and C. W. Smith, 1995, “The Maturity Structure of Corporate Debt,” *Journal of Finance*, 50, 609–632.

Bennett, R. L., L. Güntay, and H. Unal, 2015, “Inside Debt, Bank Default Risk, and Performance during the Crisis.” *Journal of Financial Intermediation*, 24, 487–513.

Bharath, S. and T. Shumway, 2008, “Forecasting Default with the Merton Distance-to-Default Model.” *Review of Financial Studies*, 21, 1339–1369.

Black, F., and M. Scholes, 1973, “The Pricing of Options and Corporate Liabilities.” *The Journal of Political Economy*, 81, 637–654.

Campbell, J. Y., G. B. Taksler, 2003, “Equity Volatility and Corporate Bond Yields.” *Journal of Finance*, 58, 2321–2349.

Carey, M., S. Prowse, J. Rea, and G. Udell, 1993, “The Economics of the Private Placement Market.” Federal Reserve Board of Governors Staff Study, 166.

Chava, S., and A. Purnanandam, 2010, “Is Default Risk Negatively Related to Stock Returns?” *Review of Financial Studies*, *23*, 2523–2559.

Chava, S., and A. Purnanandam, 2011, “The Effect of Banking Crisis on Bank-Dependent Borrowers.” *Journal of Financial Eco*nomics, 99, 116–135.

Chen, H., Y. Xu, and J. Yang, 2012, “Systematic Risk, Debt Maturity, and the Term Structure of Credit Spreads.” Working Paper No. w18367, National Bureau of Economic Research.

Chiu, W.-C. and J. I. Peña, and C.-W. Wang, 2015, “Financial Crises, Debt Financing, and Default Risk.” Available at SSRN: http://ssrn.com/abstract=2564896 or http://dx.doi.org/10.2139/ssrn.2564896.

Diamond, D. W., 1991, “Debt Maturity Structure and Liquidity Risk.” *Quarterly Journal of Economics*, 106, 709–737.

Diamond, Douglas W., and Philip H. Dybvig, 1983, “Bank Runs, Deposit Insurance, and Liquidity.” *Journal of Political Economy*, 91, 401–419.

Flannery, M, 1986, “Asymmetric Information and Risky Debt Maturity Choice.” *Journal of Finance*, 41, 19–37.

Forte, S. and J. I. Peña, 2011, "Debt Refinancing and Credit Risk." *Spanish Review of Financial Economics*, 9, 1–10.

Gatev, E., T. Schuermann, and P. E. Strahan, 2009, "Managing Bank Liquidity Risk: How Deposit–Loan Synergies Vary with Market Conditions." *Review of Financial Studies,* 22, 995–1020.

Gopalan, R., F. Song, and V. Yerramilli, 2014, "Debt Maturity Structure and Credit Quality." *Journal of Financial and Quantitative Analysis*, 49, 817–842.

Harford, J., S. Klasa, and W. F. Maxwell, 2014, "Refinancing Risk and Cash Holdings." *Journal of Finance*, 69, 975–1012.

He, Z., and W. Xiong, 2012, "Rollover Risk and Credit Risk." *Journal of Finance,* 67, 391–430.

Hovakimian, A., A. Kayhan, and S. Titman, 2012, "Are Corporate Default Probabilities Consistent with the Static Trade-off Theory?" *Review of Financial Studies*, 25, 315–340.

Hu, X., 2010, "Rollover Risk and Credit Spreads in the Financial Crisis of 2008." Working Paper, Princeton University.

Jensen, M. C., and W. H. Meckling, 1976, "Theory of the Firm: Managerial Behavior, Agency Costs, and Capital Structure." *Journal of Financial Economics*, 3, 305–360.

Leland, H. E. and K. B. Toft, 1996, "Optimal Capital Structure, Endogenous Bankruptcy, and the Term Structure of Credit Spreads." *Journal of Finance*, 51, 987–1019.

Lemmon, M. L. and J. F. Zender, 2010, "Debt Capacity and Tests of Capital Structure Theories." *Journal of Financial and Quantitative Analysis*, 45,1161–1187.

Merton, Robert C., 1974, "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates." *Journal of Finance*, 29, 449–470.

Mian, A., and J. A. Santos, 2011, "Liquidity Risk and Maturity Management Over the Credit Cycle." Working Paper, University of California, Berkeley.

Morris, S., and H. S. Shin, 2009, "Illiquidity Component of Credit Risk." Working Paper, Princeton University.

Myers, S., 1977, "The Determinants of Corporate Borrowing." *Journal of Financial Economics*, 5, 147–175.

Ohlson, J. A., 1980, "Financial Ratios and the Probabilistic Prediction of Bankruptcy." *Journal of Accounting Research*, 109–131.

Santos, Joao A. C., and A. Winton, 2008, “Bank Loans, Bonds, and Information Monopolies across the Business Cycle.” *Journal of Finance*, 63, 1315–1359.

Valenzuela, P., 2015. “Rollover Risk and Credit Spreads: Evidence from International Corporate Bonds.” *Review of Finance*, forthcoming.

Vassalou, M. and Y., Xing, 2004, “Default Risk in Equity Returns.” *Journal of Finance,* 59, 831–868.

Table 1. Summary statistics

Panel A shows the summary statistics of the sample of 67,609 firm–year observations from 1986 to 2013, where *EDF* is the expected default probability, measured according to Merton's model; *StockVol* is annualized volatility over the next year; and $(LT)\text{-}1_{,t\text{-}1}$ is the amount of a firm's long-term debt outstanding at the end of year t – 1 that is due for repayment in year t, scaled by the current book value of total assets. The control variables are *Cash*, *MTB*, *Idiovol* (idiosyncratic risk), *Tangibility*, *Size*, *R&D*, *Tax*, *Profitability*, *Leverage*, and *IntCov* (interest coverage). For details, see Appendix B. Firms are identified as either BD, with 45,529 firm–year observations, or non-BD, with 22,080 firm–year observations. The identification of bank dependence is based on ratings, in which unrated firms are BD firms. The descriptive statistics for the subsamples of BD and non-BD firms are reported in Panel B. The statistically significant differences between the characteristics of BD and non-BD firms are at the 1% level, as indicated by ***.

Panel A: All firms

Variable	Mean	Std. Dev.	25th Percentile	Median	75th Percentile	Interquartile
EDF	0.117	0.232	0	0.001	0.100	0.100
StockVol	0.617	0.418	0.336	0.492	0.753	0.417
$LT\text{-}1_{,t\text{-}1}$	0.029	0.066	0.002	0.012	0.032	0.030
Cash	0.103	0.134	0.017	0.051	0.133	0.116
MTB	1.416	1.360	0.681	0.995	1.601	0.921
Idiovol	0.038	0.026	0.020	0.030	0.047	0.026
Tangibility	0.342	0.237	0.151	0.289	0.499	0.347
Size	5.608	2.283	3.909	5.562	7.209	3.300
R&D	0.027	0.061	0	0	0.025	0.025
Tax	0.019	0.030	0	0.014	0.035	0.035
Profitability	-0.084	0.868	0.013	0.063	0.118	0.105
Leverage	0.317	0.190	0.174	0.284	0.418	0.244
IntCov	4.746	15.342	1.515	3.750	7.756	6.241
Idebt3y	0.537	0.333	0.247	0.590	0.828	0.581

Panel B: BD firms versus non-BD firms

	BD Firms		Non-BD Firms		Difference of Means
Variable	Mean	Std. Dev.	Mean	Std. Dev.	
EDF	0.137	0.247	0.077	0.193	0.060***
StockVol	0.701	0.447	0.444	0.280	0.258***
$LT\text{-}1_{,t\text{-}1}$	0.034	0.077	0.018	0.033	0.016***
Cash	0.114	0.146	0.081	0.100	0.033***
MTB	1.474	1.484	1.296	1.048	0.178
Idiovol	0.044	0.028	0.025	0.014	0.019***
Tangibility	0.327	0.237	0.374	0.236	-0.048***
Size	4.593	1.840	7.702	1.572	-3.109***
R&D	0.033	0.071	0.015	0.032	0.018***
Tax	0.017	0.031	0.022	0.028	-0.005***
Profitability	-0.162	1.021	0.079	0.343	-0.241***
Leverage	0.299	0.188	0.353	0.187	-0.054***
IntCov	3.776	17.445	6.748	9.343	-2.972***
Idebt3y	0.454	0.338	0.706	0.249	-0.252***

Table 2. Correlation matrix

The table presents the correlation matrix for the variables used in the empirical model based on the sample of 67,609 firm–year observations from 1986 to 2013, where *EDF* is the expected default probability; *StockVol* is the annualized volatility over the next year; and $(LT)\text{-}1_{,t-1}$ is the amount of a firm's long-term debt outstanding at the end of year t – 1 that is due for repayment in year t, scaled by the current book value of total assets. The control variables are *Cash*, *MTB*, *Idiovol* (idiosyncratic risk), *Tangibility*, *Size*, *R&D*, *Tax*, *Profitability*, *Leverage*, and *IntCov* (interest coverage). For details, see Appendix B. Panels A to C report the Pearson correlations for the entire sample, for the subsample of BD firms, and for the subsample of non-BD firms, respectively.

Panel A: All firms													
	EDF	*StockVol*	$(LT)\text{-}1_{,t-1}$	*Cash*	*MTB*	*Idiovol*	*Tangibility*	*Size*	*R&D*	*Tax*	*Profitability*	*Leverage*	*IntCov*
StockVol	0.68												
$(LT)\text{-}1_{,t-1}$	0.16	0.16											
Cash	-0.03	0.08	-0.02										
MTB	-0.19	-0.01	0.04	0.28									
Idiovol	0.55	0.80	0.20	0.07	0.00								
Tangibility	-0.02	-0.07	0.02	-0.27	-0.10	-0.06							
Size	-0.17	-0.47	-0.14	-0.12	-0.19	-0.54	0.12						
R&D	-0.01	0.15	0.02	0.43	0.33	0.16	-0.24	-0.18					
Tax	-0.23	-0.29	-0.10	-0.01	0.15	-0.31	-0.04	0.16	-0.10				
Profitability	-0.11	-0.24	-0.08	-0.32	-0.23	-0.25	0.05	0.23	-0.40	0.18			
Leverage	0.25	0.14	0.24	-0.15	-0.01	0.14	0.15	0.03	-0.10	-0.24	-0.03		
IntCov	-0.18	-0.30	-0.08	-0.13	-0.01	-0.32	0.00	0.25	-0.29	0.46	0.43	-0.17	
ldebt3y	-0.12	-0.21	-0.24	0.00	-0.04	-0.26	0.17	0.35	-0.10	0.05	0.07	0.19	0.06
Panel B: BD firms													
	EDF	*StockVol*	$(LT)\text{-}1_{,t-1}$	*Cash*	*MTB*	*Idiovol*	*Tangibility*	*Size*	*R&D*	*Tax*	*Profitability*	*Leverage*	*IntCov*
StockVol	0.69												
$(LT)\text{-}1_{,t-1}$	0.16	0.14											
Cash	-0.07	0.04	-0.04										
MTB	-0.20	-0.02	0.04	0.28									
Idiovol	0.56	0.79	0.18	0.02	-0.01								
Tangibility	-0.00	-0.06	0.04	-0.27	-0.10	-0.05							
Size	-0.15	-0.41	-0.10	-0.06	-0.21	-0.48	0.10						
R&D	-0.03	0.13	0.01	0.44	0.34	0.14	-0.25	-0.17					
Tax	-0.24	-0.29	-0.10	-0.01	0.11	-0.31	-0.03	0.16	-0.12				
Profitability	-0.10	-0.21	-0.08	-0.33	-0.25	-0.22	0.04	0.22	-0.41	0.18			
Leverage	0.28	0.16	0.28	-0.16	0.00	0.17	0.16	0.00	-0.07	-0.23	-0.05		
IntCov	-0.18	-0.30	-0.08	-0.16	-0.06	-0.32	0.02	0.28	-0.33	0.46	0.44	-0.14	
ldebt3y	-0.11	-0.17	-0.21	0.04	-0.03	-0.20	0.16	0.27	-0.05	0.06	0.04	0.15	0.07
Panel C: Non-BD firms													
	EDF	*StockVol*	$(LT)\text{-}1_{,t-1}$	*Cash*	*MTB*	*Idiovol*	*Tangibility*	*Size*	*R&D*	*Tax*	*Profitability*	*Leverage*	*IntCov*
StockVol	0.64												
$(LT)\text{-}1_{,t-1}$	0.10	0.06											
Cash	0.04	0.10	0.00										
MTB	-0.20	-0.06	-0.03	0.23									
Idiovol	0.50	0.73	0.10	0.10	-0.08								
Tangibility	-0.02	-0.02	0.00	-0.26	-0.07	0.00							
Size	-0.06	-0.28	0.00	-0.07	-0.12	-0.36	0.00						
R&D	-0.05	-0.01	-0.03	0.35	0.25	-0.01	-0.25	0.06					
Tax	-0.18	-0.24	-0.06	0.03	0.30	-0.29	-0.06	0.09	0.04				
Profitability	-0.11	-0.18	0.01	-0.18	-0.01	-0.20	0.04	0.11	-0.10	0.21			
Leverage	0.25	0.29	0.20	-0.08	-0.01	0.35	0.10	-0.25	-0.17	-0.31	-0.09		
IntCov	-0.14	-0.19	-0.07	0.12	0.29	-0.24	-0.11	0.19	0.13	0.50	0.24	-0.39	
ldebt3y	-0.01	0.10	-0.30	0.06	0.00	0.08	0.10	-0.14	-0.10	-0.09	-0.05	0.18	-0.14

Table 3. RRE on default risk

This table presents the results of regressions aimed at understanding the impact of rollover risk on the default probability. The dependent variable is *EDF*, the expected default frequency. The main independent variable is $(LT)\text{-}1_{,t-1}$, the long-term debt outstanding at the end of year $t-1$ that is due for repayment in year t. The control variables are: *Cash*, *MTB*, *Idiovol* (idiosyncratic risk), *Tangibility*, *Size*, *R&D*, *Tax*, *Profitability*, *Leverage*, and *IntCov* (interest coverage). For details, see Appendix B. Column (1) reports the estimators without control variables. Columns (2) to (4) report the estimators with controls with correlations between each other below 0.3, 0.4, and 0.5, respectively. Column (5) reports the estimators with all the control variables. All specifications include firm and year fixed effects (FE). Standard errors (in parentheses) are robust to heteroskedasticity and autocorrelation and are clustered at the firm level. The superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Choice of control variables				
	No	Correlations < |0.3|	Correlations < |0.4|	Correlations < |0.5|	All
	(1)	(2)	(3)	(4)	(5)
$(LT)\text{-}1_{,t-1}$	0.202 ***	0.114 ***	0.131 ***	0.126 ***	0.058 **
	(0.029)	(0.027)	(0.025)	(0.025)	(0.023)
$Cash_{t-1}$				–0.056 ***	–0.015
				(0.012)	(0.010)
MTB_{t-1}			–0.031 ***	–0.030 ***	–0.018 ***
			(0.001)	(0.001)	(0.001)
$Idiovol_{t-1}$					3.974 ***
					(0.072)
$Tangibility_{t-1}$		0.000	–0.001	–0.020	–0.028 **
		(0.013)	(0.013)	(0.014)	(0.012)
$Size_{t-1}$					0.037 ***
					(0.002)
$R\&D_{t-1}$				0.103 ***	0.088 ***
				(0.039)	(0.034)
Tax_{t-1}				–0.248 ***	–0.063 *
				(0.037)	(0.033)
$Profitability_{t-1}$				–0.010 ***	–0.005 ***
				(0.002)	(0.002)
$Leverage_{t-1}$		0.210 ***	0.209 ***	0.192 ***	0.117 ***
		(0.010)	(0.010)	(0.010)	(0.008)
$IntCov_{t-1}$				–0.000	0.000 **
				(0.000)	(0.000)
Constant	0.035 ***	–0.023 ***	0.026 ***	0.048 ***	–0.237 ***
	(0.005)	(0.007)	(0.007)	(0.008)	(0.012)
Obs.	67,609	67,609	67,609	67,609	67,609
R^2	0.048	0.095	0.133	0.155	0.297
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Table 4. Bank financing dependence on the RRE

This table presents the results of regressions on the impact of bank dependence on the rollover risk channel to increase the default probability. The dependent variable is *EDF*, the expected default frequency. The main independent variable is $(LT)\text{-}1_{,t-1}$, the long-term debt outstanding at the end of year t – 1 that is due for repayment in year t. The control variables are *Cash*, *MTB*, *Idiovol* (idiosyncratic risk), *Tangibility*, *Size*, *R&D*, *Tax*, *Profitability*, *Leverage*, and *IntCov* (interest coverage). For details, see Appendix B. Column (1) reports the estimators without control variables. Columns (2) to (4) report the estimators with controls with correlations between each other below 0.3, 0.4, and 0.5, respectively. Column (5) reports the estimators with all the control variables. Panels A and B present the results for BD and non-BD firms, respectively. All specifications include firm and year fixed effects (FE). Standard errors (in parentheses) are robust to heteroskedasticity and autocorrelation and are clustered at the firm level. The superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: BD firms

	Choice of Control Variables				
	No	Correlations < |0.3|	Correlations < |0.4|	Correlations < |0.5|	All
	(1)	(2)	(3)	(4)	(5)
$(LT)\text{-}1_{,t-1}$	0.199 ***	0.102 ***	0.121 ***	0.115 ***	0.057 **
	(0.032)	(0.029)	(0.027)	(0.027)	(0.025)
$Cash_{t-1}$				–0.068 ***	–0.031 ***
				(0.013)	(0.012)
MTB_{t-1}			–0.032 ***	–0.032 ***	–0.020 ***
			(0.001)	(0.001)	(0.001)
$Idiovol_{t-1}$					3.690 ***
					(0.077)
$Tangibility_{t-1}$		–0.001	–0.008	–0.034 **	–0.042 ***
		(0.017)	(0.016)	(0.017)	(0.014)
$Size_{t-1}$					0.040 ***
					(0.003)
$R\&D_{t-1}$				0.106 **	0.104 ***
				(0.042)	(0.037)
Tax_{t-1}				–0.277 ***	–0.086 **
				(0.046)	(0.041)
$Profitability_{t-1}$				–0.008 ***	–0.005 **
				(0.002)	(0.002)
$Leverage_{t-1}$		0.234 ***	0.238 ***	0.216 ***	0.132 ***
		(0.012)	(0.012)	(0.012)	(0.010)
$IntCov_{t-1}$				0.000 **	0.000
				(0.000)	(0.000)
Constant	0.039 ***	-0.026 ***	0.030 ***	0.058	–0.211 ***
	(0.006)	(0.009)	(0.009)	(0.010)	(0.013)
Obs.	45,529	45,529	45,529	45,529	45,529
R^2	0.046	0.102	0.147	0.171	0.342
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Panel B: Non-BD firms					
	Choice of Control Variables				
	No	Correlations < |0.3|	Correlations < |0.4|	Correlations < |0.5|	All
	(1)	(2)	(3)	(4)	(5)
(LT)-1$_{,t-1}$	0.144 **	0.068	0.072	0.072	0.018
	(0.061)	(0.061)	(0.060)	(0.060)	(0.055)
Cash $_{t-1}$				–0.009	0.035 *
				(0.024)	(0.021)
MTB$_{t-1}$			–0.025 ***	–0.025 ***	–0.013 ***
			(0.002)	(0.002)	(0.002)
Idiovol $_{t-1}$					5.095 ***
					(0.226)
Tangibility $_{t-1}$		–0.020	–0.009	–0.009	–0.007
		(0.022)	(0.022)	(0.024)	(0.021)
Size $_{t-1}$					0.041 ***
					(0.003)
R&D $_{t-1}$				–0.071	–0.011
				(0.093)	(0.079)
Tax $_{t-1}$				–0.138 **	0.030
				(0.063)	(0.058)
Profitability $_{t-1}$				–0.011 *	0.004
				(0.006)	(0.006)
Leverage $_{t-1}$		0.139 ***	0.132 ***	0.134 ***	0.067 ***
		(0.018)	(0.018)	(0.019)	(0.016)
IntCov $_{t-1}$			–0.001 ***	0.001 ***	0.000 *
			(0.000)	(0.000)	(0.000)
Constant	0.031 ***	0.000 ***	0.030 **	0.034 **	–0.334 ***
	(0.007)	(0.013)	(0.013)	(0.014)	(0.028
Obs.	22,080	22,080	22,080	22,080	22,080
R^2	0.060	0.111	0.150	0.155	0.252
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Table 5. Declining profitability and poor credit

This table presents the results of regressions to test whether the RRE is conditional on a firm's characteristics of declining profitability and credit quality. Panels A and B present the results for subsamples that contain BD and non-BD firms, respectively. The dependent variable is *EDF*, the expected default frequency. The main independent variable is $(LT)\text{-}1_{,t-1}$, the long-term debt outstanding at the end of year t – 1 that is due for repayment in year t. The control variables are *Cash*, *MTB*, *Idiovol* (idiosyncratic risk), *Tangibility*, *Size*, *R&D*, *Tax*, *Profitability*, *Leverage*, and *IntCov* (interest coverage). For details, see Appendix B. The variable *Decline* is a dummy that identifies firms having a decline in profitability during the year compared to the previous year. The *poor credit indicators* are as follows: (1) *Altman_Z-B50* is a dummy variable that identifies firms with an Altman Z-score (1968) below the median value among all firms for a given year; (2) *Ohlson-A50* is a dummy variable that identifies firms with an Ohlson score above the median value among all firms for a given year; (3) *Idiovol-A50* is a dummy variable that identifies firms with idiosyncratic risk above the median value among all firms for a given year; and (4) *Leverage-A50* is a dummy variable that identifies firms with leverage above the median value among all firms for a given year. All specifications include firm and year fixed effects (FE). Standard errors (in parentheses) are robust to heteroskedasticity and autocorrelation and are clustered at the firm level. The superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: BD firms

		Poor Credit Indicator			
		Altman_Z-B50	*Ohlson-A50*	*Idiovol-A50*	*Leverage-A50*
	(1)	(2)	(3)	(4)	(5)
$(LT)\text{-}1_{,t-1}$	–0.048 *	–0.080 **	–0.076 **	–0.050	–0.198 ***
	(0.026)	(0.032)	(0.031)	(0.038)	(0.044)
Decline	0.034 ***				
	(0.002)				
$(LT)\text{-}1_{,t-1}$ x *Decline*	0.183 ***				
	(0.030)				
Poor Credit		0.074 ***	0.055 ***	0.095 ***	0.024 ***
		(0.003)	(0.003)	(0.003)	(0.002)
$(LT)\text{-}1_{,t-1}$ x *Poor Credit*		0.148 ***	0.139 ***	0.126 ***	0.290 ***
		(0.045)	(0.043)	(0.045)	(0.049)
Control Variables	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes
Obs.	45,529	39,640	40,058	45,529	45,529
R^2	0.37	0.315	0.296	0.395	0.355
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Panel B: Non-BD firms

		Poor Credit Indicator			
		Altman_Z-B50	*Ohlson-A50*	*Idiovol-A50*	*Leverage-A50*
	(1)	(2)	(3)	(4)	(5)
$(LT)\text{-}1_{,t-1}$	–0.028	0.034	0.047	–0.015	0.085
	(0.051)	(0.062)	(0.067)	(0.045)	(0.071)
Decline	0.021 ***				
	(0.003)				
$(LT)\text{-}1_{,t-1}$ x *Decline*	0.138				
	(0.101)				

Poor Credit		0.036 ***	0.035 ***	0.042 ***	0.023 ***
		(0.004)	(0.003)	(0.003)	(0.004)
$(LT)\text{-}1_{,t-1}$ x *Poor Credit*		–0.002	–0.021	0.054	–0.086
		(0.107)	(0.102)	(0.081)	(0.092)
Control Variables	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes
Obs.	22,080	20,372	20,595	22,080	22,080
R^2	0.263	0.224	0.215	0.267	0.256
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Table 6. Benign credit market versus stressed credit market

This table presents the results of regressions to examine the RRE in times of benign credit markets versus stressed credit markets. Panels A and B present the results for the BD and non-BD firm subsamples, respectively. The dependent variable is *EDF*, the expected default frequency. The main independent variable is $(LT)\text{-}1_{,t-1}$, the long-term debt outstanding at the end of year $t-1$ that is due for repayment in year t. The control variables are *Cash*, *MTB*, *Idiovol* (idiosyncratic risk), *Tangibility*, *Size*, *R&D*, *Tax*, *Profitability*, *Leverage*, and *IntCov* (interest coverage). For details, see Appendix B. There are three stressed credit market indicators: (1) *Baa-Aaa Spread* is a dummy variable that equals one if the spread between yields on Baa- and Aaa-rated corporate bonds increases, (2) *TED Spread* is a dummy variable that equals one if the three-month TED spread–the difference between the interest rate on interbank loans and the T-bill rate–increases, and (3) *Recession* is a dummy variable that identifies recession years classified by the NBER. All specifications include firm and year fixed effects (FE). Standard errors (in parentheses) are robust to heteroskedasticity and autocorrelation and are clustered at the firm level. The superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: BD firms	(1)	(2)	(3)
$(LT)\text{-}1_{,t-1}$	0.018	0.002	0.002
	(0.027)	(0.029)	(0.024)
$(LT)\text{-}1_{,t-1}$ x *Baa-Aaa Spread*	0.095 ***		
	(0.033)		
$(LT)\text{-}1_{,t-1}$ x *TED Spread*		0.115 ***	
		(0.037)	
$(LT)\text{-}1_{,t-1}$ x *Recession*			0.255 ***
			(0.048)
Control Variables	Yes	Yes	Yes
Constant	Yes	Yes	Yes
Obs.	45,529	45,529	45,529
R^2	0.342	0.343	0.343
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Panel B: Non-BD firms	(1)	(2)	(3)
$(LT)\text{-}1_{,t-1}$	0.046	–0.010	0.025
	(0.064)	(0.056)	(0.058)
$(LT)\text{-}1_{,t-1}$ x *Baa-Aaa Spread*	–0.055		
	(0.089)		
$(LT)\text{-}1_{,t-1}$ x *TED Spread*		0.068	
		(0.094)	
$(LT)\text{-}1_{,t-1}$ x *Recession*			–0.023
			(0.113)
Control Variables	Yes	Yes	Yes
Constant	Yes	Yes	Yes
Obs.	22,080	22,080	22,080
R^2	0.252	0.252	0.252
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Table 7. Alternative default risk measure: Annualized stock volatility

This table reports the results of regressions aimed at understanding the impact of the rollover risk on the default probability. The dependent variable is *StockVol*, the annualized volatility computed by the standard deviation of logarithm daily stock returns over the next one year. The main independent variable is $(LT)\text{-}1_{,t-1}$, the long-term debt outstanding at the end of year $t - 1$ that is due for repayment in year t. Columns (1) and (3) (Columns (2) and (4) report the estimators without (with) control variables for the BD and non-BD groups, respectively. The control variables are *Cash*, *MTB*, *Idiovol* (idiosyncratic risk), *Tangibility*, *Size*, *R&D*, *Tax*, *Profitability*, *Leverage*, and *IntCov* (interest coverage). For details, see Appendix B. All specifications include firm and year fixed effects (FE). Standard errors (in parentheses) are robust to heteroskedasticity and autocorrelation and are clustered at the firm level. The superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Subsample			
	BD	BD	Non-BD	Non-BD
	(1)	(2)	(3)	(4)
$(LT)\text{-}1_{,t-1}$	0.251 ***	0.100 ***	0.081	–0.018
	(0.044)	(0.037)	(0.064)	(0.067)
Control Variables	No	Yes	No	Yes
Constant	Yes	Yes	Yes	Yes
Obs.	45,258	45,258	22,064	22,064
R^2	0.083	0.326	0.164	0.277
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Table 8. Micro-level amplification forces and a stressed credit market: Results for annualized stock volatility

This table presents the results of regressions to re-examine the RRE on default risk conditional on micro-level amplification forces and the overall credit market situation. The dependent variable is *StockVol*, the annualized stock volatility, computed by the standard deviation of logarithm daily stock returns over the next one year. The main independent variable is $(LT)\text{-}1_{,t-1}$, the long-term debt outstanding at the end of year $t-1$ that is due for repayment in year t. Panels A and B present the results for the BD and non-BD firm subsamples, respectively. The indicator of declining profitability (i.e., *Decline*), the poor credit indicator (i.e., *Altman_Z-B50*, *Ohlson-A50*, *Idiovol-A50*, and *Leverage-A50*), and the stressed credit market indicator (i.e., *Baa-Aaa Spread*, *TED Spread*, and *Recession*) are described in Tables 5 and 6. All specifications include firm and year fixed effects (FE). Standard errors (in parentheses) are robust to heteroskedasticity and autocorrelation and are clustered at the firm level. The superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: BD firms

	Micro-Level Amplification Forces					Benign Credit Market versus Stressed Credit Market		
		Poor Credit Indicator						
		Altman_Z-B50	Ohlson-A50	Idiovol-A50	Leverage-A50			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$(LT)\text{-}1_{,t-1}$	0.008	–0.076 *	–0.009	–0.266 ***	–0.113	0.071	0.084 *	0.079 *
	(0.042)	(0.045)	(0.043)	(0.047)	(0.071)	(0.043)	(0.050)	(0.041)
Decline	0.043 ***							
	(0.003)							
$(LT)\text{-}1_{,t-1}$ x *Decline*	0.162 ***							
	(0.051)							
Poor Credit		0.091 ***	0.061 ***	0.293 ***	0.026 ***			
		(0.005)	(0.005)	(0.005)	(0.004)			
$(LT)\text{-}1_{,t-1}$ x *Poor Credit*		0.220 ***	0.119 *	0.407 ***	0.243 ***			
		(0.068)	(0.063)	(0.060)	(0.079)			
$(LT)\text{-}1_{,t-1}$ x *Baa-Aaa Spread*						0.074		
						(0.052)		
$(LT)\text{-}1_{,t-1}$ x *TED Spread*							0.034	
							(0.064)	
$(LT)\text{-}1_{,t-1}$ x *Recession*								0.097
								(0.048)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	45,258	39,632	40,050	45,258	45,258	45,258	45,258	45,258
R^2	0.34	0.363	0.34	0.507	0.329	0.326	0.326	0.326
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Non-BD firms

	Micro-Level Amplification Forces					Benign Credit Market versus Stressed Credit Market		
		Poor Credit Indicator						
		Altman_Z-B50	*Ohlson-A50*	*Idiovol-A50*	*Leverage-A50*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$(LT)\text{-}1_{,t-1}$	–0.054	–0.109 *	–0.047	–0.068 *	–0.040	–0.058	0.007	–0.016
	(0.072)	(0.064)	(0.072)	(0.041)	(0.071)	(0.076)	(0.072)	(0.066)
Decline	0.023 ***							
	(0.003)							
$(LT)\text{-}1_{,t-1}$ x *Decline*	0.111							
	(0.107)							
Poor Credit		0.048 ***	0.034 ***	0.162 ***	0.025 ***			
		(0.005)	(0.004)	(0.004)	(0.005)			
$(LT)\text{-}1_{,t-1}$ x *Poor Credit*		0.170	0.068	0.075	0.036			
		(0.106)	(0.107)	(0.087)	(0.100)			
$(LT)\text{-}1_{,t-1}$ x *Baa-Aaa Spread*						0.078		
						(0.107)		
$(LT)\text{-}1_{,t-1}$ x *TED Spread*							–0.061	
							(0.098)	
$(LT)\text{-}1_{,t-1}$ x *Recession*								–0.005
								(0.143)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	22,064	20,372	20,595	22,064	22,064	22,064	22,064	22,064
R^2	0.289	0.347	0.315	0.437	0.279	0.276	0.276	0.277
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes