Three Essays on Capital Structure Determinants

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ABSTRACT

Three essays on capital structure determinants

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The first essay studies the influence of credit ratings on the time-series evolution of corporate capital structures. We show that better rated firms have significantly more stable leverage ratios over time. By comparing firms across the investment-grade cut-off, we conclude using treatment effects estimation, that assignment to more stable rating classes leads to more stable capital structures over time. Extending this study across the whole range of ratings, we show that a one standard deviation improvement in credit-rating quality can reduce the leverage hazard ratio by more than 70%. In alternative investigations, rated firms tend to have largely more stable leverage ratios compared to not-rated firms. Matching firms based on their propensity to have credit ratings, rated firms take between 1.5 and 9 years longer to change their leverage ratios to the same levels as their not-rated counterparts. Our results are robust to the choice of different time frames and variety of controls. They extend the literature of the effects of credit ratings on capital structures by highlighting the importance of credit ratings on the long-run financing behaviors of firms.

The second essay studies the stability of various debt-structure dimensions. Survival and long-run clustering analyses are used to assess the stability of debt-rank orderings, debt heterogeneity and main debt type(s). Firms only maintain stability in their main debt type, while frequently changing the weights and priorities of other debt types, heterogeneity indexes and rank orderings. While all debt structure metrics are less stable with the assignment of a credit rating, the effect on the stability of the main debt type is minor. Firms with higher tax rates, market leverages and cash flow volatilities exhibit higher stability in their debt structures.

The final essay investigates how the optimal corporate debt maturity is influenced by the strength of creditor rights and the efficiencies of contract enforcement mechanisms. Using a correlated random effects specification, we find that across 42 countries stronger creditor rights are associated with shorter corporate debt maturities while greater contract enforcement leads to longer maturities. These empirical results are consistent with the differing effects of creditor rights and contract enforcement on the choice of corporate maturity predicted by our model. Our results are robust to using different measures of debt maturity, individual components of creditor rights and different measures of contract enforcement. Our results are mostly driven by developed country debt and hold with the inclusion of various controls.

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To my mother and father

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CHAPTER 1:

Introduction

How firms set their financing decisions and optimal capital structures long been of interest in corporate finance. Such decisions are influenced by a variety of determinants including firm-specific, macroeconomic, legal and institutional factors. Capital structures have three essential components: first, choice of the amount of debt and thus the resulting leverage ratio; second, the combination of different debt types and their relative weights in capital structures that we refer to as debt-type structure; and finally, the choice of debt maturity. This thesis addresses the above three aspects of capital structure in three separate studies presented in Chapters 2, 3 and 4, respectively.

In this thesis we investigate (1) the stability of corporate capital structures and specifically, how such stability is influenced by the stability of credit ratings, (2) the stability of corporate debt-type structures, and (3) the determinants of debt maturity.

In Chapter 2 (Essay 1), we explore corporate debt stabilities and investigate how the stability of credit rating classes can lead to the choice of more stable capital structures over time. The importance of capital structure stability is well documented in the related literature and particularly in the seminal work of Robert, Lemmon and Zender (2008). This study suggests that corporate leverages are so stable over time that the importance of a firm's leverage history on today's leverage decision is much higher than that of conventional determinants of capital structure combined. The first essay contributes to this discussion by documenting that such stable leverage patterns are largely influenced by firms' tendency to maintain stable credit ratings.

In doing so, we argue that the influence of credit ratings on corporate leverages can be explored using two complementary hypotheses. In the first hypothesis, we suggest that if credit rating stability leads to leverage stability, more stable credit rating classes should have more stable capital structures over time. In the second hypothesis, we suggest that if firms' stable leverages are the results of their tendency to maintain stable credit ratings, rated firms should exhibit more stable leverage ratios over time than unrated firms.

To deal with the inherent endogeneity between credit ratings and leverage ratios, we follow the literature on treatment estimation by focusing on firms just above and just below the narrow band of investment grade cut-off (BBB- and BB+). The related literature documents that there is considerable randomness for the assignment of firms across this cut-off particularly due to three reasons: (a) the muddled origins of the cut-off, (b) noise and (c) inertia in the assignment of credit ratings. We find that an assignment to just above the cut-off significantly lengthens the life of a stable leverage policy.

Methodologically, this study adds to the related literature by introducing a new methodology for estimating treatment effects on survival data. This method enables us to directly measure leverage stability. Our method follows matching firms based on their propensity score to be located just above the cut-off, followed by estimation of the treatment effect while accounting for censoring as well as the possibility of missing counterfactuals in the control sample. To address any shortcomings of survival analysis, we introduce an alternative home-made test that computes the probability of leverage fluctuations across the matched samples without excluding firms from the sample as soon as they experience the event. Finally, we document that such stable leverage ratios in response to stable credit ratings are actively managed.

This paper makes four important contributions. First, we extend the literature on credit rating targets (Hovakimian, Kayhan and Titman, 2009 a, b; Graham and Harvey, 2001; Kisgen, 2009; Altman and Rijken, 2004, Nickell, Perraudin and Varotto, 2000) and the literature concerning the inter-relationship between credit ratings and capital structures by showing that the stability of credit ratings induces firms to maintain more stable leverage paths over time. Next, our proposed methodology effectively addresses the critique of DeAngelo and Roll (2015) that the conventional methods used to capture leverage stability, e.g. in Lemmon, Roberts and Zender (2008), are deficient and possibly misleading. Incorporating survival analysis, we are able to directly measure how stable corporate leverages are with no reliance on mean-taking or over-interpretation of fixed effect regression results. Third, to the extent of our knowledge, this paper is the first to introduce the method for the estimation of treatment effect on survival data to the related literature. Finally, we contribute to the policy debate about the regulatory role of credit ratings in financial markets by showing that credit rating considerations have long-term effects on corporate capital structure behavior.

In Chapter 3 (Essay 2), we study debt-type structures, as an integral part of capital structure decisions. The importance of debt structure has been theoretically known for many decades, which include the seminal works of Diamond (1991), Park (2000), and Bolton and Freixas (2000). However, empirical studies of debt structure have only been made possible recently as the debt structured data has become available only over the past few years. Therefore, this paper is one of the first to explore the determinants of debt structure.

A large body of the related literature deals with debt structure as a uniform variable. However, the emerging literature on corporate debt structures has documented considerable variability in debt structures. In this paper, we shed light on an unexplored aspect of debt structures, namely the stability of debt structures over time. This study is motivated by the first essay as well as the findings of Lemmon, Roberts, and Zender (2008) both documenting long-run stabilities in corporate capital structures over time. Particularly, we investigate whether such stable behavior in capital structure decisions can also influence debt structures.

This study enables us, to shed light on two opposing views in the literature regarding the possibility of debt structure stability. The first viewpoint, implied by Lemmon, Roberts and Zender (2008), asserts that similar to capital structures, debt types can also demonstrate stable time-series behaviors. In other words, firms may tend to maintain a stable combination of different debt types in their capital structures over time. The opposing viewpoint is provided by Rauh and Sufi (2010). They argue that large variations in corporate debt structures are in fact a mechanism employed by firms to compensate for the lack of variability in capital structures. We find supportive evidence for both of these predictions, and provide a more thorough understanding of debt structure decisions over time that incorporates both of these seemingly opposing views.

This study has two goals. First, using the newly available Capital IQ database on debt types, we empirically study the stability of debt structures from different perspectives. Using the debt categories introduced in the Capital IQ database, we categorize the debt types into the following seven distinct categories: (1) Capital Leases, (2) Commercial Papers, (3) Lines of Credit, (4) Term Loans, (5) Bonds and Notes, (6) Trusts, and (7) Other Debt.

Second, we empirically study the influence of credit ratings on the stability of debt structures. This examination is particularly motivated by the findings of Rauh and Sufi (2010) that credit ratings influence debt structures. This paper suggests that large and rated firms tend to use multiple debt types in their debt structures whereas unrated, smaller firms incorporate fewer debt types. Using propensity score matching of Dehejia and Wahba (2003) we are able to study the effect of treatment (being rated) on the stability of corporate debt structures.

We introduce a wide range of debt type constructs, including the relative weights and the number of different debt types (debt heterogeneity), ranks of different debt types in the debt structure based on their relative weights, the choice of main debt type and the choice of second largest debt type. To the extent of our knowledge, this is the first study in the literature to provide such alternative constructs.

Our findings can be summarized as follows. First, we find large time-series variations across all different measures of debt structure including debt heterogeneity and debt rank indexes. In sharp contrast with other debt-structure metrics, the main debt type stays largely stable over time. Over a 12 year period, close to 50% of the firms never change their main debt types. Second, we find that rated firms tend to have less stable debt-type structures compared to not-rated firms. This finding, compared to the findings in the first essay, provides evidence consistent with the idea that higher variations in debt structures can compensate for more stability in capital structures.

This chapter makes four contributions. First, we contribute to the emerging literature of corporate debt structures by introducing a comprehensive set of alternative measures of debt structures. We also contribute to this literature by investigating the time-series stabilities of these measures. Second, we contribute to the literature on the stability of capital structures by documenting that firms maintain their single main debt types largely stable over time while changing all other debt types, their weights and ranks frequently. Third, we complement the findings of Colla et al. (2013) by showing that when extended over multiple years, firms' specialization in a few debt types is almost solely the domain of a single main debt type and does not extend to even the second most important debt type. Finally, we contribute to the literature on the effects of credit ratings on capital structure decisions by showing that having a credit rating largely results in less stability of debt structures.

In chapter four (third essay), we study corporate debt maturities. Particularly, we investigate internationally how the strength of creditor rights and efficiency of contract enforcements influence firms' choices of optimal debt maturities. This study is mainly necessitated by a plethora of opposing views about the influence of creditor rights on optimal debt maturity. In this paper, we tackle this long standing debate by arguing that this problem is caused by bundling creditor rights and contract enforcements together while they have independent and opposing effects on optimal debt maturities.

Across 42 countries, our empirical results show that the strength of creditor rights and efficiencies of contract enforcement are largely independent of each other, and have merely a correlation of 5%. Using a stylized theoretical model, we are able to disentangle the effect of these two institutional determinants on optimal corporate debt maturity. This is possible since stronger creditor rights give upper legal hand at liquidation to the creditors, while better enforcement efficiencies shrink the time and costs needed to enforce contracts, i.e. to liquidate a firm's assets.

Our model is constructed in the context of asset substation of Jensen and Meckling (1976) and Park (2000). We assume there are two projects: safe and risky, where the payoff of the risky projects is higher for the manger. Shorter term debt is cheaper for the manager since it relaxes the monitoring incentives of creditors. However it restricts the options of the manager particularly in terms of being able to choose riskier projects and to engage in risk-shifting activities. Thus when creditor rights are strong, the ex-ante costs of bankruptcy for the manager increase and in turn, act as a disincentive for taking risky projects. In this regard, it is optimal for the manager to choose the safe project and finance the project with short term debt. With no risk-shifting incentives, the manager finds long-term debt unnecessarily expensive.

Longer term debt, on the other hand, is more expensive as creditors need to monitor and thus charge additional premiums for the supposedly increased risk associated with longer-term contracts. With weak creditor rights the costs of bankruptcy for a manager declines ex-ante, and therefore the less restrictive long-term debt with monitoring becomes beneficial.

On the other hand, contract enforcement reduces the costs of liquidation and simultaneously provides legal guarantees that the contract will be implemented in the future according to the terms agreed to at the time of contracting. We show that these features of better contract enforcement induce both managers and creditors to agree on longer term maturities. In short, our model predicts that stronger creditor rights leads to shorter debt maturity while better enforcement lengthens it.

We address cross-country unobservable heterogeneities using a correlated random effect specification (CRE). This method enables us to estimate the time-varying determinants of maturity with fixed-effects and its time-invariant determinants with random effects specifications. Our results confirm the above hypotheses and document that stronger creditor rights shorten corporate debt maturities while better enforcements lengthens them. These effects are robust to firm and industry specific controls as well as to the inclusion of countries' institutional, political and macroeconomic determinants. Our results are also robust to the alternative measures of debt maturity as introduced by Fan, Titman and Twite (2012) and Saretto et al. (2013), and to alternative estimation methods and different subsamples.

The study reported in this chapter makes three contributions. First, by documenting the opposite and largely independent impacts of creditor rights and contract enforcement efficiencies on capital structure decisions, our study contributes to the literature on the effects of the institutional environment on a firms' capital structure decisions (Demirguc-Kunt and Maksimovic, 1999; Giannetti, 2003; Qian and Strahan, 2007; Bae and Goyal, 2009; Cho et al., 2014; Fan et al., 2012). Second, we contribute to the literature on the disentanglement of the effects of institutions on economic activities and corporate decisions (North, 1981; and Acemoglu et al., 2005) by unbundling the impacts of creditor rights and contract enforcement efficiencies on optimal debt maturities. Third, we contribute to the literature concerning the optimal levels of creditor rights in an economy by documenting inefficiencies associated with strong creditor protection laws (Aghion, Hart, and Moore, 1992; Hart et al., 1997; Acharya et al., 2011; Vig, 2013; and Cho et al., 2014).

CHAPTER 2:

Credit Ratings and Capital Structure Persistence

2.1 INTRODUCTION

The inter-relationship between credit ratings and capital structure decisions is well-documented in the corporate finance literature (Kisgen, 2006, 2009; Kisgen and Strahan, 2010; Ellul, Jotikasthira, and Lundblad, 2011). Leverage changes can lead to changes in credit ratings and credit-rating changes can motivate changes in financing decisions (Kisgen, 2006; Kisgen, 2009).[1] Interestingly, both leverage ratios and credit ratings exhibit persistence over time. Various studies document the long-run targets of credit-ratings over time (e.g., Hovakimian, Kayhan and Titman, 2009; Altman and Rijken, 2004; Nickell Perraudin and Varotto, 2000). Lemmon, Roberts and Zender (2008) document that leverage ratios are stable over long time periods and question the validity of conventional theories of capital structure including the trade-off and pecking order theories (Graham and Leary, 2011). The magnitude of leverage stability documented by Lemmon, Roberts and Zender (2008) is so large that they conclude that a firm's history of capital structure is a more important determinant of its current capital structure than the combined effect of all classic capital structure determinants.

In this paper, we introduce a new and unexplored dimension of capital structure persistence and study whether credit-rating stability leads to leverage-ratio stability. To do so, we test two complementary hypotheses. Our main hypothesis is that firms with more stable rating classes have more stable capital structures over time. In order to study this question, we use the rating-based market segmentation between investment and speculative grade firms in the capital markets (Chernenko and Sunderam, 2012). Specifically, we set up novel treatment effects specifications, and use duration and survival analyses to infer causality between these two stable patterns. Our second hypothesis is that the stability of capital structure is different across rated and not-rated firms. Confirming this hypothesis enables us to extend our results to a broader set of firms.

Several a priori reasons underpin the expectation that firms with more stable rating classes maintain more stable leverage paths, and that rated firms have more stable leverages than their not-rated counterparts. First, there is the literature on credit-rating targets and the influence of

[1] Moreover, Graham and Harvey (2001) use survey data to document that maintaining a good credit rating is one of the main priorities of CFOs when making capital structure decisions.

credit ratings on corporate capital structure decisions. Hovakimian, Kayhan and Titman (2009), Altman and Rijken (2004), and Nickell, Perraudin and Varotto (2000) find that firms have credit-rating targets. The link between capital structure decisions and target ratings is corroborated by Kisgen (2009) who reports that firms adjust their leverage ratios in response to departures from their target ratings. Studies find that the commencements of bond or syndicated loan ratings influence the capital structure decisions of firms (Kisgen, 2006; Sufi, 2009a) and that credit ratings can influence the cross-sectional variations in leverage ratios by enhancing access to external capital. For example, rated firms have higher leverage ratios mostly due to greater access to capital markets (Faulkender and Petersen, 2006) or loanable funds (Leary, 2009). Moreover investment grade firms have access to more sources of external capital than speculative grade firms (Chernenko and Sunderam, 2012). Refinements in rating-agency criteria significantly affect leverage ratios (Tang, 2009) and ratings reflect target leverage ratios (Elkahmi, Pungaliya and Vijh, 2010). Rated firms also tend to have debt with longer average maturities (Faulkender and Petersen, 2006), which contributes to lower rollover risk. In turn, this is expected to lead to more stable leverage ratios.

Second, there is a large body of literature on how leverage variations may result in changes in rating qualities. All else equal, higher leverage decreases the distance to default in a structural credit approach (Leland and Toft, 1996; Duffie, Saita, Wang, 2007). Conditional on different determinants of credit quality (Duffie and Singleton, 2003), leverage directly affects a firm's default probability. Not surprisingly, the level of a firm's leverage is one of the main determinants of credit-rating decisions by rating agencies such as S&P and Moody's,[2] where an increase in leverage is commonly associated with a decline in rating quality all else held equal, and vice versa. Reductions in leverage are also generally associated with improvements in credit ratings, and therefore can cause a firm to deviate from its target credit rating (Hovakimian, Kayhan and Titman, 2009; Kisgen, 2009). Thus, firms can be unwilling to put their credit rating status in jeopardy by allowing large fluctuations in their leverage ratios, and particularly when they have a high rating. Therefore, we expect that better-rated firms have more stable leverage patterns over time since increased leverage signals higher risk to the market and may adversely affect a firm's credit rating, value and operations.

[2] For example, refer to Moody's Credit Rating Prediction Model document found at: https://www.moodys.com/sites/products/DefaultResearch/2006200000425644.pdf

In this study, it is necessary to account for the inherent endogeneity between credit ratings and capital structures. Specifically, credit ratings or their qualities are not exogenously assigned to firms and thus a third determinant (unobserved characteristic) may be driving the cross-sectional heterogeneity of both credit-rating assignments and leverage ratios. Moreover, the self-selection into different rating categories makes the use of appropriate econometric methods even more necessary. We address these identification challenges using a set of identification strategies introduced below.

We first formally document the long-run stability of rating classes. We do so using the portfolio formation method of Lemmon, Roberts and Zender (2008). Forming quartile portfolios of firms based on their initial credit rating, we show that the average credit rating for these quartiles stays highly stable after a period of 27 years but becomes less stable with a lower credit rating. More intuitively, an examination of a typical credit rating matrix validates the idea of rating stability since there are consistently higher probabilities that a firm preserves its rating unchanged over the next period.

We cannot simply compare investment and speculative grade firms to test our main hypothesis, because such a comparison can be confounded by differences in the characteristics between firms in these two credit-rating categories. To address this issue, we follow the literature on treatment effects estimation and focus predominantly on firms located just above and just below the investment grade cut-off (i.e. on firms with BBB- and BB+ ratings with S&P). Economic theory suggests that across this threshold firms have similar fundamentals and therefore exhibit similar credit risk as well as capital structure determinants. Therefore, a focus on this cut-off provides an identification opportunity for estimating the *treatment effect* of being located *just above* the cut-off on the outcome variable, which is the number of years that a firm waits before changing its leverage beyond some arbitrary threshold. This strategy to large extent mitigates the problem of endogeneity between credit ratings and choice of leverage, when coupled with propensity score matching for receiving treatment and appropriate assignment of counterfactuals. To the best of our knowledge, we are the first to introduce the estimation of treatment effects for survival data to deal with an issue in finance.[3]

[3]Discussions of the estimation of treatment effects for survival data are found in Rotnitzky and Robins, 2006; Vittinghoff, Glidden, Shiboski and McCulloch, 2012; Bai, Tsaitis and O'Brien, 2013.

Our treatment effect estimation methodology is different in three main aspects from that of Chernenko and Sunderam (2012) where they use the treatment effect to show the existence of market segmentation across investment and speculative grade firms. First, we match firms across the investment-grade cut-off not based on similarity in firm-level characteristics, but rather based on every firm's propensity to receive the treatment (Cameron and Trivedi, 2005; Dehejia and Wahba, 2002). Based on the related literature of program evaluation (Rosenbaum and Rubin, 1893; Hirano, Imbens and Ridder, 2003; Guo and Fraser, 2015), this should provide more reliable results for causality inference than simple characteristic matching. Second, we not only use a matched sample to increase the soundness of the comparison, but we also account for possible discontinuities in treatment and control samples by generating comparable counterfactuals using Weighted Regression-Adjusted (WRA) estimators. Third, since our outcome of interest is survival, we account for possible censoring and missing data using classic survival data censoring adjustments.

Despite the mostly arbitrary nature of the investment-grade cut-off and our use of the propensity score matching strategy, concerns may still remain about the effect of unobserved variables on our results. There may be some unobserved determinants that are only known to the rating agencies and may affect the assignment of firms across the investment-grade cut-off. Although we cannot perfectly rule out the impact of possible unobservables, we provide two additional examinations to address this concern. First, we argue that if the relationship between rating stability and capital structure stability exists, it should not be confined to the narrow band just above and below the investment grade cut-off. Thus, we use hazard regressions to examine the effect on capital-structure stability from any improvement in credit-rating quality over the whole spectrum of ratings.

Second, we argue that our results should hold with observable-based model-generated counterfactuals. The idea here is that a test that compares treatment firms with model-generated observable-based counterfactuals should fail to produce our primary results if the assignment of firms across the cut-off is influenced by CRA-specific unobservables. We show that our results are robust to this consideration using different estimation methods that include the Regression Adjustment (RA), Weighted Regression Adjustment (WRA), Inverse-Probability Weighting (IPW), and Inverse-Probability-Weighted Regression Adjustment (IPWRA).

We find that while firms in higher rating classes have more persistent transition probabilities and thus more stable credit ratings over time, they also have largely more stable leverage ratios. Matched firms just above the investment grade threshold maintain their leverage stability 3.67 years longer compared to their speculative grade counterparts, considering a threshold of a 50% change in leverage. Extending our study across all credit-rating classes using hazard regressions conditional on a set of covariates from the capital structure and credit risk literatures, we show that each standard deviation improvement in rating quality (i.e. four notches) results in more than a 70% reduction in the hazard rates of leverage-ratio changes. Furthermore, the effect of credit-rating quality on increased leverage stability is much higher than the effect of any other determinant.

We use a number of strategies to test our second hypothesis. First, we test if rated firms have more stable leverage ratios over time compared to not-rated firms. Second, we investigate whether individual firms with periods of rated and not-rated regimes have significantly more stable leverage ratios during their rated periods. Finally, we examine whether the probability of leverage ratio changes above any given threshold for rated firms is lower than that of the matched not-rated firms.

To conduct these examinations, we first replicate the portfolio formation method of Lemmon, Roberts and Zender (2008) and show that a stable leverage pattern is more dominant for the rated sample. We then introduce an alternative strategy to study whether rated firms have more stable leverage ratios than not-rated firms. For that we borrow from the literature of program evaluation where no basis for a natural experiment is available. Since in this setting there is no clear-cut cut-off between the treatment and control samples, we match rated and not-rated firms based on their propensity to have credit ratings using the sophisticated method of Dehejia and Wahba (2002) and report how the application of a treatment (i.e. having credit ratings) to one group of firms stabilizes their leverage ratios over time. While causal inference in this sample is not as strong as for the tests of the main hypothesis due to the effect of unobserved determinants, a propensity score matching makes the two samples largely comparable. Using a formal survival analysis on the matched samples, we find that rated firms change their leverage ratios less than not-rated firms and that this difference becomes larger at higher leverage variation thresholds. Controlling for firm, macroeconomic and industry effects, we show that rated firms minimize leverage fluctuations as having a credit rating reduces hazard rates by almost 20%. We further study how the treatment effect of being rated increases the number of years in which the firm maintains a stable leverage policy. Using different matching methods and therefore different numbers of control and treatment firms in each setting, our results show robustly that credit ratings have a significant impact on leverage stability. For example, we document that rated firms delay leverage changes of more than 50% by almost 9 years more compared to their not-rated counterparts in cluster-matched samples.

In a set of identification strategies designed to rule out the endogeneity effect, we document that starting (or stopping) of credit ratings reports has a significant influence on the future evolution of leverage ratios. Firms that begin to have credit ratings tend to maintain more stable leverage ratios in the rated periods, while firms whose credit ratings are discontinued tend to exhibit less stable leverage ratios in the not-rated periods. Our results are robust to the inclusion or exclusion of zero-leverage firms (as suggested by Lemmon, Roberts and Zender, 2008; DeAngelo and Roll, 2015).

We also introduce an alternative to survival tests by measuring the fluctuations of leverage ratios over time across different thresholds. This new test is motivated by a possible shortcoming of survival analyses. As a firm crosses a leverage threshold for the first time, its future leverage fluctuations are no longer under study using a survival analysis setting. In our alternative test, we retain firms in the sample over the whole study period regardless of how many times a firm crosses different leverage thresholds. We then calculate the probability of fluctuations across different thresholds for the whole sample at any given point in time. We show that rated firms tend to have fewer fluctuations in their leverage ratios over short and long horizons and across different thresholds than not-rated firms. This implies that the leverage-ratio stability in rated firms is not merely a long-run effect but is a pervasive behavior that extends over both short and long horizons.

Finally, we address whether the additional leverage stability for rated firms is due to active management. Based on active net debt and equity issuance portfolios, we document that rated firms have a greater tendency to maintain stable leverages and that active leverage management is influenced by the existence or absence of credit ratings. This result leads to the inference that the stability and convergence patterns in the rated and not-rated firm samples are in fact due to differences in active management.

This paper makes a number of important contributions to the existing literature. First, we extend the credit-rating targets literature (Hovakimian, Kayhan and Titman, 2009 a, b; Graham and

Harvey, 2001; Kisgen, 2009; Altman and Rijken, 2004, Nickell, Perraudin and Varotto, 2000), and the literature on the relationship between credit ratings and capital structures by documenting that credit-rating stability induces leverage stability. Our results suggest that the interdependence of leverage ratios and credit ratings not only influences the amount of debt in every period, but also the evolution of and variations in leverage ratios over long periods of time.

Our second contribution addresses a recent critique dealing with the stability phenomenon by DeAngelo and Roll (2015) that the reliance on firm fixed effects and formation of quartile portfolios as indicators of leverage stability by Lemon, Roberts and Zender (2008) are problematic since these methodologies cannot account for short-term leverage variations. We demonstrate that a survival analysis setting with its high sensitivity to short-term leverage fluctuations can be an appropriate alternative for exploring such stability. Furthermore, our home-made test for the measurement of the probability of leverage fluctuations is another alternative for such measurements.

Third, our empirical methodology which provides a setting for the estimation of treatment effects with survival data using matching and assignment of counterfactuals adds to the literature on the use of treatment effect evaluations in finance (Villalonga 2000; Malmendier and Tate, 2009; Campello, Graham, and Harvey 2010; Chernenko and Sunderam, 2012).

Fourth, by studying the relationships between different rating categories and having a credit rating on the financing and capital structure behaviors of firms over time, we contribute to the literature on the regulating role that ratings play in capital markets. In this regard, we also extend the literature on market segmentation by showing that segmentation across investment and speculative grade categories leads to differential capital-structure behaviors over time.

The remainder of this paper is organized as follows: Section 2.2 describes the sample and data. Section 2.3 provides evidence on the stability of rating classes. Section 2.4 studies the relationship between the stability of rating classes and leverage stability using samples of firms with ratings just above and just below investment grade. Section 2.5 studies the second hypothesis, and compares the stability of capital structures across rated and not-rated firms. Section 2.6 concludes the paper.

2.2 SAMPLE AND DATA

The initial sample consists of all COMPUSTAT firms drawn from the period of 1985 to 2012 from which we remove all financial firms (SIC codes 6000 to 6999).[4] The beginning year corresponds with the year that credit-rating reports commenced for a considerable number of firms. Our choice of an annual frequency is to maintain consistency with the use of annual datasets in the debate about leverage stability (specifically, Lemmon, Roberts and Zender, 2008; DeAngelo and Roll, 2015). Outliers are also eliminated by removing the top and bottom 0.1% of this initial sample based on their market and book leverage observations.

The full sample is divided into not-rated and rated firms where not-rated firms are those with no credit ratings reported by S&P at any point of time or non-temporary length of time during our sample period. COMPUSTAT is our source for S&P credit ratings for the long-term bonds and other financial and accounting information for our sample firms. Since the S&P ratings are reported mostly on a monthly basis and our data frequency is annual, the assigned credit rating for each firm for each fiscal year is based on that firm's last S&P rating report for that fiscal year.[5] For measuring credit-rating changes, we convert the ratings into a numeric format between 1 and 24, with AAA as 1, AA+ as 2,…, and ending with D as 24 (as in Hotchkiss, Strömberg and Smith, 2014).

Before proceeding to the empirical results, we examine the summary statistics for the variables for each of the three samples (rated, not-rated and combined). Table 2.1 shows that rated firms are, on average, larger and more volatile in terms of cash flows. They also have higher average sales, profitability, tangible assets and book and market leverage ratios.

[Please insert Table 2.1 about here]

2.3 THE STABILITY OF CREDIT-RATING CLASSES

To test the main hypothesis of the paper that rating stability results in leverage stability, we first need to investigate whether credit-rating classes are stable over time, and whether credit-rating stability declines with lower credit-rating quality. To examine the stability of rating classes, we

[4] Based on untabulated results, we obtain similar results when the sample is confined to those firms with data for at least ten years on book assets during our sample period. All untabulated results are reported in an internet appendix that is available from the authors of this paper.

[5] We obtain similar untabulated results when we assign an annual rating measure by using fiscal year averages of monthly numerical rating equivalents for each firm. This is primarily due to our study conditioning largely on the existence of a rating, and not the specific rating itself.

apply the portfolio formation method of Lemmon, Roberts and Zender (2008) to the S&P credit ratings for firms. Specifically, we construct quartiles of sample firms based on their relative credit ratings in each base year x until the base year is 2012, and then measure the average credit ratings of the firms in each quartile over the next 2013-x years from each base year. We then take the calendar-year averages of these average credit ratings for each quartile. The upper panel of Figure 2.1 shows that the rating quartiles are highly stable over a 20-year period. The average rating improves over time for the lowest rated quartile (line with triangles) and deteriorates for the highest and second to highest rated quartiles (curves with squares and dots). The average ratings hardly change for the second to lowest rated quartiles (curve with asterisks). The convergence is largely a result of this differential deterioration and improvement in credit ratings over time, especially when the highest rated (curve with squares) deteriorates the most and the lowest rated quartile (curve with triangles) improves the most.

Based on the numerical credit-rating equivalents (Hotchkiss, Strömberg and Smith, 2014), the deterioration in the highest rated quartile is about 2 notches. This moves the average rating of 5 (A+) to 7 (A-) for this quartile over 27 years. Deterioration in the credit-rating of the second-highest rated quartile is similar, with the equivalent average rating declining from 8 (BBB+) to 10 (BBB-) over 27 years. The credit-rating improvement for the lowest rated quartile is almost one notch from an average of 13 (BB-) to 14 (B+). Since convergence generally is slight, there is little change in a firm's rating class over a 20 year period. This finding is consistent with the findings of Alp (2013) that investment grade ratings tightened and speculative grade ratings loosened over the period of 1985 to 2002, and that this drop was followed by another drop of 1.5 notches between 2002 and 2007.

To account for possible attrition effects, we construct an alternative sample of firms with at least 20 years of observations. Based on the plots of the average ratings for each quartile over each of the 27 years reported in the lower panel of Figure 2.1, we observe almost a non-existent transitory (converging) component. A deterioration of about 2 notches occurs over 27 years for each of the categories in a similar fashion, while each rating class remains persistent over time. Considering both panels together suggests that average ratings are highly stable over long periods of time. This finding is also consistent with the findings of Baghai, Servaes, and Tamayo (2014) that average ratings declined by three notches from 1985 to 2009 after controlling for firm characteristics due to the increasing conservatism of rating agencies.

[Please insert Figure 2.1 about here]

To further explore how ratings evolve over time, we measure the magnitude and test the significance of the differences in mean ratings between event years 0 and 10, 10 and 20, and 0 and 20. The results for the total sample and the sample of firms with at least 20 annual observations are reported in Panels A and B, respectively, of Table 2.2. The improvements in the credit ratings of low and medium rated firms (negative sign) and the deteriorations in the ratings of high and very highly rated firms (positive sign) is evident in Panel A. However, the rating deteriorations are generally more significant than the improvements, consistent with the findings of Alp (2013). As reported in Panel B, the general deterioration in ratings across all four quartiles is significant. This shows that although the relative position of different rating groups is largely stable, there is a significant difference in the base year 0 rating classes going forward. Therefore, stability is chiefly a result of a similar magnitude of deterioration (or improvement) across the different rating quartiles.

[Please insert Table 2.2 about here]

The notion of credit-rating stability is further supported by investigating a typical rating transition matrix. For example, a Moody's Rating Transition Matrix (2007)[6] is reported in Figure 2.2 for probabilities over 1-year intervals in 2007. The diagonal of this matrix reports the much higher probabilities that a firm preserves its credit rating unchanged in the next period (i.e. next year). Furthermore, the probabilities located on the diagonal decline almost monotonically with a decrease in the credit-rating class. For example, an Aaa-rated firm has a 89% likelihood that it will preserve its credit rating in the next period, while this likelihood for a Baa1, Ba1, Caa1, and Ca-C firm is 75%, 65%, 59% and 35%, respectively. We discuss the possible reasons for this observation later in the paper.

[Please insert Figure 2.2 about here]

[6] From Moody's website: http://www.moodysanalytics.com/~/media/brochures/credit-research-risk-measurement/quantative-insight/credit-transition-model/introductory-article-credit-transition-model.ashx

2.4 DOES CREDIT-RATING STABILITY RESULT IN LEVERAGE-RATIO STABILITY?

2.4.1 Empirical Methodology

Building on the result of the previous section that credit-rating stability exists in the long run, we now formally test our main hypothesis of whether a firm's tendency to maintain stable credit ratings results in higher leverage stability. In preparation for that examination, we first explain our empirical strategy, possible limitations to causal interpretations, proposed solutions, econometric model set up and specification methods.

An important econometric problem that needs to be addressed when investigating the effects of credit-rating stability on leverage stability is that a simple comparison of leverage stability across different rating classes (e.g. investment grade versus speculative grade) can be methodologically problematic. Such a comparison can be confounded by considerable endogeneity between the credit ratings and corporate capital structures. The endogeneity between credit ratings and leverage ratios stems from two main sources: (1) Self-selection of firms into the different rating classes arising from the possibility that higher-rated firms may have entirely different fundamentals from lower-rated firms; and (2) the omitted variable problem since unobserved determinants may affect both leverage and credit-rating decisions concurrently.

To address these concerns, we employ an econometric approach to measure the treatment effect by matching firms just above and just below the investment-grade cut-off (i.e., firms with S&P credit ratings in the narrow band of BBB- and BB+). In our setup, firms that are assigned to the lowest (just) investment-grade class are in the *treatment* sample, and those just below the cut-off (just speculative-grade) are in the *control* sample. As an outcome, we expect to detect more stable leverage ratios for the matched firms located just above the investment-grade cut-off.

The first concern about the characteristics of firms assigned across the investment grade cut-off is that a matching method based on observables may fail to capture important unobserved determinants. While the selection of different observables as well as a robust matching method is effective, the origin of the cut-offs themselves can mitigate further concerns. Fons (2004) and Chernenko and Sunderam (2012) report no significant differences in firm fundamentals above and below the investment-grade cut-off. What firms are in fact "*speculative-grade*" has long been a source of debate and confusion. Chernenko and Sunderam (2011) refer to this situation as the "muddled origins" of the investment grade cut-off. In the 1930's when regulatory bodies began applying restrictions on the holdings of "speculative-grade" bonds by financial institutions, a serious policy limitation was the definition of such assets and what delineated speculative from investment grade bonds. By 1938, Moody's was able to convince regulators that BBB-rated bonds are not "distinctly" speculative. This suggests that at the threshold that divides investment from speculative grade there are no material fundamental differences in firm observables across the cut-off. We argue that this historic concept still applies, and is corroborated by arguments and findings of noise and inertia in credit-rating assignments by the rating agencies.

The noise and inertia arguments in credit-rating assignments suggest that although credit ratings should contain information about a firm's credit quality and arguably capital structure preferences, they are subject to errors, delays and mis-assignments. That being the case, one should be able to match firms across rating thresholds so that the matched firms are sufficiently similar in every fundamental respect. We now expand on these two arguments.

Convincing evidence for the inertia argument is provided by Altman and Rijken (2004) and Cantor and Mann (2006). Altman and Rijken (2004) discuss that credit-rating agencies (CRA's) are slow in adjusting their credit-rating assignments primarily due to the fact that they consider ratings as reflecting long-term default probabilities. These deviations between what ratings indicate and what the actual credit quality of the firms are implies that the investment-grade cut-off used by the rating agencies can be a very imprecise delineator of the credit quality of firms above and below this cut-off. Cantor and Mann (2006) corroborate this argument by showing that CRAs have to trade-off the accuracy of ratings they assign versus the stability of these ratings. Altman and Kao (1992) show that CRA adjustments in credit ratings are mostly done partially.

There are additional reasons to believe that rating assignments are noisy. As argued by Chernenko and Sunderam (2012), the organizational structure of CRAs can lead to credit-rating noise. For example, Moody's has separate departments for evaluating investment grade and speculative grade credits. The limits of information flow and conflicts of interests in such an organizational structure can affect the relative quality of rating assignments. The accuracy of credit-rating outlooks as precursors for possible changes in credit ratings further supports the noise argument. Cantor and Hamilton (2005) show that firms with positive outlooks default at the same frequency as firms with a one-notch better rating over the 1995-2005 period. Moody's adjusts the ratings of issuers one notch higher (lower) for positive (negative) outlooks in order to assess its quality of rating assignments versus historical default rates. In this regard, firms just below the investment grade cut-off (BB+) with positive outlooks should have at least the same rating quality as firms above the cut-off (BBB-). Finally, conflicts of interest in CRAs and imprecision in the models that they use to determine credit quality also add to the noise in credit ratings (e.g., Bolton, Freixax and Shapiro, 2012),

2.4.1.1 Estimation Method for the Treatment Effects for the Survival Data

The above argument about the similarity in firm fundamentals across the investment grade cut-off provides an interesting opportunity for studying the causal effects of better credit-rating status on capital-structure stability, since assignment of firms just above the cut-off can be arguably considered as being exogenous. In this setting, the outcome variable of interest is the number of years it takes for a firm to change its leverage ratio more than some arbitrary threshold, e.g. 10%, 20% or 50%, compared to its initial leverage. More formally, we study the "*survival outcomes*" as a result of the treatment, which is being located *just above* the investment grade cut-off as opposed to being located just below it. This answers the question of: "How many years longer does it take for a "treatment" firm to change its leverage ratio above some arbitrary threshold compared to a "control" firm?"

There are still remaining concerns about the matching of firms across the cut-off. The first problem is that we need to have close-enough counterfactuals to each treatment observation. Suppose, for example, that assignment to the just-investment-grade category is still influenced by a set of covariates X, whose effects are not yet perfectly exhausted by noise or inertia. For simplicity, let us assume that the matrix X contains only one single covariate, the firm-level volatility. In this regard, firms with higher volatility are more likely to fall below the cut-off and vice versa. As long as firms above and below the cut-off have comparable volatilities, we can safely estimate the treatment effects. Since there may be situations when no firms with comparable volatilities below the cut-off can be found, the minimum volatility in the control sample may correspond only to the medium volatilities in the treatment sample. Thus, we need to appropriately account for limitations in inference due to missing data, or as it is called in the literature, the censoring problem. We use a set of observables from the literature of capital structure (Parsons and Titman, 2008) and credit risk (Leland and Toft, 1996; Duffie and Singleton, 2003) to *match* the firms just above and just below the cut-off. This matching is done using propensity scores estimated using a multivariate Logit specification (Cameron and Trivedi, 2005). The matching is based on the initial observations of each firm in our sample. For every sample firm, we determine the first observation in the sample and then keep only those with the initial rating of BBB- and BB+ and then find matches for the two samples based on the aforementioned set of observables.

Another aspect of the censoring problem is that firms in either sample may have missing observations or have no events during the study period. To address this concern we use weight-adjusted censoring estimators. An assumption behind this method is that the time to censoring is subject to the following three assumptions: (a) censoring is random, (b) the time to censoring comes from a known distribution, and (c) the treatment level does not affect the censoring time. Since the censoring in our sample comes mostly from the coverage by the database (Compustat/ Capital IQ), we can appropriately proceed as if the above three assumptions hold.

Now we discuss how the time to event (survival time) is estimated using the random censoring determinant, t_C, and a treatment indicator dummy τ that equals 1 if the observation comes from the treatment sample and zero otherwise. Let us denote the time to event (i.e., the change of leverage above some arbitrary threshold) for an investment grade firm (treatment) and a speculative-grade firm (control) with t_0 and t_1. These potential outcomes can be censored or not. More formally:

$$\begin{aligned} \widetilde{t_0} &= t_c(t_0 \geq t_c) + t_0\{1-(t_0 \geq t_c)\} \\ \widetilde{t_1} &= t_c(t_1 \geq t_c) + t_1\{1-(t_1 \geq t_c)\} \end{aligned} \tag{2.1}$$

The potential outcome conditional on knowing τ can be expressed as:

$$t = (1-\tau)\, \widetilde{t_0} + \tau\, \widetilde{t_1} \tag{2.2}$$

Our main estimator in this paper is the Weighted Regression Adjustment (WRA). To test the robustness of our results to the influence of possible counterfactuals, we also replicate our studies using alternative estimators including Regression Adjustment (RA), Inverse-Probability Weighting (IPW) and Inverse-Probability-Weighted Regression Adjustment (IPWRA). The WRA estimators are obtained through a four-step procedure described below. In the first step, we estimate $\widehat{\boldsymbol{\gamma}}$ where $\boldsymbol{w}, \boldsymbol{\gamma}$ are covariates and related parameters, respectively, assuming that the time-to-censoring distribution is $F_c(t_c|\boldsymbol{w}, \boldsymbol{\gamma})$. In the second step, we estimate the parameters of a parametric survival-time model, denoted by $\hat{\beta}_\tau$ for each of the treatment levels $\tau \in \{0,1\}$ where the survival time distribution is denoted by $F(t|X, \tau, \beta_\tau)$. Here, X denotes the matrix of covariates (i.e., the factors that lead to longer or shorter waiting times until the threshold change in the leverage ratios). $\hat{\beta}_\tau$ captures the contribution of each of these covariates to the waiting time while τ indicates whether the sample is derived from investment grade or speculative grade firms. $\hat{\beta}_\tau$ are estimated using the Weighted Maximum Likelihood (WML) method, where weights are the inverse of the estimated probabilities of no censoring, or:

$$\widehat{\omega} = \frac{1}{1 - F_c(t_c|\boldsymbol{w}, \widehat{\boldsymbol{\gamma}})} \tag{2.3}$$

Next, we need to estimate the expected survival time, $\widehat{\mathrm{E}}(\mathrm{t_i}|\mathrm{X_i}, \tau, \hat{\beta}_\tau)$, using $\hat{\beta}_\tau$ and the distribution $\mathrm{F}(\mathrm{t}|\mathrm{X}, \tau, \beta_\tau)$, that shows the possible outcome means (POM) for the treatment effect. Finally, we can estimate the average treatment effects (ATE) by comparing the estimated POMs. Specifically, ATE can be estimated using a set of simultaneous equations as in Newey (1984) and Wooldridge (2010):

$$\frac{1}{N}\sum_{i=1}^{N} \widehat{\omega}_i \{\hat{E}\left(t_i \middle| x_i, \tau = 1\,, \hat{\beta}_{\tau=1}\right) - \widehat{POM}_0 - \widehat{ATE}\} = 0 \tag{2.4}$$

The ATET is estimated by:

$$\frac{1}{N_1}\sum_{i=1}^{N} \widehat{\omega}_i (\mathbf{1}_{\{\tau_i=1\}})\{\hat{E}\left(t_i \middle| x_i, \tau = 1\,, \hat{\beta}_{\tau=1}\right) - \widehat{POM}_0 - \widehat{ATE}\} = 0 \tag{2.5}$$

We also create alternative counterfactual samples with different models of the IRW, RA, IPW, and IPWRA methods. These methods create model-generated counterfactual observations based on a select set of observables in the treatment and control samples. We argue that if our primary results are influenced by the effects of any unobserved determinants, then similar tests that compare the treatment sample with counterfactual observations created using only observables should not confirm our main findings. Using all these alternative methods, we find that our results which are only tabulated using the IRW method, are almost identically replicated using the model-generated counterfactuals. Based on these findings, we contend that our econometric approach minimizes any concerns regarding the influence of unobservable variables.

2.4.2 Results for the Treatment Effects for Survival Data

In table 2.3, we report the average treatment effect (ATE) and average treatment effect for the treated (ATT) across the investment grade cut-off, where the treated and control samples are the ones just above and just below the cut-off point (BBB- and BB+), respectively. The ATE and ATT are reported in the first and second rows, respectively, of every panel (50, 20 and 10 percent thresholds). The potential-outcome means (POM) are reported in the fifth column. As expected for the main hypothesis, there is a large and significant difference across firms above and below the investment grade cut-off in terms of their leverage stability. In the first panel, the average time to change leverage by more than the 50% threshold for a firm just above the investment grade cut-off is 3.55 years longer than the 9.15 years for a firm just below the investment grade. The importance of this effect can be understood by examining the ratio of the average treatment effect to the potential outcome means. In this case, when all firms are located just above the 50% threshold, the time to the first cross above the 50% threshold falls by almost 39% relative to the case when all firms are located just below the 50% threshold.

The second row confirms this finding when the average treatment on treated (ATT) is considered (i.e. only the treatment on the just investment-grade firms is taken into account). For firms that are located just above the threshold, it takes 3.67 years longer to cross the 50% threshold at least once, compared to firms that are located below the 50% threshold. A similar leverage stabilizing effect in response to rating quality above the threshold is prevalent for the 20% and 10% thresholds. Focusing on the ATT estimates, it takes 2.12 (1.88) years longer for firms just above the investment-grade cut-off to cross the 20% (10%) leverage threshold, compared to firms just below it. In contrast, it takes 7.13 (3.21) years for a firm located below the threshold to cross these thresholds. In other words, being rated just above the investment grade cut-off leads to a 30% (59%) increase in leverage stability based on the 20% (10%) leverage thresholds.

These results strongly confirm our main hypothesis by identifying a causal relation between credit rating stability and the stability of leverage ratios over time, where the former influences the latter. The large and significant magnitude of this effect implies that long-term credit rating targets (Hovakimian, Kayhan and Titman, 2009) can largely influence how firms set their capital structure decisions. Compared to the findings of Lemmon, Roberts and Zender (2008), this finding shows that a sizeable portion of the leverage stability is induced by the tendency of firms to keep ratings stable. Considering that a firm's capital structure history largely affects today's leverage decisions even more than the conventional determinants (Lemmon, Roberts and Zender, 2008), our findings imply that credit-rating considerations are one of the most important capital structure determinants both cross-sectional and across time.

[Please insert Table 2.3 about here]

For illustrational purposes, we also compare the cumulative hazard and survival rates across two samples graphically in Figure 3. These graphs take the number of years until the first pass of leverage above thresholds of 10%, 20% and 50% compared to the previous leverage ratios. We observe a considerable difference between the survival rates of the leverage ratios across the two samples. Firms just above the cut-off threshold tend to have more stable leverage ratios across all thresholds. The gap between just investment and just speculative grade firms for both the survival and cumulative hazard rates widens with the passage of time, and the difference in the survival rates of the two samples is more pronounced at wider thresholds.

[Please insert Figure 2.3 about here]

2.4.3 Evidence from a Parametric Hazard Model

We extend the above examinations to investigate the relationship between the stability of credit-rating classes and leverage stability across the range of all different ratings. For this purpose, we use a conditional hazard regression setting, where the covariates are selected from capital structure and credit risk literatures and include market leverage, profitability, tangibility, natural logarithms of size and sales, total debt and cash flow volatility. We begin by specifying a *population distribution* for the duration outcome (Wooldridge, 2010). This distribution can be specified conditional on some covariates listed above. After this conditional distribution is specified, we can estimate the parameters of interest, and especially time to the first-pass event using Maximum Likelihood Estimation (MLE) methods. The first-pass event in this paper, as explained previously, is when a firm changes its leverage by more than some arbitrary threshold (10%, 20% or 50%).

For this purpose, we use an exponential distribution with its time-invariant hazard rate, which is referred to as the memory-less property (Cameron and Triverdi, 2005). In unreported results, we obtain confirming results with three other distributions including Weibull, Gompertz and Gamma. Our parametric regression model estimates the effect of these covariates on the hazard rate, where negative estimates indicate reductions in the hazard rate (more stable leverage ratios).

As discussed earlier, we expect that higher credit quality leads to higher leverage stability. The credit rating variable is the numerical equivalent of S&P's alphabetical ratings, where better credit ratings are assigned greater numbers as in Hotchkiss, Strömberg and Smith (2014). We find that the credit-rating quality by itself explains the largest portion of the variations in leverage stability and each notch improvement in the rating adds one unit to the numerical measure. Thus, if a better credit rating is associated with more stable leverage ratios, we expect a negative and significant relationship between the two.

The results summarized in Table 2.4 strongly support this expectation as the effect of credit-rating quality on the hazard functions is larger than for all other determinants. The right panel reports results for the 50% leverage change threshold and the left panel for the 20% threshold. The reduced number of observations is due to the sample that only includes rated firms. In the most conservative case, a standard deviation improvement in credit quality of 4.03 notches (for example from BBB to A+) translates into a 81% (73%) reduction in the hazard rate in the univariate regression (column 1). This translates into a 51% (51%) lower hazard rate based on the exponential hazard distribution for a 50% (20%) threshold for the leverage change. Results clearly support the importance of credit-rating quality and the significance of the association of rating quality with leverage stability. These results also confirm our findings in the previous section that an assignment just above the investment grade cut-off can lengthen leverage stability.

[Please insert Table 2.4 about here]

2.5 LEVERAGE STABILITY ACROSS RATED AND NOT-RATED FIRMS

In this section, we investigate the complementary hypothesis that rated firms tend to have more stable capital structures over time compared to not-rated firms. This is expected if ratings are a leverage-stabilizing motivation. This leads to tests of three specific predictions.

First, we expect that rated firms wait more years before changing their leverage above any given threshold compared to a sample of matched not-rated firms after controlling for other firm-specific, industry-specific and macroeconomic variables. Second, we expect that firms with periods of rated and not-rated regimes exhibit more leverage stability in their rated regimes. Finally, if rated firms are more cautious about changing their leverage ratios, they will change their leverage ratios less frequently or by smaller amounts for any given time period. In other words, the more stable pattern should not be confined to only longer time-frames or depend on any process of mean-taking. Thus, rated firms should show fewer tendencies to cross various arbitrary leverage thresholds than not-rated firms, where the thresholds are defined as the differences between leverage ratios in two different periods. Thus, if our complementary hypothesis cannot be rejected, any leverage stability difference across the two samples has to persist over both the short and long runs.

In the following sections, we start by a simple comparison of rated and not-rated firms in terms of their leverage stability using the portfolio formation method of Lemmon, Roberts and Zender (2008). Since this method cannot address the endogeneity issue and is useful only in showing associations, we continue our examination with a more formal investigation of the causal effect across rated and not-rated samples using a propensity score matching method.

2.5.1 Evolution of Leverage Ratios across Rated and Not-rated Firms

We start by examining the existence of stable patterns in leverage ratios by applying the method of Lemmon, Roberts and Zender (2008) to a cross-section of rated and not-rated firms. The methodology is as follows: first, we form four quartiles of firms with very high, high, medium and low leverage ratios in each calendar year by ranking firms based on their actual leverages. We call the year of sorting and grouping the "starting" or "base" or event 0 year for the remainder of this paper. Second, we compute the average leverage ratios for firms in each quartile over the next 27 years (always ending with year 2013) assuming no subsequent rebalancing of the membership in each quartile (except for firms no longer in our sample due to firm attrition). Third, we repeat these two steps for each subsequent year in our dataset until the base year is 2012. Finally, we compute the average leverage ratio for each quartile for each calendar year.

The average market and book leverage ratios over 20 years based on this methodology are depicted in the upper and lower panels of Figure 2.4, respectively. The left-hand side (LHS) and right-hand side (RHS) of both panels are for the rated and not-rated samples, respectively. The graphs suggest that the converging and stable leverage patterns for the combined sample are mixes of the different time-series behaviors for rated and not-rated firms (particularly for market leverage). The stable patterns are more dominant for the rated sample and the converging pattern is more dominant for the not-rated sample.

[Please insert Figure 2.4 about here]

The converging pattern of the leverage ratios for the not-rated firms reduces the variability of the leverage ratios by almost four times over 27 years from 32% (38% less 6% in Event Year 0) to as low as 8% (24% less 16% in Event Year 27). In contrast, the reduction in the variability of leverage over time for the rated sample is reduced around two times from 47.73% (48% less 27% in Event Year 0) to 22% (45% less 23% in Event Year 27). The same holds to a lesser extent for book leverage.[7] While this result suggests that the evolution of leverage ratios can be influenced by the existence of credit ratings, it cannot identify the causes of these cross-sectional differences. Lemmon *et al.* (2008) argue that a permanent and a converging factor should be present in capital structure decisions since leverage portfolios follow both a stable and converging pattern. If such is the case, then Panel A of Figure 2.4 illustrates that rated firms are influenced largely by the stable component while the not-rated firms are largely influenced by the transitory component. One of the implications of the existence of a permanent component is that it largely influences capital structure tests (Hsiao, 2003) since regression models will yield inconsistent results due to correlated errors terms. Thus, inconsistency may be a larger concern for rated firms.

A potential concern is that our results may be biased due to the effects of attrition induced by firms that exit the leverage portfolios over the years since formation. Another concern is that the quartile paths shorten as the quartile formation year approaches 2012, since fewer years remain for average taking and generating leverage paths. To address this potential concern, we construct a sample of survived firms, which only includes firms with at least 20 annual observations. We repeat the methodology applied above and plot the results in Panel B of Figure 2.4. These results are similar to those for the full samples, and their overall leverage paths are more stable and relatively smoother. At the quartile formation year (Event Year 0), the distance between the highest and lowest quartiles in the rated sample is larger (55% for the very high quartile vs. 12% for the very low quartile) than for the corresponding quartiles in the not-rated sample (36% vs. 14%). However, the reduction in this distance is larger for the not-rated sample at the end of the 20th year at 50% than for the rated sample at 37%. The book leverage graphs (lower figures) yields the same, yet stronger, conclusion. This implies that the differentiation between the leverage ratios of rated firms is larger than for not-rated firms and that this cross-sectional difference is robust to the passage of time. What contributes to this more stable and distinctive pattern is a question that we address in the subsequent sections of this paper.

[7] Unreported plots using the logit conversion approach of Lemmon, Roberts and Zender (2008) produce qualitatively similar results. These results are also robust to the inclusion or exclusion of zero leverage ratios.

To further investigate long-run stability, we measure changes in market leverage ratios for rated and not-rated samples over 10 and 20 years using the following method. First, we compute the average market leverages of each of the quartiles formed using the above method in event years 0, 10 and 20. Then we test the differences of the average leverages between event years 0 and 10, 10 and 20 and 0 and 20. The results, which are reported in Panels A and B of Table 2.5 for the rated and not-rated samples, respectively, support the notion that the leverages of rated firms tend to remain more stable. The leverage ratio differences are significantly different from zero for only one and two of the quartiles of rated firms at the end of the first 10 and 20 years, respectively. In contrast, the differences are significant for all quartiles of not-rated firms at the end of the first 10 and 20 years. While all of the significant differences for the quartiles of rated firms are equal to -2%, the significant differences for the quartiles of not-rated firms vary between -5% and 7%.

[Please insert Table 2.5 about here]

2.5.2 Propensity Score Matching

While the endogeneity concerns in the main hypothesis are addressed by focusing on the investment-grade cut-off and employing related statistical adjustments, there is no room for such a method for testing the second hypothesis. To mitigate these effects, however, we borrow from the literature of program evaluation where assignment to a different program can be endogenous. The wealth of related literature, particularly in development and labour economics, focuses mainly on developing reliable "matching" methods. An assumption in these matching methods is that when there is no ground for an experimental setting where treatment and control samples are only different at receiving a "random" treatment, one can yet match the treatment and control samples based on their propensity to receive treatment conditional on a set of "observables". Being appropriately done, the propensity-score-matched samples provide adequate statistical grounds for the study of treatment effects (Rosenbaum and Rubin, 1983; Hirano, Imbens and Ridder, 2003; Cameron and Trivedi, 2005; Cattaneo, Drukker and Holland, 2013). In our case, the treatment of interest is assignment to a "rated" sample, and thus the control sample includes not-rated firms. Considering the rated sample as treated and the matched sample of not-rated firms as control allows us to test the expectation that the rated firms should take longer periods before changing their leverage ratios than the matched not-rated firms, across different matching methods.

We first match rated and not-rated firms based on a set of observables. For the set of observables, we include leverage determinants (Parsons and Titman, 2008) and credit-rating determinants according to Moody's KMV method (Duffie and Singleton, 2003) that include firm value and idiosyncratic volatility. We use the matching algorithm in Dehejia and Wahba (2002), which is based on propensity scores to acquire a rating (treatment) using a Logit model. In doing so, we first sort data according to the propensity score $p(x)$. Then the observations are grouped into strata in which the propensity scores of treated (rated) and control (not-rated) groups are close enough. In each stratum, the ideal would be to have no significant differences in the propensity scores between rated and not-rated observations. However, if a significant difference exists, then a finer grid is used within that stratum (Cameron and Trivedi, 2005). Any unmatched firms are removed from the study, both in plotting the survival and hazard graphs and in reporting the related treatment effects.

This matching method provides grounds for causal inference of the treatment (being rated) on the variable of interest (leverage stability), although there are limitations to a causal interpretation as well. The most important limitation of this method, compared to the method employed for the main hypothesis, is that there may still be unobserved variables that determine assignment to the "rated" sample. Since the propensity score matching is essentially performed using observables, we cannot rule out this possibility. Thus, while our results suggest large and significant effects on the treatment sample, their interpretations have to be done with caution.

After the matching is done, we perform a variety of different statistical tests. First, we investigate the effect of "being rated" graphically using Kaplan-Meyer survival graphs. We further investigate how "being rated" contributes to stabilizing the leverages of firms compared to other determinants using conditional hazard models and show that being rated is the single most important determinant of higher leverage stability. We then formally estimate the treatment effect (being rated) on leverage stability using the above mentioned matching method of Dehejia and Wahba (2002), and report the number of additional years a firm waits before changing its leverage above different thresholds when assigned to the rated category. In the next set of studies, we compare the probabilities of changes in leverage for individual firms during their rated versus not-rated periods using a home-made unconditional test of leverage fluctuations. Finally, we provide evidence that the stability in leverage ratios is actively managed and in fact this management is more crucial in the sample of rated firms.

2.5.2.1 Survival Analysis

We measure changes in the leverage ratios of the sample firms in 1-year intervals extending over a 27 year period. To study leverage behavior, we measure the probability that a firm passes a certain leverage threshold (i.e., arbitrarily chosen thresholds of 10%, 20% and 50% above or below its current leverage ratio in absolute value) in any given year and record the first time any of these thresholds are crossed as the event time. We record these first-pass times for the two samples of rated and not-rated firms. Since our database is annual, this translates into the number of years prior to the crossing of each of the three leverage thresholds. Our data in some cases is censored (a no-event) because a firm crosses none of the above thresholds during the available years of observation (Cameron and Trivedi, 2005). We compare the hazard function and survival rates across rated and not-rated firms using the Nelson–Aalen cumulative hazard and Kaplan–Meier survival function estimates across different leverage thresholds in Figure 5.

Figure 5 reports the estimates from survival and hazard functions across different leverage thresholds. The Left panel reports hazard function estimates and the right panel reports survival function estimates. Upper, mid and bottom graphs use 50%, 20% and 10% leverage thresholds respectively. Solid blue curves are for rated firms and the dashed red curves are for not-rated firms. This figure shows the important differences in the hazard and survival rates across these two samples. In Panel A, rated firms have visibly lower hazard estimates and the difference for this measure between the two samples widens over time. After 27 years, the survival rate of the rated sample is almost 89%, whereas the survival rate of the not-rated sample is roughly 82%. The hazard rates are in general very low, especially for the rated firms. Even after almost three decades, only 11% (18%) of the rated (not-rated) firms have ever changed their leverage ratios beyond 50% in a given year. Based on Panel B, the difference between the rated and not-rated sample also continues over 27 years at the 20% threshold. The survival rate for rated firms is 10% higher (35%) after 27 years compared to not-rated firms (25%). These results are noteworthy since the lower propensity to change leverage in the rated sample provides support for the hypothesis that rated firms tend to surpass leverage thresholds less frequently. We note that this observation does not provide causal inference but helps to identify the mechanism on which such a test is subsequently built. We further investigate the causal effect of ratings on leverage stability in later tests.

[Please insert Figure 2.5 about here]

Same inferences are drawn from the mid panel. At a 20% leverage threshold level, rated firms have consistently longer survival rates and lower hazard functions over the 27 years examined herein. However, the magnitude of hazard is increased for both samples. In 27 years, the cumulative hazard estimate for rated firms is less than 1 while it reaches 1.3 in the not-rated sample. The hazard rates increase further for both samples in the two bottom panels (Panels E and F). The striking difference between this panel and the others is the switch in the position of rated and not-rated firms after the first 19 years, which widens thereafter until the year 27. At a 10% leverage threshold, there are horizons at which rated firms tend to diverge more than not-rated firms. Overall, we conclude that rated firms appear to be more cautious about material leverage variations compared to not-rated firms and that this tendency becomes particularly important as the leverage threshold increases.

2.5.2.2 The Treatment Effects of being Rated on Leverage Stability

We estimate the average treatment effect using the different methods of nearest neighbor, stratification and kernel matching. For each method, we report standard errors and t-statistics using analytical and bootstrapping methods in Table 2.6. The outcome variable here is whether the market leverage crosses upper or lower thresholds with 10, 20 and 50 percent differences from its current leverage ratio over each of the next 20 years. The first time that a leverage ratio crosses any of these thresholds is recorded as the event year. We also note that the stratification method can, arguably, yield the more reliable estimates of the average treatment effect on the treated. The reason is that about 17% of our sample firms are rated and are better represented in some strata.

[Please insert Table 2.6 about here]

As Table 2.6 shows, rated firms tend to be more stable than not-rated firms, and all of the differences are highly significant across all three matching methods. This effect is much larger as the leverage thresholds widen from 10% to 50%. For example, rated firms tend to cross the 10% thresholds on average 1.4 years later than not-rated firms based on the stratification matching results. Rated firms tend to cross the 50% threshold 9.2 years later than their not-rated matched firms. All the differences in the leverage stability durations are highly significant. These stability differences further corroborate the association of being rated with the duration of leverage stability.

2.5.3 Effect of Being Rated on Leverage-stability Duration

We extend the above analyses by investigating what factors lengthen the duration of leverage stability. Table 2.7 lists the key variables that could influence the duration of leverage stability and their expected directional impacts. While this table reports the results of an exponential hazard function that assumes that the survival rate is constant, we obtain similar untabulated results using three additional hazard distributions (Weibull, Gompertz, and Cox PH). The rated dummy is a binary variable that equals one if a firm reports a credit rating and zero otherwise. We note that rated firms are generally larger, with more sales and larger leverage ratios. To account for multicollinearity, we orthogonalize the rated dummy and these four variables using a modified Gram-Schmidt procedure (Golub and Van Loan, 1996). For ease of interpretation, all variables with the exception of the dummies are standardized.

[Please insert Table 2.7 about here]

The left panel in Table 2.7 studies cases where leverage diverges more than 50% from its past lags and the right panel repeats the same examination for a 20% divergence. Being rated, as column 1 in the first panel shows, is associated with a 26% reduction in the hazard coefficient. With an exponential distribution, this translates into a 21% ($e^{-.26} - 1 = 21\%$) reduction in the hazard rate. Being rated also elongates leverage stability with a 20% threshold. Column 1 in the right panel shows that being rated is associated with a 14% lower hazard rate ($e^{-.15} - 1 = 14\%$). The second column includes other firm-specific determinants including market leverage, profitability, tangibility, natural logarithms of size and sales, total debt and cash flow volatility. Rating still largely and significantly reduces the hazard ratio. Moreover, this column documents that larger firms and firms with more cash flow volatility tend to have lower leverage stability durations, and that larger firms with higher sales, profitability and asset tangibility tend to have longer leverage stability durations. The third and fourth columns include additional control variables including collateral, capital expenditures and initial market leverage.

The largest effect on leverage stability comes from market leverage. Taking the most conservative estimate (fourth column), a one standard deviation increase in market leverage leads to a 42% (51%) increase in the hazard rate using an exponential distribution with 50% (20%) threshold. For each of the other specifications, a one standard deviation increase in market leverage leads to a larger increase in the hazard rate. Size and credit ratings are the largest contributors to the reduction of the hazard rate. Based on the fourth column, a standard deviation increase in size reduces the hazard rate by 52% (27%) while having a credit rating reduces the hazard rate by 21% (10%) in the left (right) panel.

2.5.4 Leverage-ratio Stability of Firms with Ratings Starts or Stops

In this section, we examine if and how leverage-ratio stability changes when a firm starts or stops having a credit rating. We test if leverage fluctuation behavior is different for firms that have sufficient observations in which they were with and without a credit rating during our test period. Thus, firms are retained for this test if they have at least 18 consecutive (annual) observations, at least seven consecutive observations in both their rated and in their not-rated regimes, and the ratio of observations in the rated period to the unrated period is between 0.4 and 0.6.

Using this sample, we calculate the level of fluctuations above the thresholds of 5, 10, 20, 30 and 50 percent of their former lags, where the lags vary between 5 and 10. Based on the results reported in Table 2.8, we observe that market leverage fluctuations are significantly different between a firm's rated and not-rated periods, and across all periods and thresholds. We conclude that leverage fluctuations decrease (increase) for firms after agencies commence (stop) to report credit ratings on these firms.

[Please insert Table 2.8 about here]

2.5.5 Fluctuations in Leverage Ratios over Time

In this section, we investigate if the short- and long-term variations in the leverage ratios differ for rated and not-rated firms. We use a non-parametric test of leverage fluctuations that captures short, medium and long-term leverage variations at different levels. This addresses the two critiques of DeAngelo and Roll (2015) about the method used by Lemmon, Roberts and Zender (2008) to test for leverage stability. By examining leverage fluctuations beyond certain thresholds at the individual firm and not aggregate quartile level, we deal with the criticism by DeAngelo and Roll that the stable patterns generated by the method of Lemmon, Roberts and Zender (2008) are influenced by the process of portfolio formation and mean taking. By applying this test to a variety of short to long term time periods, we also address the criticism by DeAngelo and Roll (2015) that the firm fixed effect cannot sufficiently convey the existence of stability since it only captures long-term mean differences and fails to capture significant short-run variations of leverage.

Our tests measure the proportion of the leverage ratios at specific numbers of years after a base year (leads or forwards of 5, 10, 15, and 20 years) that differ from the base year's leverage ratio by various thresholds (5%, 10%, 20%, 30% and 50%). The proportion for a specific lead and threshold is obtained by dividing the number of threshold crosses for that specification by the number of firms in the base-year sample. Implementation of the test methodology begins with the 1985 base year, then repeats with the 1986 base year, and continues until base-year 2004 has been completed. Then the average proportion for each of the 20 leads for each threshold is calculated. For example, for a starting 1985 base year and a threshold of 5%, we first count the number of firms that were in the 1985 base-year sample and have changed their leverage ratios in 1990, 1995, 2000 and 2005 (i.e., 5, 10, 15 and 20 years after the base-year of 1985) by more than 5% from their leverage ratios in 1985. Next, we repeat the same procedure for a 1986 base year by measuring the proportion of leverage ratios in years 1991, 1996, 2001 and 2006 that are more than 5% different from their values in base-year 1986. We continue this one-year-forward base-year augmentation until we have completed base-year 2004.

We report double-digit average proportions of crosses across all thresholds and all leads for each of four representative forward-looking years for each of the five thresholds in Panel A of Table 2.9. We observe that the leverage ratios of rated firms fluctuate significantly less than those of not-rated firms at all lags and across all thresholds. To illustrate, 38.39% and 46.54% of the rated and not-rated base-year firms have leverage ratios that are more than 10% different ten years after the base year. We also observe significant differences in the leverage ratios between the rated and not-rated firms across all thresholds and at all leads of between 14% and 29%. The differences increase from the 5th to 15th lead and then decline for the 20th lead. One likely reason for this anomaly is attrition where the number of included firms decreases with a larger lead length.

[Please insert Table 2.9 about here]

To examine the possible impact of firm attrition, we report the averages for each of the four representative forward-looking years for each of the five thresholds in Panel B of Table 2.9 for the base-year firms that survived over a 20 year period (i.e., have at least 20 years of data ending with 2012). As the last column (Dif.) shows, the difference in variations between rated and not-rated firms increases with increases in the number of leads from 5 to 20 monotonically. The magnitude of the fluctuation difference is also larger for this sample of firms. For example, the average proportions increase from 29% to 33% for a 10% threshold and a lead of 15. Such large and highly significant differences in both panels are supportive of our conjecture that rated firms tend to maintain a more stable leverage path over time than their not-rated counterparts.

2.5.6 Active Leverage Management and Leverage Stability

In this section, we investigate the stability of leverage ratios from an "active debt management" perspective. Specifically, we address the following questions: Do firms "actively" maintain stable leverages through security issuances? If they do, is this behavior more aggressive for rated versus not-rated firms? There is a rich body of literature suggesting that firms have rating targets (Hovakimian, Kayhan and Titman, 2009a) and that they actively manage their leverage ratios to maintain a target leverage ratio (e.g., Hovakimian, Opler and Titman, 2001; Kayhan and Titman, 2007; Graham and Harvey, 2001; Leary and Roberts, 2005). Furthermore, firms reduce net debt issuance following a credit downgrade (Kisgen, 2009), and change their security issuance behavior to move towards their target leverage ratio (Hovakimian, Kayhan and Titman, 2009a).

To answer these questions, we use a methodology similar to the one used to construct Figure 1 earlier. Specifically, we first form quartiles of firms based on their relative net equity (debt) issuance in a base year, and then follow the market leverage ratio behavior of each quartile for the following years. We repeat this process until the base year is 2012. The average leverage ratios for each calendar year for each net debt and net equity quartile are depicted in Figure 6.

[Please insert Figure 2.6 about here]

Figure 6 shows the market leverage plots for the sample of not-rated firms in the upper panel and rated firms in the lower panel for net debt issuance (NDI) and net equity issuance (NEI) quartiles in their respective right- and left-side graphs. The NDI graphs depict a clear distinction between the debt issuance behavior of rated and not-rated firms. We observe the same ordering from very high to low propensities to issue net debt for the quintiles of both the rated and not-rated firms and their respective leverage ratios. However, the differences are substantially less distinct for the not-rated sample. As in Figure 1, there is a "convergence" in market leverage for the quartiles of not-rated firms and greater time-series stability for the quartiles of rated firms. The convergence in not-rated firms in the NDI-sorted quartile graph eliminates any easily observable differences between the leverage ratios of the quartiles by the end of year 27. The leverage difference between the lowest and highest quartiles is a significant 11% (37% - 26%) at its maximum (year 5, NDI sorted quartiles), and reduces to a weakly significant -4% (18% - 22%) by the end of year 27. The negative sign indicates that the relative position of these two quartiles has reversed.

Inferences based on the NEI-sorted quartile graph are similar to those for the NDI-sorted quartile graph. For example, there is a clear distinction at the beginning of the period between the leverages of the high and very high NEI quartiles of not-rated firms, which almost disappears as the ending event years are approached. We observe a similar convergence over time of the leverage differences between the medium and low NEI quartiles of not-rated firms. In contrast, leverage stability persists over time for the quartiles of rated firms. The clear distinction between the leverages of all quartiles of rated firms remains until the end of the study period. The leverage difference between the highest and lowest NEI quartiles of rated firms remains significant and is only reduced slightly from 10% (40% less 30%) to 8% (34% less 26%) over the 27 years. Most of this reduction is due to the decrease in the leverage difference between the medium and high NEI-sorted quartiles, which remains significant and goes from 5% (38% - 33%) to 4% (32% - 28%) over the 27 years.

Our results complement the findings of Lemmon, Roberts and Zender (2008). They argue that a "converging" pattern may emerge due to active equity management. We show that active debt or equity management is in fact influenced by the existence or absence of a credit rating, and, in turn, helps to determine the ultimate influence of active security-issuance management on leverage. This is a significant result since it implies that the existence or absence of a credit rating can affect the leverage management decisions of a firm over its life.

To further investigate the differences between the leverage behaviors of rated and not-rated firms, we compare the mean leverages at event times from 0 to 20 for all NDI- (and NEI-) sorted quartiles of the rated firms with their not-rated counterparts. Untabulated results confirm that there are significant differences in the leverages between the rated and not-rated firms for all the NDI- and NEI-sorted quartiles.

2.5.7 Role of Initial Leverage Across Rated and Not-Rated Firms

In this section, we study how different capital structure determinants influence leverage choices for rated and not-rated firms. We begin by showing that the associations between leverage and previously identified determinants differ for rated and not-rated firms by estimating the following model for leverage type ι (market or book) for firm i for month t, or $Lev_{i,t}^{l}$:

$$Lev_{i,t}^{l} = \beta_0 + \beta_1 Lev_{i,t-10}^{l} + \beta_2 Log\big(Size_{i,t-1}\big) + \ \beta_3 \ Log(Sales)_{i,t-1} + \beta_4 MTB_{i,t-1} + \beta_5 \ Profit_{i,t-1} + \beta_6 Tang_{i,t-1} + \beta_7 IndLev_{i,t-1} + \beta_8 CFVol_{i,t-1} + \beta_9 DivPayer_i + \varepsilon_{i,t} \tag{2.6}$$

The independent variables in (2.6) include the corresponding book or market leverage lagged ten years (referred to as initial leverage herein), firm size, sales, market/book ratio, profitability, tangibility, industry leverage, volatility of cash flows, and dividend payer dummy (equal to 1 if a firm pays a dividend and zero otherwise). Appendix 1 provides definitions and the expected coefficient signs for each of these variables in Table A1 based on the generally consistent findings previously reported in the literature (particularly, Frank and Goyal, 2009; Titman and Wessels, 1988; Rajan and Zingales, 1995; Mackay and Phillips, 2005; Parsons and Titman, 2008; and Graham and Leary, 2011). Some of these studies deal with firm, year and industry fixed effects and net debt and equity issuance (e.g., Frank and Goyal, 2009; Lemmon, Roberts and Zender, 2008). As Parsons and Titman (2008) note, the use of lagged regressors is the default method for regression-based empirical research on capital structure. Gulen *and Ion* (2016) argue that using lagged regressors significantly reduces simultaneous effects and omitted variable bias. By standardizing all variables, each estimated coefficient is interpreted as the change in the dependent variable from a one standard deviation change in the independent variable. The reported t-values are robust to year clustering effects.

For comparability with prior studies, we begin with a classic pooled regression. The R^2 values reported by Lemmon, Roberts and Zender (2008) range between 18% and 29% and that reported by Hanousek and Shamshur (2011) is around 8%. Our pooled regression results for the full (All) sample are reported in Panel A of Table 2.10. Results for market and book leverages (Mkt and Book Lev) are reported in columns 1 to 7 and 8 to 14, respectively. The explanatory power of initial leverage as the only explanatory variable is reported in four columns (1, 2 and 7 and 8) and the absence of this variable is reflected in columns 4 and 10. Columns 2 and 8 show that adding year fixed effects and reflecting year clustering adds minimally to the explanatory power of the regressions. While all of the estimated coefficients for the initial leverages are highly significant, the explanatory power is higher using market (6% to 8%) versus book (0% to 1%) leverage. The traditional variables together explain as much as 18% of market leverage (column 4) and adding the initial market leverage increases the R-square to 20% (column 6). The R-squares for the book leverage regressions including the traditional variables remain at 11% after adding the initial book leverages (columns 10 and 12).

[Please insert Table 2.10 about here]

From the second columns in Panels B and C of table 2.10, we observe that the explanatory power of the initial leverage by itself is higher at 10% for the rated firms compared to 3% for the not-rated firms. Furthermore, a one standard deviation increase in the initial market leverage corresponds to a 29% and 15% increase in the current leverage ratios for rated and not-rated firms, respectively. The explanatory powers of the traditional variables separately and together with the initial market leverage in columns (4) and (5) are substantially lower for not-rated than for rated firms (16-17% and 43-44%, respectively). The large differences in the explanatory power of the initial leverage between the not-rated and rated firms illustrate how the effects of their leverage histories differ in arriving at their current capital structures.

To further study stability, we examine the firm fixed-effects influence on the regression results using regression model (1) for rated and not-rated firms. In these estimations the intercept is allowed to vary on a firm-to-firm basis while the error variances and the slopes are held constant. We expect to see an increase in the explanatory power for a fixed-effects regression for firms with more stable capital structures.

The fixed-effect dummies in (1) are estimated using the least squares dummy variable (LSVD) technique. The significance of the model and each of the coefficient estimates is tested using the incremental F-test. These regression results including all but the initial leverage regressor for the "all", "rated" and "not-rated" samples are reported in Panels A, B and C, respectively, of Table 2.11. The first (last) two columns of each panel report results for market (book) leverage. The even (odd) numbered columns report results for regressions with (no) fixed effects or clustered standard errors and t-values which are robust to clustering on both firm and time using the method suggested by Petersen (2009).

[Please insert Table 2.11 about here]

As expected, the explanatory power of the regressions increases substantially after the inclusion of firm fixed-effects for all three samples. For the full sample (see Panel A of Table 2.11), the explanatory power increases from 18% to 71% for market leverage and from 11% to 70% for book leverage. This result is consistent with the notion of leverage persistence, as noted by Hennessy, Livdan, and Miranda (2010) and Malmendier, Tate, and Yan (2011). The explanatory power is consistently higher with fixed effects for the sample of rated than that for not-rated firms (see Panels B and C of Table 2.11) for both market and book leverages. This further supports our conjecture that the leverages of rated and not-rated firms are influenced differently by time-invariant unobserved effects.

2.5.8 Analysis of Variance

Before concluding, we do a parametric analysis using a covariance model to examine how much of the variations in leverage ratios for rated and not-rated firms is explained by variations in traditional leverage determinants (sales, size, M/B, profitability, tangibility, industry leverage, and cash-flow volatility) versus firm and year fixed effects. If rated firms are influenced by their history, then the variations in firm-fixed effects and past leverage ratios should contribute relatively more to explaining the variations in the current leverage ratios. The summary results for the all, rated and not-rated firm samples are reported in Panels A, B and C of Table 2.12, respectively. Except for the last row of each panel with R-square values, we report the fraction of the total Type III partial sum of squares (PSS) as a measure of the contribution of each of the independent variables to the total variation of the leverage ratios for each of the regression models (as in Lemmon, Roberts and Zender, 2008).[8] These values are obtained by first computing the partial Type III sum of squares for different specifications for each of the variables identified in the left-most column (such as profitability and size). This measures the fraction of the total sum of squares that is explained by each of the regressors, and the firm, year, and industry (based on two-digit SIC) fixed effects after normalization by dividing each partial sum of squares by the total sum of squares. To illustrate using a specification similar to that used by Rajan and Zingales (1995), column (4) of Panel A shows that most of the total variation is explained by profitability (15%) and tangibility (56%).[9]

[Please insert Table 2.12 about here]

[8] A discussion of why Type III sum of squares should be selected instead of Type I SS, please refer to Lemmon, Roberts and Zender (2008), p.1588, footnote 10.

[9] When the model only includes one variable, the total variation is explained by that same variable so that the number 1 (100%) is reported.

For the "all" sample, a firm fixed effect by itself explains 47% (50%) of the variations for market (book) leverage ratios. In contrast, the explanatory power of a year fixed effect does not exceed 1% (2%) for market (book) leverage. If credit-rating is one of the time-invariant unobserved variables that increase leverage stability for individual firms, we expect that such fixed effects are more pronounced for rated than not-rated firms. Our results confirm this possibility as a firm fixed effect explains as much as 58% (63%) of the market (book) leverage for rated firms compared to 43% (44%) for not-rated firms. As for the all sample, the year-fixed effect has only a marginal explanatory power (≤ 2%) for both leverage measures for both rated and not-rated firms.

The more striking result in the table is that a firm fixed effect accounts for more than 90% of the leverage variations that are explained by the regression models. For example, a firm fixed effect in a regression including a year fixed effect can explain 98.3% (95.6%) of the variations in market (book) leverages for the all sample [Panel A, Table 2.12, col. (3)]. Furthermore, the firm-fixed effect accounts for 95.1% (89.4%) of the total model variations explained by the model while all the other variables merely capture 4.9% (10.6%) of the variations in the explained market (book) leverages in the "all" sample [Panel A, Table 2.12, col. (8)]. These findings extend to the two sub-samples where a firm fixed effect explains 95.4% (82.4%) of total variations explained by the model for market (book) leverage ratios for the rated sample and 90.9% (88.1%) for the not-rated sample. Similarly, the explanatory power of the traditional variables generally is very limited but twice as much for the rated than the not-rated firms. To illustrate, the R-square for a model excluding a firm-fixed effect and including all traditional variables for market (book) leverage is about 11% (21%) for the all sample, 20% (51%) for the rated sample and 13% (15%) for the not-rated sample [Panels A, B & C, Table 2.12, col. (6)].

The results so far suggest that the explanatory power of traditional variables and the firm-fixed effect for our total sample is lower than those reported in Lemmon, Roberts and Zender (2008). Since we use a similar construction of the sample and regression specifications, these differences may be due to our examination of a different and more volatile time period.[10]

[10] For example, the dot com bubble and its deflation and the 2008-2009 global financial crisis (GFC) may have adversely affected the explanatory power of the traditional variables.

2.6 CONCLUSION

This paper examines the impact of credit ratings on the leverage stability of firms. We employ innovative identification strategies to capture the mechanisms through which credit ratings stabilize capital structure decisions over long periods of time, and infer causality. Our various strategies are a mix of different econometric approaches to address two questions. First, does membership in a more stable credit-rating class lead to a more stable leverage ratio? Second, do rated firms have more stable leverage ratios than not-rated firms? We design different statistical methods for answering these different questions. To address the first question, we primarily focus on the survival rates for the narrow band of BBB-, BB+ firms (i.e., just above and just below the investment-grade cut-off) where the latter firms are considered as the treatment. The selection of this narrow band is motivated by the vast literature of credit ratings, arguing that being located just above the investment-grade cut-off can be effectively interpreted as an exogenous event (Cantor and Mann, 2006; Altman and Kao, 1992; Cantor and Hamilton, 2005; Chernenko and Sunderam, 2012). To ascertain the robustness of our causal inference we provide appropriate counterfactuals using Weighted Regression Adjustment (WRA) across the cut-off and also make sure that we are comparing firms with similar propensities to receive the treatment. We also use the necessary censoring-adjustment methods using different distributions to rule out possible censoring biases, and show that assignment to just above the cut-off leads to large and significant increases in corporate leverage stability. We show that better ratings are associated with largely more stable capital structures, and that this effect applies across all different rating classes. Based on a hazard regression across all rating classes, a standard deviation improvement in credit ratings (four notches) reduces the hazard rates by as much as 79%.

To address the second question, we use a propensity score matching strategy and apply survival analysis to the matched samples. Matching firms based on their propensity to acquire credit ratings, we show that being rated significantly elongates the duration of stable leverage policies. We report survival rates, cumulative hazard rates, and measure the treatment effect (being assigned to the rated sample) in number of years, and show that the treatment group takes between 1.5 to 9 years longer than the not-rated group to change its leverage ratios by a specific percentage. In other tests, we show that leverage is more stable during the rated than the not-rated periods for individual firms that experience both regimes.

Finally, we introduce our own test to address a shortcoming of hazard models. Since a firm is not studied after it first crosses the leverage threshold using a hazard model, we keep firms in our test over the whole study period and compute the probability of leverage fluctuations across different leverage thresholds at different points in time. Based on this test, we conclude that the difference in leverage stability across the rated and not-rated samples persists both over the short and long runs, and is also robust to the choice of the fluctuation threshold. We investigate leverage stability further using additional tests. Variance decomposition shows that time-invariant variables can explain more than 90% of a firm's leverage choices, and that this explanatory power is higher for rated firms. We also show that the higher stability in the leverage ratios of rated firms is related to the intensity of their active debt and equity management behaviors. Overall, our results show that leverage stability is a reality in corporate capital structures, is mostly confined to the domain of rated firms and is particularly prevalent for the higher rated firms.

CHAPTER 3:

Stability of Corporate Debt Structures

3.1 INTRODUCTION

Most of the capital structure literature considers debt structure (i.e. choice and combination of different debt types in a firm's capital structure) to be a uniform variable. However, an emerging body of research documents the importance of debt structures and their determinants as important considerations in capital structure decisions. While various theoretical examinations of debt structures exist (e.g., Diamond, 1991; Park, 2000; Bolton and Freixas, 2000), only a few empirical studies examine debt structure determinants, mainly due to the recent availability of debt structure databases (e.g., Rauh and Sufi, 2010). In this paper, we investigate a new and unexplored dimension of debt structure. Motivated by Lemmon, Roberts, and Zender (2008) who document that corporate leverage is stable over long periods of time and that this phenomenon is largely the result of unobserved firm-specific factors, we investigate whether a similar stable pattern exists in a firm's choice of debt structure. The documentation of capital structure stability by Lemmon et al. (2008) is currently at the core of capital structure studies, and questions the validity of conventional theories including the trade-off and pecking order theories (Graham and Leary, 2011). Study of such patterns in debt structure is important due to the recent understanding of the large role they play in capital structure decisions (Rauh and Sufi, 2010; Colla, Ippolito, and Li, 2013). To the extent of our knowledge, our study is the first to address this question.

The literature provides two opposing viewpoints about the existence of debt structure stability. The first viewpoint is inferred from the findings of Lemmon, Roberts, and Zender (2008). This viewpoint asserts that debt structures could also be stable if such is the case for capital structures. This has been partly confirmed by Colla, Ippolito, and Li (2013) who find that firms in fact "specialize" in few debt types as they mostly follow a year-to-year "one-debt type" policy. The second viewpoint asserts that debt structures vary largely and compensate for the lack of variability of capital structures. Rauh and Sufi (2010) illustrate the importance of debt structures as an essential component of capital structure decisions, and show that debt heterogeneity exhibits significant variability over time unlike mostly invariant leverage ratios for a sample of 305 U.S. non-financial firms.

Thus, this paper has two primary objectives. The first objective is to empirically investigate whether the debt structures of publicly traded U.S. firms exhibit time-series stability. This question is important mainly because the literature on debt structure determinants is in its early stages and the existence of such stability can change our understanding of debt and capital structure choices. To this end, we utilize a newly available database from Capital IQ that provides the book values of various debt types in a firm's debt structure, classified into seven debt-type categories of (1) Capital Leases, (2) Commercial Papers, (3) Lines of Credit, (4) Term Loans, (5) Bonds and Notes, (6) Trusts, and (7) Other Debts. We find that debt structure behaviour is partially consistent with each viewpoint. We show that firms tend to maintain a stable "main" debt type (i.e., the one with the highest weight) over time but frequently change the weights, priorities and combinations of the other debt types in their debt structures.

The second objective of this paper is to study the effect of credit ratings on the stability of debt structures. While credit ratings can influence the capital structure and cost of capital decisions of firms (Kisgen, 2006; Kisgen and Strahan, 2010; Ellul, Jotikasthira, and Lundblad, 2011), the importance of credit ratings for a firm's debt structure is also studied in the literature. Rauh and Sufi (2010) find that large rated firms use multiple debt types, while Colla et al. (2013) find that the majority of largely unrated U.S. firms specialize in a few debt types. Building on these studies, we investigate how the stability of debt structures differ among rated versus unrated firms. For this purpose, we match firms based on their propensity to be rated and study the survival of various debt structure metrics across the two matched samples of rated and unrated firms.

Our study faces two important empirical challenges. The first is that unlike the simple ratio metrics typically used to measure capital structure (such as the debt-to-equity ratio), debt structure needs to be measured using a "*composite"* metric that captures one or more of its various dimensions. These dimensions include the relative weights and number of different debt types, the relative weight-based rank ordering of the different debt types in a firm's capital structure, and the choice of the main debt type (i.e. the debt type with the largest weight in a firm's debt structure), based on their relative representations in the debt structure. An examination of the interaction of various debt structure dimensions is important for a more comprehensive understanding of debt structure behaviour, since Rauh and Sufi (2010) are primarily concerned with the "number" of different debt types while Colla, Ippolito, and Li (2013) are predominantly concerned with the "heterogeneity" of debt types.

The Herfindahl-Hirschman Index (HHI) is a commonly used measure of debt heterogeneity (Colla, Ippolito, and Li, 2013). This index merely captures the relative weight structure of the various debt types. As more fully explained later, the HHI remains unchanged if the relative weights remain the same but are merely reshuffled among different debt types. To address this limitation, we use the following four measures of debt structure: (1) debt heterogeneity index, (2) debt composition based on the ranks of all seven debt types (7D-T rank ordered), (3) the top ranked debt type (1D-T rank) and (4) the top two ranked debt types (2D-T ranks). To the best of our knowledge, this paper is the first to study these new dimensions of debt structure.

The second empirical challenge is how to measure debt structure stability (persistence). The three classical methods introduced by Lemmon, Roberts, and Zender (2008) could be used to assess debt structure persistence. These methods are the use of (1) quartile portfolios, (2) firm fixed-effects regressions and (3) variance decompositions (ANCOVA). The main limitation to the use of quartile portfolios is its smoothing of short-term variations in capital structures (DeAngelo and Roll, 2014) or similarly in debt structures due to its embedded average-taking procedure. The second and third methods are also overly focused on long-run persistence while disregarding short-run instabilities. For example, while a high firm fixed-effect conveys the existence of a large effect from a long-run firm-specific average on its capital structure, it essentially ignores short-run fluctuations, and thus cannot authentically settle whether stability does or does not exist (Mueller, 2013).

We address the above limitations by using survival analyses over short and long periods. Compared to the portfolio formation method of Lemmon, Roberts, and Zender (2008), survival analysis has many advantages in capturing persistent patterns. The most important advantage is that a survival analysis is not prone to the critique of DeAngelo and Roll (2014) about the portfolio formation method whose embedded mean-taking inflates a finding of stability. Survival analysis is also robust to the long-run bias of firm-fixed effects specifications because it accounts for both short- and long-run debt structure variations.

We find considerable time-series variations in the debt heterogeneity and debt rank indexes that are robust to alternate methods of capturing changes in debt-composition characteristics. Importantly, however, we find large persistence in the choice of the main but not the second main debt type. Considering debt heterogeneity variation thresholds of 10% (and 20%), we document that only about 10% (25%) of the firms maintain their original debt heterogeneity after 11 years. Considering the seven broad debt type categories stated above, we find that firms change the relative priority of all but the first debt type considerably over time. Around 50% of the firms never change their main debt type for periods up to 12 years. Comparing the debt-type clusters in firm-1year observations versus firm-12year observations, we find that the tendency to maintain a persistent main debt type is stronger using firm-12year observations than firm-1year observations. Thus, our findings indicate that firms finance their activities so that a single debt type retains its top ranking and that the combination and priorities of their other debt types in their debt structure change frequently. With regard to the main contributors to debt structure stability over time, we document that firms with higher leverage ratios and lower idiosyncratic volatilities tend to have more stable debt-type structures.

In order to study the stability of debt type choices and priorities, we sort debt types in a firm's debt structure based on their relative weights in every year and compare the similarity between the sorted debt ranks across every two consecutive years using Kendall's tau-b and Spearman's rho rank-order correlation coefficient indexes. These rank-order indexes measure similarity between the sorted debt type sequences. Measuring the survival of these similarity indexes is less restrictive compared to a rank-order metric that measures any ranking changes in the strings being compared. Small changes in the ordering of different debt types, especially those that are lowly ranked, result in minor changes in these two test statistics. Since our results remain robust using these two additional indexes, they support the existence of large annual variations in the debt structures with the exception of the single main debt type.

We find that rated firms have less stability in debt-type structures, consistent with the viewpoint of Rauh and Sufi (2010) and that this stability reduction is large and significant for various debt structure metrics except for the main debt type. For example, comparing the number of years that rated and not-rated firms maintain a stable debt structure, we find that reduced stability is as high as 30% for the rank orderings and debt heterogeneity indexes while the same reduction for the main debt type is limited to only 1%. Our results reported throughout the paper are robust to an alternative categorization of the various debt types that is introduced by Colla et al. (2013).

We also investigate the stability of the main debt type over time using an alternative approach. This is necessary since the stability results from a survival analysis may be under-estimated as this test only accounts for the first change in the main debt type and ignores all later changes. To address this limitation, we employ a clustering analysis of different debt types over both short- and long-runs. The clustering analysis using the long-term averages of relative debt-type weights can mitigate the downward bias embedded in the survival analysis. The results of the clustering analysis support the existence of long-run stability of the main debt type.

This paper makes three important contributions to the existing literature. The first contribution is to the fledgling literature on the importance of debt structure and debt heterogeneity in capital structure studies by documenting how debt structures evolve over the long run.[11] We extend this literature by studying what determines the main debt type in terms of its relative proportion in a firm's debt structure and by documenting the determinants of more stable debt structures. The second contribution is to the literature on the stability of capital structure determinants by providing the implications of debt structure stabilities for the capital structure stability arguments of Lemmon, Roberts, and Zender (2008) and DeAngelo and Roll (2014). We document that firms consistently change their debt structures while maintaining the main debt type stable. This is consistent with the empirical inference of Rauh and Sufi (2010) that significant variations remain in debt structures although capital structures are largely invariant. The third contribution is to show under what contexts there is empirical support for the inference drawn by Colla, Ippolito, and Li (2014) that firms chiefly specialize in one or a few debt types from year-to-year. Specifically, we conclude that such specialization does not extend beyond the main debt type. Fourth, we contribute to the literature on the effects of credit ratings on capital structure decisions (Kisgen, 2006; Kisgen and Strahan, 2010; Ellul, Jotikasthira, and Lundblad, 2011) by documenting how credit ratings affect the stability of various debt structure metrics.

The remainder of the paper is organized as follows. Section 3.2 discusses the data and sample construction. In Section 3.3, the empirical results are presented and discussed for debt structure stability, the determinants of such stability using different empirical methodologies, and the role of credit ratings. In section 3.4, various robustness checks are conducted and reviewed. Section 3.5 concludes the paper.

[11] These include Rauh and Sufi (2010); Colla, Ippolito, and Li (2013); Diamond (1991); Park (2000); Bolton and Freixas (2000); and DeMarzo and Fishman (2007).

3.2 SAMPLE, DATA AND SUMMARY STATISTICS

The Capital IQ database covering the period from 2001 to 2012 is our main source of debt types and for creating the debt structure index. Capital IQ contains data regarding every debt component in a firm's capital structure. The broader of its two groupings (namely capital structure type) categorizes debt types into seven groups. A finer grouping (named capital structure sub-type) elaborates on the terms of each contract, such as seniority, security, and interest charges. To minimize any subjectivity due to debt-type aggregation, we use the following seven main debt types used by Capital IQ: (1) Capital Leases, (2) Commercial Papers, (3) Lines of Credit, (4) Term Loans, (5) Bonds and Notes, (6) Other Debt, and (7) Trusts. In contrast, Colla, Ippolito, and Li (2013) split the *notes* category into senior and subordinate and merge trusts with the *other debt category*. This leads to a significant loss of observations in the data since senior and subordinate sub-types constitute only a portion of the "*note*" debt type. Such losses include debt sub-types such as profit participating certificates; promissory note loans; Class A, B, C and D bonds; market debt securities; interest-bearing bonds; (long-term) borrowings from certain institutions; bank loans in other currencies; credit from banks, and so forth.[12]

We draw data for the firm-specific variables in the resulting sample from Compustat. The variables chosen are based on their relevance to capital structure theories (Frank and Goyal, 2009; Titman and Wessels, 1988; Rajan and Zingales, 1995; Parsons and Titman, 2009; Graham and Leary, 2011) and their relevance to debt structures (Rauh and Sufi, 2010; Colla, Ippolito, and Li, 2013). We briefly describe the rationale for the choice of each of the possible determinants of debt structure used herein, and provide further details on their computations in Appendix 2. We begin with the firm-specific variables which are all winsorized at the 1% level at both tails, and then standardized by their respective standard deviations. *Market leverage* is included to account for the possible effect of relative leverage on the choice of debt types and their weightings. *Maturity* is included since longer debt maturities can lock a firm into a certain debt type over time and thus influence debt-type stability. *Market to book* ratio is included to capture growth opportunities since firms with more growth opportunities may use lower leverage (Myers, 1977). *Firm size* and *firm sales* are included since leverage can increase with firm size and firm sales (Lewellen, 1971). *Cash-flow volatility* increases default probabilities and thus decreases leverage capacity (Saretto

[12] For robustness, we test our results with the classification of Colla, Ippolito and Li (2013) and document that our results are robust to the choice of debt-type classification.

and Tookes, 2013) and increases debt-structure heterogeneity (Colla, Ippolito, and Li, 2014).[13] *Profitability* is included because it can increase leverage according to the cash flow hypothesis (Jensen, 1986) or decrease leverage according to the pecking order theory (Myers, 1984), although its effect on debt structure is found to be mixed (Colla, Ippolito, and Li, 2013). *Tangibility* is included because it can influence leverage (Saretto and Tookes, 2013) and firms with more tangible assets have lower debt heterogeneity (Colla, Ippolito, and Li, 2013). The *rating dummy* variable is included since having a bond rating facilitates access to capital and can lead to higher leverage (Faulkender and Petersen, 2006) and more feasible debt type choices. The d*ividend payer dummy* variable is included since it can affect capital structures (DeAngelo and Masulis, 1980). *Marginal Tax rates* are included because they can increase the incentive to use debt (Graham, 2000) and can influence the relative value of long-term debt contracts (Brick and Ravid, 1985). *Idiosyncratic volatility* is included since increased volatility may induce a firm to delever or choose different debt types or different mixes of debt types.

We also include various possible non-firm determinants. *Industry heterogeneity* is included since certain industry affiliations can significantly determine corporate capital structure behaviour. For example, Rauh and Sufi (2012) show how similar "lines of business" can affect corporate capital structures over time. *Rollover risk* is included since greater rollover risk can induce firms to choose longer maturities and therefore induce greater stability in debt-type structures. GDP per capita, GDP growth and inflation are included because their higher values are associated with better economic conditions and a greater availability of capital for firms. Finally, term spread changes are included because of their effect on the choice of certain debt maturities and the resulting impact on the stability of the structure of debt types.

Table 3.1 reports summary statistics for the firms in our sample and their characteristics. There are only moderate differences between the summary statistics reported in the left- and right-most panels for the full sample and for the sample of firms with at least 10 years of observations (henceforth referred to as the longer-lived firms). The longer-lived firms tend to be moderately larger, with higher cash flow volatilities, profitabilities, and asset tangibilities. They also have a larger mean proportion of rated firms (33% versus 22%), a larger mean proportion of dividend

[13] This variable is measured as in Kryzanowski and Mohsni (2013) and alternatively as the volatility of a firm's earnings per share (Compustat item # 19) over the past six years as a test of robustness which yields similar empirical results.

payers (31% versus 26%), longer mean debt maturities (72% versus 68%) and similar mean idiosyncratic volatilities (14% versus 14%).

[Please insert Table 3.1 here]

3.3 DEBT STRUCTURE METRICS

The first metric used herein to study corporate debt structures is a normalized Herfindahl-Hirschman index (HHI) similar to the one used by Colla, Ippolito, and Li (2013). This *debt heterogeneity index* (HHI) is given by:

$$HHI_{i,t} = \frac{\sum_{j=1}^{7}\left(\frac{DebtType_{j,i,t}}{TotalDebt_{i,t}}\right)^2 - \frac{1}{7}}{1-(1/7)} \qquad (3.1)$$

where $DebtType_{j,i,t}$ is debt type j for firm i at time *t*. The debt structure only includes one debt type when HHI equals one, and includes all seven debt types in equal proportions when HHI equals zero.

One problem with *HHI* is that it is defined as the relative weight of different debt types in a firm's debt structure for each year, without fully considering what specific debt types are so included. For example, a debt structure with 50%, 30% and 20% consisting of debt types A, B and C has the same index value as a debt structure consisting of the same proportions of debt types C, B and A. Thus, using the HHI to study debt structure has somewhat limited power to explain a firm's actual debt-structure behaviour and preferences, mostly due to its particular substitutability assumption among the different debt types in a firm's debt structure. Therefore, the information obtainable from the debt heterogeneity index, HHI, is limited to the format of the debt structure, as it provides no insights into what debt types are chosen, how the choices between debt types are made, or what specific debt types in fact contribute to the formation of a specific debt structure.

As noted earlier, we introduce several variants of another debt structure metric based on rank orders to address the shortcomings of the HHI. Each variant uses an annual ranking of the seven debt types in a firm's debt structure where the first (seventh) rank is for the debt type with the largest (smallest) relative weight in the firm's debt structure. Studying the behaviour of debt type ranks over time answers an unexplored dimension of debt structure that is: Do firms maintain a stable *debt preference structure* over time when we consider all or only some of the rank-ordered debt types in their debt structures?

The first variant of this rank-ordered metric uses the rank-ordered set for all seven debt types. Unlike the corresponding HHI, this 7*debt-type (7D-T) rank-ordered* index is sensitive to changes in the relative weight-based ordering of the different debt types even if the HHI based on the debt weights remains constant. To compute a value for this index variant, we first assign a one-letter moniker (in parenthesis) to the seven debt types of Capital Leases (S), Commercial Papers (C), Lines of Credit (L), Term Loans (T), Bonds and Notes (N), Trusts (R) and Other Debt (O), respectively. We obtain a string of seven elements for each firm-year where the one-letter monikers are used for the debt types that are in the debt structure and the moniker X is used for all debt types not in the debt structure. We then sort each string of seven monikers by their relative weights in a firm's debt structure so that the first (seventh) moniker in the string contains the most (least) important debt type. Two debt structure index values are considered to be different when the two strings being compared have different ranked monikers. Unlike the identical HHI values, the *7debt-type rank-ordered index* values differ when a firm has a debt structure with 50%, 30% and 20% weights in debt types T, C and S compared to when it has a debt structure with the same ordered weights for debt types T, S and C, respectively.[14] The debt-type rank index value can change with the introduction or termination of a specific debt type in a firm's capital structure or a change in the relative weights for the same types of debt in a firm's debt structure. One limitation of this variant is that it may be adversely sensitive to "relative" changes in the rankings of more minor or even trivially weighted debt types.

The second and third variants of this metric use only the debt type in the *first* or the *first two* ranks, respectively, from the rank-ordered index for each firm-year. Thus, the second (third) variant has (generally) no sensitivity to the "relative" changes in the rankings of more minor debt types, e.g. sixth and seventh debt types in the rank-ordered string.

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[14] As another example, assume that a firm's debt structure in year 2005 consists of 50% lines of credit, 30% term loan and 20% capital leases. The ranked preference string for this firm's debt structure is LTSXXXX. If the firm changes the relative weight of its debt structure in 2006 by adding additional commercial paper and reducing the amount of capital leases so that their new relative weights are both 10%, the string for this new debt structure changes to LTCSXXX. This would indicate a change in its debt structure based on the 7*debt type ranks index* but not the 2*debt type ranks index*. In short, any changes within the string indicate an event.

We also measure the similarity of each variant at different points in time using Kendall's tau-b and Spearman's rho rank-order correlation coefficient indexes. Kendall's tau-b and Spearman's rho indexes are less sensitive measures of debt structure stability, since minor changes in debt-type ranks over time result in only marginal variations in these indexes. This allows for a different quantification of how "similar" are a firm's debt-type rank structures over time, and for how long does it take for a firm to move to a sufficiently dissimilar rank-ordered structure.

3.4 EMPIRICAL RESULTS ON THE STABILITY OF DEBT-TYPE STRUCTURES

In the following sections, we compare the debt-structure stability over time using the HHI metric and the three variants of the rank-ordered metric. Briefly summarizing our results, we find that firms consistently change their debt structures, debt heterogeneities and preferences. We document that only the main (first rank-ordered) debt type stays largely stable over time, and that this finding is robust to the choice of evaluation metric. We show that the rank-ordered set of all seven debt types exhibits the least stability, which indicates that firms greatly change their debt-type preferences over time. Rank-ordered stability based on the first two rank-ordered (main) debt types and all seven rank-ordered debt types are almost identical. Thus we conclude that except for the main and second debt types, there are significant variations in the choice of all other debt types over time. By matching rated and unrated firms based on their propensity to acquire credit ratings, we find based on a survival analysis that the former have significantly less stable debt structures. We now discuss these findings in greater detail.

3.4.1 Results from a survival analysis

In this section we apply a formal survival analysis to the two metrics of debt-type structure to measure the duration of stability in debt-type structures. We graphically depict the stability of these metrics based on the Kaplan-Meier Estimator and study the determinants of higher stability using parametric survival regressions. We use a logit model to determine the selection of each of the main debt types in the debt structures.

3.4.1.1 Survival analysis of the debt heterogeneity index (HHI)

Figure 3.1 reports the Kaplan-Meier survival estimates for the debt heterogeneity index, HHI. The vertical axis shows the survival probabilities and the horizontal axis shows the number of years from base year 0 to the year of an event. Panels A and B report the results for debt heterogeneity fluctuations beyond the 10% and 20% thresholds, respectively. We observe that only about 10% (25%) of the firms retain their original HHI values after 11 years using the 10% (20%) change threshold. The important take-away from these graphs is that the relative composite weighting of different debt types in the debt structure is short-lived for individual firms.

[Please insert Figure 3.1 here]

3.4.1.2 Survival analysis of the predominant (main) debt type

We now address an unexplored aspect of the findings of Colla, Ippolito, and Li (2013); namely, that primary debt-type specialization may involve a different debt type at different points in time. To illustrate, a firm whose primary debt type is lines of credit in year 1 and notes in year 2 would be classified as specializing in its debt structure using the methodology of Colla, Ippolito, and Li (2013). However, this could be interpreted as not indicating main debt-type stability over longer periods of time. Thus, in this section, we address the following question: Do firms rely on the same single debt type as their major debt type on an ongoing basis?

The Kaplan-Meier survival curve using the main source of debt financing (main debt type in the 1D-T rank-ordered index) based on the sample firms for each year is plotted in Figure 3.2. The solid dark line shows the estimated survival function and the two light lines are 95% confidence intervals. Based on this figure, we observe that 63% (50%) of the firms maintain the same debt type over a 5 (full 11) year period. The stability of the main debt type is in stark contrast with the instability indicated by the HHI. This infers that firms tend to have an ongoing preference for the same single main debt type, and that this preference does not extend to less dominant debt types.

[Please insert Figure 3.2 here]

3.4.1.3 Survival analysis of debt-type ranks

In this section, we study the survival of the two *debt-type ranks indexes*. As discussed earlier, changes in the sequence of different debt types in the rank structure indicate the end of a stable debt-type rank policy. Based on the 7D-T ranks ordered index plotted in Panel A of Figure 3.3, we observe that almost all firms change the structure of their debt preferences after 11 years, and only 17% of the firms maintain their initial 7D-T rank-ordered structure by the 5^{th} year. A problem with this test, however, is that the sensitivity of this index to any change in the debt structure may bias it towards finding more instability. Specifically, changes in less important debt types (e.g., rank orders of 6^{th} and 7^{th}) are not as important as changes in the main debt types (1^{st} and 2^{nd} in the rank structure) and therefore the instability result in this figure may be inflated. To account for any possible effects from ranking instabilities of less frequently or intensely used debt types, we plot the 2D-T rank ordered index in Panel B of Figure 3.3. The resulting survival graph is almost identical to that in Panel A. While the main debt type is largely stable, the second debt type is highly unstable. Firms change or discontinue the second important source of their debt financing often, and almost as often as they change or discontinue debt types of much lower importance in the debt-type structure. This result shows that the main debt type (1^{st} in the debt-type structure) is unique in debt structure decisions, and its stability cannot be extended to any other debt type. Therefore, we suggest that studies of capital and debt structures should account for the determinants of stability of the main debt type and the determinants of the main debt type.

[Please insert Figure 3.3 about here]

One final problem with the rank-ordered index is that it may still be too limiting in terms of capturing changes in the rank-ordered debt-type structure. To examine this possibility, we measure the similarity between debt ranks in the firm's debt structure using Kendall's tau-b and Spearman's Rho[15] measures. These indexes are less sensitive compared to the simple rank-ordered index in that minor changes in the debt preference structure translate into only small changes in the similarity index. To implement this test, we compare the debt-type rank index for every firm across every two years; e.g. the debt rank index in 2001 is compared to that in 2002, the debt rank index in 2002 is compared to that in 2003, and so on. We then investigate how long it takes for the Kendall's tau-b (Spearman's Rho) to change by more than 10% or 20% compared to its previous values. A stable rank-ordered debt-type policy ends the first time a change in the Kendall's tau (Spearman's Rho) exceeds 10% (20%). Results are shown in Figures 3.4 and 3.5 using the Kendal's tau index and Spearman's Rho, respectively. The graphs in each Panel A (B) depict the results with the 10% (20%) threshold. We observe almost no stability in the debt ranks for both of

[15] This rank correlation coefficient is defined as the Pearson correlation between the ranked variables. This measure suggests an alternative similarity index between the ranks of different debt types across different years.

these measures. After 11 years (10 comparisons) and using Kendal's tau index, almost all firms have changed their debt preferences beyond 10%, and almost 88% of the firms have done so using the 20% threshold. Similar results are obtained based on Spearman's Rho index. These results confirm our previous findings that debt structure and debt preferences are highly volatile.

[Please insert Figures 3.4 and 3.5 here]

3.4.2 What determines the stability of debt-type structures?

Our main finding to this point is that debt-type structures are generally unstable, with the exception of the main debt type. The question that we now address is: What factors lead to more stable corporate debt-type structures? To do so, we estimate the following parametric hazard regression model using an exponential hazard function:

$$\lambda(t|\boldsymbol{x}) = \lambda_0(t,\alpha)\phi(\boldsymbol{x},\beta) = e^{\alpha}\, \mathrm{e}^{x'\beta}$$

where the second equality holds because $\lambda_0(t,\alpha) = constant = e^{a}$.

The time until event, t, is estimated conditional on a set of observable variables $\boldsymbol{x}$ that includes market leverage, market to book, logarithm of size and sales, cash flow volatility, profitability, tangibility, rated dummy, dividend payer dummy, marginal tax rate, maturity index, debt heterogeneity of the related industry, term spread, inflation rate, GDP growth and per capita GDP.

The estimates are reported in Table 3.2. Across all specifications, we control for macro variables including term spread, inflation, per capita GDP and the growth rate of GDP. The first two columns report the determinants for the stability of the debt heterogeneity index for 20% and 10% thresholds, respectively. Column 3 does the same for the largest debt type. The results for the debt-type rank-ordered indexes with the first two main debt types are reported in Column 4 and with all seven debt types in Column 5. The last four columns report results for the stability in debt-type ranks using Kendall's tau-b and Spearman's Rho rank correlation measures for different change thresholds.

[Please insert Table 3.2 here]

Based on Table 3.2, we find that larger firms with higher leverages and lower cash flow volatilities tend to have more stable debt-type structures. Increased market leverage, firm size, tangibility, marginal tax rates, and idiosyncratic volatility reduce the hazard rate for the main debt type. Market leverage is the most important determinant of debt-type structure stability for almost all specifications. For example, the hazard ratio for market leverage is -32% in the first specification. The effect of market leverage on Spearman's Rho coefficient is even larger, where a standard deviation increase in market leverage almost halves the hazard rate. With an exponential distribution, this translates into a 27% $(1 - e^{-0.31} \approx 0.27)$ reduction in the hazard rate with a one standard deviation increase in market leverage. The most important factor in destabilizing the debt-type structure is being rated which increases the hazard function by 15% $(1 - e^{-0.16} \approx 0.15)$.

An important result in this table concerns the debt-type ranks. Based on the results reported in the third and fourth columns, size, industry heterogeneity, and term spread reduce the hazard rate and lead to more stable debt-type ranks, while sales, cash flow volatility, and being rated lead to less stable debt-type ranks. The almost identical estimates across both columns support the notion that there are no meaningful differences in the stability of debt-type ranks for all seven or simply the two largest debt types because most of the firms only use a few debt types in their capital structures.

The destabilizing effect of credit ratings on the debt-type structure complements the findings of Kaviani et al. (2015) that rated firms have relatively more stable *leverage* ratios over time. The findings in this table provide primary evidence for the conjecture of Rauh and Sufi (2010) that variations in debt-type structures are used to compensate for the relative lack of variability of capital structures.

3.4.3 Further evidence on one debt-type policy

3.4.3.1 Long-term stability using cluster analysis

The finding of Colla et al (2013) that firms predominantly use one or a few debt types in their debt structures on a year-to-year basis may be interpreted incorrectly as an indicator of longer-term debt structure stability. The reason is that Colla et al. (2013) use firm-1year observations based on the assumption that annual debt structure choices are independent. To assess the implications of this assumption, we extend the tests of Colla et al. (2013) to firm-12year observations. This tells us whether the average behavior of firms indicates debt-type specialization over longer periods of time.

We now illustrate the importance of such an examination. Assume that the main debt-type for a firm is lines of credit for all (12) years except for the fifth year where the firm temporarily switches to capital leases. A survival analysis in this case will indicate instability in the choice of the main debt type although the firm has a high preference to use lines of credit. However, if we take the average invested in each debt type over the 12 years and compare their relative weights, we obtain a highly skewed distribution towards the use of a single debt type, which is lines of credit in this example. Now consider another example where a firm uses lines of credit for the years 1 to 3, capital leases for years 4 to 6, and annually switches between term loans, notes and other debt types for the remaining 6 years. Here, the same survival analysis will indicate long-run instability in the choice of different debt types, and the average invested in each debt type over the long-run would be more uniformly distributed compared to the previous case.

Thus, the questions we address in this section are: Does the average behavior of firms over the long-run still signal a preference for one debt type? What are the behaviors of different debt types in clusters over the short and long run? To do so, we conduct a clustering analysis similar to Colla et al. (2013) not only using firm-1year observations but also firm-12years observations. Firm clustering is based on the contribution of each debt type to the debt structure. The number of clusters within a range of 2 to 10 is determined using a Calinski-Harabasz stopping rule. The number of optimal clusters is 5 and 6 for firm-1year and firm-12year observations, respectively.

Results are reported in Panels A and B of Figure 3.6. As this figure suggests, we recognize different specializing clusters. For example in tPanel A based on firm-1year observations, “capital leases”, “bonds and notes” and “term loans” reach the 80% threshold based on their relative weights in their respective clusters (e.g., second for capital leases). Similarly Panel B of Figure 3.6 indicates that firms not only specialize in a certain type of debt in any given year but also maintain this single debt-type policy and their debt-type preferences over long periods of time. The concentration in single debt types in each of the clusters is now further magnified. Our inferences are robust when we repeat the clustering analyses using 7 clusters for firm-1year and firm-12year observations (see the Panel C and D of Figure 3.6).

[Please insert Figure 3.6 here]

Table 3.3 reports the clustering results using firm-1year and firm-12year observations in the Panel A and B, respectively. In the firm-1year examination, the weight of the main debt type is higher than 50% in 5 of the 7 clusters. Particularly, capital lease (91.4%), other debt (66.5%), term loans (83.3%), lines of credit (84.5%), and notes (89.4%) are the largest debt types and constitute a large fraction of the debt structures in firm-1year observations in clusters 2, 3, 4, 5, and 7, respectively. More than 80% of total debt is captured by lines of credit and notes in cluster 1 and by term notes and notes in cluster 6. The clustering is even more significant in Panel B based on firm-12year observations. In six of the seven clusters, single debt types constitute more than 50% of the debt-type structure. This finding supports the survival analysis results reported previously. Firms tend to rely on a single debt type extensively both over the short and long run.

[Please insert Table 3.3 here]

3.4.3.2 What determines the main debt type?

Given the finding of a widespread and long-run reliance on a single debt type, we investigate the following question in this section: What are the determinants of such a reliance? To do so, we identify the determinants of preferences for one debt type (i.e., the one with the largest weight) versus the other six debt types.

Table 3.4 reports the results for seven distinct Logit regression models. Each Logit model has as its dependent variable a dummy variable that equals one for the main debt type in every year, and zero otherwise. Our choice of firm- and macro-variables is those described earlier in section two. Some of the firm-specific explanatory variables are selected from the capital structure and debt structure literatures, particularly Parsons and Titman (2009) and Colla et al. (2013), as introduced in the data section.

Columns 1 to 7 in Table 3.4 report the fixed-effects regression results with year and industry dummies when the main debt type is commercial paper, lines of credit, term loans, notes, capital leases, trusts, and other debt types, respectively. Each of the seven debt types as the main debt type is significantly more likely with higher market leverage. With regard to the first five debt types, commercial paper as the main debt type is significantly more likely with higher firm sales and marginal tax rates and being rated, and significantly less likely with a higher firm book-to-market ratio, firm size and maturity index. Lines of credit as the main debt type are significantly more likely with higher firm sales, marginal tax rate, firm idiosyncratic risk and inflation rate, and significantly less likely with higher firm sales, maturity index, industry heterogeneity and GDP per capita, and being rated.

[Please insert Table 3.4 about here]

Term loans as the main debt type are significantly more likely with higher firm size, asset tangibility, marginal tax rate, maturity index and GDP growth, and significantly less likely with higher industry heterogeneity, GDP per capita and GDP growth, and with being a dividend payer. Notes as the main debt type are significantly more likely with higher market-to-book ratio, firm size, maturity index, term spread, and being rated, and significantly less likely with greater cash-flow volatility, firm profitability, and asset tangibility. Capital leases as the main debt type are significantly more likely with higher market-to-book ratio, firm size, asset tangibility, maturity index, term spread, inflation rate, short interest volume and being rated, and significantly less likely with higher tax rate and GDP per capita. Thus, greater firm size or longer maturity indexes are associated with greater likelihoods of term loans, notes and capital lease usage, and lesser likelihoods of commercial paper and lines of credit usage. The results for maturity indexes is as expected since Jiménez, Lopez, and Saurina (2009) find that most lines of credit have maturities of one year or less.

3.4.3.3 What proportion of the firms utilizes a "one debt-type" policy?

In this section we investigate the percent of firms that rely on a one debt-type policy in every year or over a decade. Our unconditional metric measures the number of firms that incorporate predominantly one particular type of debt in their debt structures as a fraction of all firms. Table 3.5 reports the percent of sample firms that have more than *x* percent of their total debt in one single debt type for various samples of the firms where *x* ranges between 10 and 90 percent. The "base case" columns for both firm-1year and firm-12year observations indicate that 100% of the firms in the full sample have more than 30% of their total debt in one single debt type. This percentage is still high for greater *x* values. To illustrate, 64% and 57% of this sample of firms have more than 70% of their total debt in one single debt type based on the firm-1year and firm-12year observations. The corresponding percentages (42% and 33%) are still high for firms with more than 90% of their total debt in one single debt type.

[**Please insert Table 3.5 about here**]

We next examine the possibility that these highly specialized debt structures may be due to very low leverage ratios (Strebulaev and Yan, 2013) whose firms do not necessarily need to diversify their debt structures. Such a test also addresses an argument similar to the one made by DeAngelo and Roll (2014) that a "stable" pattern in leverage ratios is predominantly confined to low leverage firms. To explore this possibility, we repeat this study after successively removing firms with less than 10%, 20% and then 50% market leverage. The results are robust to these exclusions. For example, 100% of the firms in the full sample still have more than 30% of their debt structures in a single debt type based on both the firm-1year and firm-12year observations. In a firm-1year setting, removing firms with less than 50% leverage reduces the percent of specializing firms only marginally from 42% to 38%. In the firm-12year panel, the same action results in a decline of 3% in the percent of specializing firms from 33% to 30%. This shows that low leveraged firms do not influence our results in either case.

3.4.4 Credit ratings and the stability of debt-type structures

In this section, we address the proposition that variations in debt-type structures are used to compensate for the relative stabilities of the capital structures. Earlier in Table 3.2 based on hazard regressions, we documented that credit ratings result in more intertemporal variation in debt-type structures. The hazard regressions provide only primary evidence on this effect, and the room for interpretation of this effect is limited due to possible collinearity between variables. To further study the effect of credit ratings on the stability of corporate debt-type structures, we run survival tests on samples of rated and unrated firms, and compare the number of years a rated versus an unrated firm maintains a relatively stable debt-type structure. Comparing the two samples within a program evaluation framework provides estimates of the treatment effects,[16] which in our context is whether a firm has a credit rating and the outcome of interest is the differential wait to change the debt-type structure.

Before applying this method, we need to ensure the comparability of the samples of rated and not rated firms since the assignment of a credit rating to the rated sample is not random and credit ratings and capital structure decisions are known to be highly endogenous. To tackle this problem,

[16] Dehejia and Wahba (2002), Lechner (2002), Jalan and Ravallion (2003), Dehejia and Wahba (1999), Smith and Todd (2001), and Rubin (2006).

we use a propensity score matching method introduced by Dehejia and Wahba (2002) where firms in the two different samples are matched based on their propensity to have ratings. The matching is performed based on a set of observables $\boldsymbol{x}$ that are drawn from the literatures on capital structure determinants (Titman and Parsons, 2008) and credit-rating determinants (Duffie and Singleton, 2012). After estimating the propensity scores of having credit ratings (x) for all firms in our sample, we group the observations into different strata based on their propensity values. The assignment to different strata is based on the difference between the (x)'s of different firms. Particularly, we require that this difference in any stratum is not significantly different from zero. If there is a significant difference between the (x)'s of different firms in a stratum, then we use a finer grid for the stratum until the differences are insignificant.

After removing firms that are not matched we are left with two comparable samples. According to Dehejia and Wahba (2002), this method sufficiently accounts for the endogenous effect in assigning the treatment especially when an experimental setting is not possible. For these two samples, we examine the survival differences of different measures of debt structure using the Kaplan-Meier survival estimates for rated and not rated firms, and we estimate the average treatment effect (ATE) and average treatment of the treated (ATT) that indicate changes in the number of years a firm takes to change its debt-type structure due to the firm being rated.

Panel A of Figure 3.7 depicts the survival estimates for the main (largest) debt type for the Kaplan-Meier estimates, where the horizontal axis measures time in years and the vertical axis reports the estimated survival probabilities. The blue solid (red dashed) line reports the estimates for the rated (unrated) sample. As the graph shows, there is a visible difference between the survival rates. The rated sample is clearly less stable than the unrated sample and the difference in their survival rates increases over time. After 11 years, 37% of the rated firms and 52% of the not rated firms have never changed their main debt type. We also plot the debt heterogeneity index for thresholds of 10% (Panel B) and 20% (Panel C) in Figure 3.7. Although the survival estimates are just marginally higher for the not rated sample with the 10% threshold, this gap widens for the 20% threshold (lower panel).[17] Repeating the same study using debt ranks in Panel C yields the same results, as the rated sample is clearly less stable compared to the matched not rated sample, for the rank index with all 7 debt types as well as the rank index with the 2 main debt types.

[17] In unreported results, we plot the same graphs with thresholds of 30, 40 and 50 percent. The gap between rated and not rated samples widens at higher thresholds.

[Please insert Figure 3.7 here]

Table 3.6 reports the average treatment effect (ATE), average treatment effect for the treated (ATT) and potential outcome means (POM) in response to a firm being rated for different measures of debt-type structure. We observe a large and significant difference between the debt-type structure stability of rated and not rated firms. For the debt heterogeneity index with the 20% threshold, being rated shortens the stable debt-type life by almost six months (-0.52 measured in years). The importance of this effect is computed as the portion of ATE or ATT to POM. The number of years for all firms (for only rated firms) to change their debt heterogeneity by more than 20% (10%) is reduced by 13% (30%).[18] The stability of the debt-type ranks are also highly affected by the assignment of a rating. The relative reduction in the life of stable debt ranks is about 30% $\left((0.64/2.60) \approx 30\%\right)$ when the debt-type ranks index considers all seven debt types and by about 29% $\left((0.63/2.60) \approx 29\%\right)$ when it considers only the first two debt types.

[**Please insert Table 3.6 about here**]

The results are even less pronounced for the largest debt type. While being rated leads to a 2.11 years reduction in the life of a stable debt-type structure based on the ATE estimate, this represents the lowest relative reduction of only 1% $\left((2.11/12.60) \approx 1\%\right)$. Although statistically significant, this change indicates that maintaining a stable main debt-type is only marginally influenced by the assignment of a rating. Thus, it appears that the greater stability of capital structures of rated firms allows them to have less stability in their debt-type structures beyond the main debt type.

3.5 ROBUSTNESS TESTS

Given the number of categories of debt types and sub-types in the Capital IQ database, results could change if they are aggregated differently. In the results presented to this point, we used Capital IQ's seven main debt types as the reference categories in our empirical analyses so as to not introduce any researcher biases in the categorization and to obtain an exhaustive set of debt types with no loss of data points. In this section, we test the robustness of our results to the following categorization of the debt types similar to that used by Colla et al. (2013): (1)

[18] For ATE: $\left((0.52/4.08) \approx 13\%\right)$. For ATT: $\left((1.18/4.08) \approx 30\%\right)$.

commercial papers, (2) lines of credit, (3) term loans, (4) senior debt, (5) subordinated debt, (6) capital leases and (7) other debt. As noted earlier, this categorization leads to a significant loss in data because the notes and debt category which is now split between senior and subordinate debt types has a variety of other sub types that are not included in these new groupings.

We repeat the clustering analysis, survival tests and hazard regressions using the new debt-type categories. The clustering results with these new debt-type definitions are reported in Figure 3.8. This figure confirms our primary clustering results by showing a high concentration of different debt types across different clusters. In the first cluster, lines of credit and term loans make up almost the total debt structure. In the second cluster, lines of credit make up more than half of the debt structure. In the third and fourth clusters, subordinated and senior debt account for the largest portion of the debt structure, respectively. In the fifth cluster, senior debt and lines of credit constitute the largest portions of the debt. In the sixth cluster, the "other debt" category plays this role, and finally in the seventh cluster almost all the debt consists of term loans. Untabulated survival graphs and hazard regressions yield similar results to those reported earlier.

[Please place Figure 3.8 about here]

We further test whether the number of clusters or the Calinski-Harabasz stopping rule influences our results using the new debt-type categories. Based on the results depicted in Figure 3.9, we observe that the effect of the main debt type and the existence of clusters with concentration in one debt type occurs when using both firm-1year and firm-12year observations. In unreported results, we obtain similar results when we test the robustness of our survival estimates using three alternative hazard functions: Weibull, Gompertz, and Cox PH.

[Please place Figure 3.9 around here]

Thus, these results suggest that our survival findings are robust to the categorizations of debt types, the use of less efficient clustering and the choice of hazard function.

3.6 CONCLUSION

The finance literature has recently placed greater emphasis on the importance of debt-type structure as an integral part of capital structure decisions. This fledgling literature has produced many unanswered questions, particularly questions dealing with how firms set their debt structure policies over time, with the intertemporal stability of the various debt types in a firm's debt structure, and with what determines relative debt-type preferences of firms. We currently know that firms choose specialized debt structures in every year, and that there is significant variability in debt structures for rated firms. However, the literature still has not adequately addressed the behavior and determinants of debt-type structures over the long-run.

In this paper, we examined whether corporate debt structures demonstrate long-run stability and whether the time-series variations in debt structures act as offsets for capital structure stability. We used formal survival tests and long-run cluster analyses to examine the stability of our newly introduced metrics of debt-structure stability; namely, the debt heterogeneity index (HHI) and varying definitions of debt-type rank orders. Our results show that firms tend to maintain a single main debt type unchanged over time, but change all other debt types in their debt structure frequently. We show that almost a quarter of the firms never change their main debt type, and more than 35% of the firms never reduce the weight of their main debt type below 90% over a 12 year period. We document that being rated significantly reduces the intertemporal stability of debt structures, consistent with the conjecture of Rauh and Sufi (2010) that being rated with its greater capital-structure stability is associated with higher debt structure instability.

CHAPTER 4:

Corporate Debt Maturity around the World: Role of Creditor Rights and Contract Enforcement

4.1 INTRODUCTION

The law and finance literature provides conflicting views about the impact of creditor rights and contract enforcement on the choice of debt maturity. A number of empirical studies find that maturity increases with the level of protection provided to creditors and the quality of law enforcement within a country (e.g., Giannetti, 2003; Qian and Strahan, 2007).[19] Other studies find that creditor rights decrease corporate debt maturity (Vig, 2013)[20] or are not important for syndicated loan maturities (Bae and Goyal, 2009). Most of the empirical and theoretical studies in this area, however, consider creditor rights and law enforcement efficiency jointly and assume that they are directional equivalent in terms of their effects on the choice of debt maturity (e.g., Diamond, 2004; Demirguc-Kunt and Maksimovic, 1999; Giannetti, 2003; Qian and Strahan, 2007; Fan *et al.*, 2012). Creditor rights are related to laws that determine who have the rights to the property of bankrupt firms and who control the insolvency procedures, while strong contract enforcement mechanisms give lenders the incentive to monitor and re-contract by increasing recovery rates and decreasing the time to handle reorganizations and defaults. The primary question that this paper addresses is: Do creditor rights and contract enforcement have similar directional impacts on corporate debt maturity choices? Considering the belief that short-term financing caused or exacerbated the last recession, the secondary question addressed herein is: Is there a case in financial economics for the strengthening of creditor rights or contract enforcements?

In this paper we revisit the above conflicting results about the impact of creditor rights on corporate debt maturity by studying the differential effects of creditor rights and debt enforcement efficiencies on corporate debt maturity. We focus on a large cross section of international corporate

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[19] Qian and Strahan (2007) use fixed-effects regressions and find that stronger creditor protection increases syndicated loan maturities. Giannetti (2003) reports that a bundle of stronger creditor rights and stricter enforcements is associated with a greater availability of long-term debt for unlisted companies.

[20] Using a quasi-natural experiment, Vig (2013) studies the impact of the passage of a mandatory secured transactions law in India and finds that corporate debt maturity shortens due to increased ex-post inefficiencies associated with increases in creditor rights.

debt maturity structures since almost all of the studies in the related literature have so far only studied bank loans. We use publicly listed firms across 42 countries which allows for a generalization of our findings to a wider cross-section of firms, especially those that are smaller in size and those from developing countries. Our study extends the literature on the effects of legal and property rights institutions on financial markets and contracts, especially by documenting that creditor rights and contract enforcement efficiencies have opposite effects on the corporate choice of debt maturity.

Our main sources for firm-level variables are the Compustat Global database, Compustat North America, and Compustat Securities Daily. We use the creditor rights index of Djankov, McLiesh, and Shleifer (2007), and the measure of the efficiency of enforcement from Djankov *et al.* (2008). We employ maturity determinants and control variables from the firm-specific, macroeconomic and institutional domains that are drawn from such sources as the World Bank Doing Business, International Country Risk Guide (ICRG), Heritage Foundation and Polity IV databases.

Our empirical strategy exploits the different levels of creditor rights and contract enforcement efficiencies in an international setting, as variations in these determinants are largely exogenous to the maturity decisions of individual firms. We improve on the econometrics used in previous cross sectional examinations of the impact of creditor rights and contract enforcement efficiency on capital structure determinants. To address the unobserved heterogeneity inherit in international level studies, previous studies have relied on either fixed effects (Qian and Strahan, 2007) or random effects (Bae and Goyal, 2009) specifications. We estimate the relationships using the correlated random-effects (CRE) model of Mundlak (1978). This modeling specification successfully addresses a long-debate in the related literature where institutional variables are largely time-invariant and firm-specific variables change over time and across firms. A fixed-effects model consistently estimates the time-variant determinants but not the time-invariant regressors. On the other hand, while a random-effects model can estimate both time-variant and time-invariant determinants, its estimates may not be consistent. The CRE estimations used herein address these shortcomings by reporting fixed-effect estimates for firm-specific variables while simultaneously reporting random-effect estimates for the institutional (time-invariant) variables.

We find that creditor rights and contract enforcement are almost independent (correlation of 0.05) and that stronger creditor rights shorten debt maturities while better enforcements lengthen them. We also observe that the significant variations in creditor rights and enforcement qualities across countries are independent of the sample countries' economic status, development status and other institutional determinants. We document that the effect of creditor rights and enforcement mechanisms are independent of the institutional setting of a country, including its legal origins, culture and religion, and the formalism of its legal system. Our results are robust to the choice of explanatory variables since all components of the creditor rights index decrease debt maturities, and all alternative proxies for contract enforcement lead to longer debt maturities. These relations remain large and significant when we use an alternative measure of debt maturity as the dependent variable, which is the weighted average of maturities of different debt types in a firm's capital structure as in Saretto *et al.* (2013). Our results are also robust to alternative estimation methods to correlated random effects, including random effects and a Tobit specification, and to alternative subsamples that, e.g., eliminate cross-listed firms.

Using a parsimonious theoretical model we provide the mechanism through which creditor rights and contract enforcement impact debt maturity. The model incorporates a costly monitoring technology into the simple model of asset substitution of Jensen and Meckling (1976) and Park (2000). The key idea behind our model is that the manager faces a trade-off in choosing short vs. long-term debt. From the manager's perspective, short term debt is cheaper but restricts his choice of different projects. Short term debt also relaxes the necessity of creditor monitoring and leads to safer debt repayments by inducing maximum managerial effort (Diamond, 1991; Gertner and Scharfstein, 1991). In contrast, long-term debt is more expensive for the manager to compensate the creditors for longer commitments and the possibility of risk shifting. This setting leads to two predictions. The first is that the manager's decision to choose between short and long term is influenced by the strength of creditor rights, where stronger creditor rights lead to the choice of shorter maturities by influencing the manager's choice between safe and risky projects. The second prediction is that weaker creditor rights are associated with riskier projects and is supported in the related literature (e.g., Acharya et al., 2011).

Unlike creditor rights, enforcement mechanisms deal with the ex-post efficiency of procedures and operations and directly influence the dollar amount received by creditors at liquidation. With low enforcement efficiency, creditors collect a smaller portion of true asset values with liquidation. Such inefficiencies include longer times spent in resolution, possible costs due to corruption, and the judiciary's inefficiency in implementing the law. We show that when enforcement efficiencies are low, creditors will not monitor since monitoring costs exceed the monitoring benefits, and thus will only offer short term debt, resulting in shorter debt maturities in response to weaker enforcements.

Our paper makes three important contributions to the literature. First, we contribute to the prior literature dealing with the effects of the institutional environment on a firm's capital structure by documenting the differing impacts of legal protection of creditors and the enforcement efficiency of contacts on corporate debt maturity. Significant determinants of corporate debt maturity previously identified in the literature include the financial development of the country (e.g., Demirguc-Kunt and Maksimovic, 1999; Giannetti, 2003), legal rights of creditors (e.g., Qian and Strahan, 2007; Bae and Goyal, 2009; Cho *et al.*, 2014), political settings (e.g., Fan *et al.*, 2012) and national culture (Zheng *et al.*, 2012). Second, we add to the literature that attempts to disentangle the institutional impacts on economic performance pioneered by North (1981) and Acemoglu *et al.* (2005). We extend this line of inquiry to financial markets by studying the impact of two different sets of institutions (namely, creditor rights and enforcement) on a firm's choice of debt maturity. Finally, our paper contributes to the literature that relates increased creditor rights to inefficiencies in financial contracting and emphasizes the demand-side determinants of debt structure (Aghion, Hart, and Moore, 1992; Hart *et al.*, 1997; Acharya *et al.*, 2011; Vig, 2013; and Cho *et al.*, 2014).

The rest of the paper is organized as follows. Section 4.2 develops our theoretical model. Section 4.3 describes the data, sample and summary statistics. Section 4.4 provides and discusses our main results. Section 4.5 reports and interprets the results of several tests of robustness. Section 6 concludes the paper.

4.2 THE MODEL

In this section, we present our theoretical model that formally describes the mechanisms by which creditor rights and contract enforcement influence the choice of corporate debt maturity. We empirically test the predictions of the model in subsequent sections of this paper. Our model is constructed in the context of an optimal contracting framework and borrows features from the Hart and Moore (1999) setting and incorporates the costly monitoring technology of Jensen and Meckling (1976) and Park (2000).

As shown in Figure 16, the model has three dates. At $t = 0$, an entrepreneur attempts to raise I to fund a completely debt-financed project. The debt obtained is in the form of a zero coupon bond, and therefore its face value D (including accrued interest) has to be repaid at the project end.

Before the start of the project, the manager decides on the debt maturity. Maturity can be long or short term, where in our set up long-term means $\mu = 2$ and short term is $\mu = 1$. Moreover, the manager decides on the quality of the project at $t = 0$. The project can be either safe with probability p and a certain[21] return of S or risky with probability $1 - p$ with the risky return R. The success of the risky project is determined with probability $q \in (0, 1)$ and this project returns R > S when successful and zero if unsuccessful. The payoff structure for the projects is

$$qD < L < D < S < qR < R \tag{4.1}$$

In (4.1), I is the initial required investment, L is the liquidation value, and D is the face value of debt. Similar to Park (2000), since the project type depends only on a manager's effort, we can also assume without loss of generality that p also reflects the manager's choice of effort. For the manager, the payoff of the risky project is more attractive than that of the safe project, even when the success probability of the risky project, q, is low. This induces a risk-shifting tendency into our contract design where a borrower may pursue a risky strategy and shift the risk to lenders. In the absence of liquidation, the manager prefers the risky project if the following risk-shifting condition holds

$$(S - D) < q\,(R - D) \tag{4.2}$$

When creditors observe the risky project, they prefer to call for project liquidation, since $L > qD$. Creditors need to monitor the project in order to observe its quality. They monitor with probability z, and incur monitoring costs c. If creditors monitor, they need to choose their monitoring intensity λ, where higher monitoring intensity leads to higher monitoring costs λc. The need for monitoring increases with a longer debt maturity since project payoff uncertainty increases with time. Thus, monitoring intensity is an increasing function of debt maturity $\lambda: \lambda(\mu)$ (Kristiansen, 2005; Prilmeier, 2013).

The project type is revealed conditional on monitoring at date one. The probability that lenders correctly identify project type is proportional to their monitoring intensity. Without loss of generality, we assume that creditors learn the project type at $t = 1$ with probability $\lambda(\mu)$, and thus do not know more than what the public already knows about the project with probability $1 - \lambda(\mu)$. If creditors learn that the project is risky, they call for liquidation. As Figure 16 shows, they can be successful in liquidating the firm's assets with probability α and the project may continue with probability $1 - \alpha$. If not liquidated at date 1, the project returns cash flows at date two. Since the project is fully debt-financed, the manager receives nothing when the project is liquidated.

[Please place Figure 16 about here]

If the project is liquidated at $t = 1$, a value L will be realized from asset sales in the market. Taking the market value of assets at the time of liquidating as A, the level of enforcement efficiencies affects the effectiveness of liquidation in terms of legal fees and other liquidation-related costs. Thus, $L = \theta A$ where θ is the portion of asset value that remains after accounting for liquidation costs.

4.2.1 Probability of Liquidation

The two ways for lenders to address the risk-shifting behavior of a manager are by issuing long-term debt with monitoring or by issuing short-term debt so that the loan has to be refinanced at date 1 with no monitoring. Since p is the manager's effort, creditors set up a monitoring objective of the form $p \geq p^c$ in which they have the right to call for the project liquidation if and only if the observed p is below the minimum desired value, p^c. In our case, the most restrictive case is debt with a maturity of one year ($\mu = 1$). Since this is equivalent to $p^c = 1$, the manager should exert the maximum effort to be able to finance the project. While creditors do not monitor short-term debt, they observe all required information at $t = 1$ in order to decide on the renewal of the financing contract. Managers do not prefer short-term debt because such a short maturity can effectively bar the manager from pursuing the risky project.

The probability of liquidation, α, is a function of debt maturity μ. When maturity is short ($\mu = 1$ in our set up), the probability that a risky project is liquidated is 1 ($\alpha = 1$). When maturity is long ($\mu = 2$ in our set up), the probability of liquidation can be a number $\alpha \in (0,1)$ which is an increasing function of the monitoring effort of the creditor and the strength of creditor rights, ω, in the economy.

The effect of creditor rights on the relationship between creditors and borrowers is extensively studied in Townsend (1979), Aghion and Bolton (1992), Hart and Moore (1994, 1998), and

Djankov et al. (2007). As these papers argue, the credit provided to borrowers is influenced by the legal power of creditors particularly in forcing repayments, seizing collaterals, and acquiring control of troubled firms. Specifically, Djankov et al. (2007) elaborate how stronger creditor rights enable creditors to more successfully call for negotiations and force liquidations in the risky states. Their index of creditor rights reflects the abilities of creditors to (1) allow or disallow a manager's debt reorganization request and effectively force liquidation, (2) seize collaterals if reorganizations are allowed, (3) effectively receive liquidation proceeds with priority over other stakeholders if firms are liquidated, and (4) remove the manager during the reorganization procedure and thus delegate the control of the firm to an administrator and not the manager. The latter also incentivizes the manager to exert more effort and authorizes the creditors to impose their desired terms more easily and to also extract more quality information about the firm's operations during the reorganization period. Thus, stronger creditor rights provide creditors with the ability to better force or convince managers to liquidate the risky project in our model. Therefore, the probability of liquidation is a function of both creditor rights and the maturity structure of debt; or $\alpha: \alpha(\omega, \mu)$. On the flip side, when the rights of creditors are not well protected, the manager has greater flexibility in pursuing his desired risky projects with fewer concerns about interventions from creditors even if his projects are monitored. Thus, after the financing phase, the manager decides on his optimal choice of effort, p, that maximize his expected payoffs based on the perceived effect of the strength of creditor rights in the economy, thereby inferring the probability that the risky project will be liquidated.

When there is a probability that the creditors may liquidate the risky project, the benefits of risk shifting from Equation (9) are given by

$$(S - D) - (1 - \alpha(\omega, \mu))\, q\, (R - D) \tag{4.3}$$

If the benefits are greater than zero, then the risky project is beneficial for the manager. The variable that can determine whether there are benefits to risk shifting is the probability of liquidation $\alpha(\omega, \mu)$. According to (10), we can derive a threshold for α as

$$\alpha^* = 1 - \frac{S - D}{q(R - D)} \tag{4.4}$$

Equation (4.4) provides the level of the liquidation probability above which risk-shifting is not beneficial.

For simplicity, we assume there are only two creditor rights regimes: strong $\overline{\omega}$ and weak $\underline{\omega}$ where strong creditor rights, $\overline{\omega}$, leads to high liquidation probability and weak creditor rights, $\underline{\omega}$ leads to a low liquidation probability. The high creditor rights state is the one in which $\alpha(\overline{\omega}, \mu) > \alpha^*$, and the low creditor rights state is the one where $\alpha(\underline{\omega}, \mu) < \alpha^*$.

4.2.2 The Manager's Problem

The manager maximizes his payoff choosing the optimal levels of effort p and maturity μ.

$$Max_{p,\mu} u = \{p(S - [D + d(\mu)]) + (1 - p)(1 - \alpha(\omega, \mu))\, q\, (R - [D + d(\mu)])\} \tag{4.5}$$

Since the manager can only select one of the projects at t=0, his problem as specified by Equation (4.5) can be simplified to

$$Max_{\mu} u = \{(S - [D + d(\mu)]), (1 - \alpha(\omega, \mu))\, q\, (R - [D + d(\mu)])\} \tag{4.6}$$

The first part of Equation (4.6) shows the payoff to the manager if the project is safe, and the second part if the project is risky. The term $\mathrm{d}(\mu)$ is the additional interest for longer term debt that the manager is required to pay. For simplicity, we can assume that $\mathrm{d}(1) = 0$ and $\mathrm{d}(2) > 0$.

The project choice of the manager depends on whether the risk-shifting condition holds based on the magnitude of $\alpha(\omega, \mu)$. In Equation (4.6), the expected payoff of the risky project for the manager depends on the probability of the project's success q and the probability of project liquidation by creditors. If risk-shifting is beneficial, the manager chooses the risky project. Next, we study the manager's choice of project and μ in response to different creditor rights regimes.

2.2.1 Strong creditor rights

With strong creditor rights, there is a high probability that the creditors will be able to liquidate the risky project. Since $\alpha(\overline{\omega}, \mu) > \alpha^*$, there is no incentive for the manager to take the risky project based on Equation (10). Therefore, his payoffs from Equation (4.6) can be written as

$$Max_{\mu} u = \{S - [D + d(\mu)]\} \tag{4.7}$$

Since the manager wants to maximize his payoff, it is easy to confirm that the optimal maturity becomes $\mu = 1$ since $d(\mu = 1) = 0$ and thus that the manager's payoff will be $S - D$.

2.2.2 Weak creditor rights

When creditor rights are weak, the ex-ante payoffs for the risky project become more attractive for the manager since creditors will not be able to liquidate the risky project effectively when $\alpha(\underline{\omega},\mu) < \alpha^*$. From Equation (10), the result from the maximizing problem (4.7) is

$$\left(1-\alpha(\underline{\omega},\mu)\right)\, q\ (R-[D+d(\mu)]) \tag{4.8}$$

We can show that the optimal choice for maturity now is $\mu = 2$ since it enables the manager to reduce the liquidation probability, α. We note that if the risky project is financed with short term debt, the probability of liquidation is 100%, or $\alpha(\omega, 1) = 1$. Therefore, the manager will not choose short term debt ($\mu = 1$) because his payoff becomes zero.

$$\left(1-\alpha(\underline{\omega},1)\right)\, q\ (R-[D+d(1)]) = 0 \tag{4.9}$$

With the choice of risky project with long term debt, the probability of liquidation depends on the strength of creditor rights, i.e., $\alpha(\overline{\omega},2) > \ \alpha(\underline{\omega},2)$.

The only cost to the manager from using long term debt is the additional financing cost, $d(2)$. It is easy to confirm that with low creditor rights since the manager will not choose short term debt that he always pays the extra $d(2)$ and chooses the long-term debt as long as

$$\left(1-\alpha(\underline{\omega},2)\right)\, q\ (R-[D+d(2)]) > 0 \tag{4.10}$$

Equation (4.10) holds as long as $R > D + d(2)$. This states that the additional premium plus the debt service required for long term debt should be smaller than the payoff of the risky project.

4.2.3 Creditors' payoffs

The creditors' expected payoff can be expressed as

$$(1-z)[pD + (1-p)\ q\ D] + z\ [pD + (1-p)\alpha(\omega,\mu)\ L - \lambda(\mu)c] \tag{4.11}$$

As shown above, the manager chooses $p = 1$ and applies for short-term debt when creditor rights are strong. In this case, creditors will receive a risk-free D at the end of the project. With weak creditor rights, the manager applies for long-term debt and pays the additional premium $d(2)$ to the creditors.

4.2.4 Enforcement

Both creditor rights and contract enforcement efficiencies affect financing contracts at the time of liquidation although their mechanisms differ. Stronger creditor rights, according to La Porta et al. (1998) enable creditors to impose more restrictions on managers, call for renegotiations, change managers and have priority on liquidation proceedings. On the other hand, better enforcement results in more effective liquidation and lowers time and cost to creditors in the case of bankruptcy. In our model, greater creditor rights increase the probability of liquidating the risky project while more efficient contract enforcement increase the liquidation payoffs for creditors and influence the decision of creditors to monitor the activities of managers prior to liquidation. For a monitoring cost c, creditors only monitor if

$$\alpha(\omega)\theta A - \big(1 - \alpha(\omega)\big)qD > c \tag{4.12}$$

More efficient enforcement leads to an increase in θ, which is the portion of the value of liquidated assets that creditors will receive after liquidation costs and inefficiencies are accounted for. Equation (4.12) indicates that creditors will monitor only if their expected incremental payoffs of monitoring and being able to liquidate the risky project exceeds their monitoring costs.

Creditors choose whether or not to monitor the firm based on three criteria; debt maturity, level of monitoring cost and strength of the enforcement system. Creditors will not monitor if the debt is short–term ($\mu = 1$) and the benefits of monitoring fall short of its costs. Creditors will monitor if the debt is long term and the benefits of monitoring exceed its costs.

As θ declines in Equation (4.12) due to enforcement inefficiencies, it becomes less profitable for creditors to monitor managers since the marginal benefits of monitoring diminish. In particular, when $\alpha(\omega)\theta A - \big(1 - \alpha(\omega)\big)qD < c$, then creditors are better off not monitoring. Creditors would not agree with long-term debt without monitoring since it means that the manager would certainly choose the risky project. Since creditors know ex-ante of this situation, they prefer to minimize maturity as a response to enforcement inefficiencies in order to maximize the manager's effort p.

4.2.5 Testable Hypotheses

We can draw two hypotheses from our theoretical model that are empirically investigated in the remainder of this paper. The first hypothesis is that shorter debt maturities are associated with stronger creditor rights. As the model implies, this is mainly due to a greater (lesser) possibility of risk shifting to creditors by the manager as creditor rights become weaker (stronger). For this to be true empirically, we expect that firms take riskier projects with weaker creditor rights and vice versa. This prediction is well confirmed in the literature. Specifically, Acharya, Amihud and Litov (2011) find that stronger creditor rights lead to reduced corporate risk-taking. Consistent with the current paper's argument, Acharya et al. (2011) argue that stronger creditor rights can mitigate the manager's risk-shifting tendencies and show that in fact they do inhibit the risk-sharing activities of managers. The second testable hypothesis is that longer debt maturities are associated with more efficient enforcement of contracts since it increases the proceeds to lenders in a liquidation scenario.

4.3 DATA

4.3.1 Main Country-level Variables

4.3.1.1 Creditor-rights index

The creditor rights index is the updated version from Djankov, McLiesh, and Shleifer (2007) for 129 countries.[22] The index is the sum of the values of four binary variables, where each variable takes a value of one in a country if the country provides a specific type of protection for creditors. The first type of protection exists if creditors can call for a reorganization based on criteria such as a minimum level of dividend payments. The second type of protection exists if debtors cannot legally obtain unilateral protection against borrowers in the case of bankruptcy or if creditors are able to discipline managers more effectively during the restructuring process by being able to seize collateral. The third type of protection exists if creditors have the highest priority to payouts of the proceeds of liquidation. Priority may be granted for managers, government or creditors, and therefore the related dummy equals one if creditors have the highest priority. The fourth type of protection exists if creditors are legally able to change managers in the case of a formal bankruptcy or reorganization.

Djankov et al. (2007) find that this index is highly persistent over time as only a few changes occurred in the index over the past 13 years (Brockman and Unlu, 2009). Thus, we take the level

[22] The initial version of the index was introduced by La Porta et al. (1998).

of creditor rights for each country as being constant and equal to its 2002 value. This is consistent with the use of a constant value of the index for each country by Cho et al. (2014), Kyröläinen, Tan and Karjalainen (2013), Miller and Reisel (2012), Benmelech and Bergman (2011), Acharya, Amihud and Litov (2011), Houston, Lin and Ma (2010) and Brockman and Unlu (2009).

4.3.1.2 Contract enforcement

Measures of contract enforcement are closely related to measures of property rights. Inter-country differences in laws and their enforcement can determine how costly contract enforcement can be (Acemoghlu et al., 2005). Glaeser, Johnson, and Shleifer (2001) show how enforcement of debt contracts varies across two post-communist countries (Poland and Czech Republic) and that strict enforcement in Poland resulted in a more rapid growth of its financial market while the inverse occurred in the Czech Republic. Below, we briefly discuss some of the factors that can influence the quality of contract enforcement and the data sources used for measuring these factors.

Our main proxy for enforcement quality is the measure for debt-enforcement efficiency for each of 88 different countries constructed by Djankov et al. (2008) based on practitioner responses to the procedures for debt enforcement for an insolvent firm in their country. Djankov et al. (2008) compute the likeliness of foreclosure, liquidation, or an attempt at reorganization as three probable procedures. Their index considers time, cost and the probability of asset deposition. Djankov et al. (2008) find that this index is related to the inefficiency of the public sector, French legal origins and general excessive bureaucracy, number of red tapes and corruption. On the financial market side, they also find that the index is related to structural characteristics of the debt market such as disrupted bankruptcy procedures, poor structure of appeals, and voting inefficiencies between debt holders.

4.3.1.3 Macroeconomic variables

The level of a country's wealth and growth can influence how its institutions are formed and function. For example, richer countries enjoy a comparative advantage in terms of debt enforcement efficiency due to their more sophisticated mechanisms (Djankov, Glaeser et al., 2003; Gennaioli and Rossi, 2007; Djankov et al., 2008; Ayotte and Yun, 2009). We obtain our macroeconomic variables (Growth in GDP, per capita GDP and inflation) from the World Bank database. We use the thresholds defined by the World Bank based on per capita GNI to categorize countries into high, middle and low income.

As an aggregate indicator, a country's sovereign rating reflects the general risk of its economy and affects the discount rate (Keck, Levengood and Longfield, 1998). Besides risk and economic factors, an increase in sovereign risk rating can be due to a set of political determinants including corruption, risk of conflict, and political tension (Kim and Wu, 2008). We use sovereign ratings from Fitch that are converted into a numerical scale between 1 and 29 where A equals 1 and D equals 29. Thus, a one-notch rating change represents a one unit increase or decrease in the equivalent numerical measure.

4.3.1.4 Legal origins

One of the important country-wide institutional determinants of creditor rights is a country's legal origin. La Porta et al. (1997) report that the origin of a country's legal system, especially in terms of civil versus common law, has a direct effect on how investors are protected. Watson (1974) finds that common law generally provides better protection for investors. Djankov et al. (2007) find that legal origins have a large and significant effect on credit-market institutions and document significantly higher creditor right scores for common law countries as opposed to civil law (French origin) countries. Similar to Djankov et al. (2007), we use four distinct legal origins being English, French, German and Nordic that are captured using four dummy variables.

4.3.2 Firm-level Variables

Our primary source of non-North American firm level data is the Compustat Global database from 1998 to 2013. This database covers more than 100 countries with about 45,000 unique firms. We use the Compustat North America database for North American firms given its greater coverage for these firms. All data is annual or annualized if it is originally not so. For example, stock prices for international firms are available only at a daily frequency in the Compustat Security Daily database. Merging these three databases provides the firm-specific dataset for our study. For comparison purposes, we convert all monetary values into U.S. dollars using the exchange rates extracted from the World Bank official exchange rate database.

The data on debt-types is obtained from the Capital IQ database, which provides such data for over 60,000 public and private world-wide firms since 2000. Other firm-level determinants are chosen based on the maturity literature findings of Barclay and Smith (1995), Lewis (1990), Guedes and Opler (1996), Stohs and Mauer (1996), Flannery (1986), and Ozkan (2000). They include firm size, market to book ratio, book leverage, profitability, tangibility and cash flow volatility (Colla et al., 2014). Variable construction is explained in detail in Appendix 3.

4.3.3 Maturity Indexes

We construct two different measures for debt maturity. The first measure is the long-term debt ratio of long-term debt to total liabilities (Fan et al., 2012). This maturity index captures the relative tendency of firms to choose short- or long-term debt in every year. Our second measure is the weighted-average debt-maturity index (which we refer to as Ave-debt-maturity hereafter) from Saretto and Tookes (2013). To construct this measure of maturity, we first group the Capital IQ debt structure data for each of our firms into the following seven categories: (1) Capital Leases, (2) Commercial Paper, (3) Lines of Credit, (4) Long-term Debt, (5) Notes, (6) Trusts, and (7) Other debt types. We then construct this debt-maturity index as the weighted average of the maturities of each of the available debt types, where the weights are determined by the market values of each of the seven debt types. If the maturity of a debt within a debt type is not available, we assume that its maturity is equal to the average maturity of the other debts that share the same debt type for that firm.

4.3.4 Summary Statistics

Table 4.1 reports the summary statistics for the institutional, macroeconomic and firm-specific variables. The first two variables are the maturity index of Fan et al. (2012) and the weighted-average debt maturity (Ave-debt-maturity) index. Our first maturity index (first column) is a proportional measure and indicates the ratio of long term to total debt. We observe that 52% of the debt of an average firm is long term. The Ave-debt-maturity in the second row displays maturity in number of years. This maturity index has a mean of 3.01. However, this index is based on only about one-half of the observations used for the long-term debt ratio index. The mean strength of creditor rights of 1.86 is below the midpoint of its range between 0 and 4. The average efficiency of the legal system at 75.71 far exceeds the median of the 0 (lowest) to 100 (highest) range for this variable and therefore an average country in our sample enjoys a moderate to high level of efficiency. Median corruption at 4 indicates that the typical country exceeds the median of the 0 (lowest) to 6 (highest) scale for this measure. The average rates of inflation and GDP growth are 2.16 and 2.86 percent, respectively. The mean for public registries indicates that on average 6.56 percent of the population are monitored by public institutions whereas the private bureau coverage is much higher at 63.86 percent. The number of private registries per capita also exhibits substantial variability with a standard deviation of 29.23%.

[Please place Table 4.1 about here]

With regard to the firm-specific variables, the market to book ratio has a mean of 1.02 (median of 0.63) and a standard deviation of 3.15. Thus, market value is slightly above (substantially below) one for an average (typical) firm in our sample. The mean and median profitability ratios are 6 and 8 percent, respectively. Tangibility ranges from 2 to 100% with a mean and median of 32% and 27%, respectively. Cash flow volatility is generally low even at the 95th percentile where it is 19 percent. Finally, the book leverage ratio for an average and typical firm tend to be low at 24% and 22%, respectively, although they reach 85% at the 95th percentile.

Table 4.2 reports the number of firms and firm-year observations for each country in our sample, and the percentage of firms in each country as a fraction of the total number of firms in the sample. The sample has 17,516 firms and 206,575 firm-year observations across the 42 countries over the 15 years examined herein. Since U.S. firms account for 22.72% of the firm-year observations, we later present our results with and without the U.S. firms. After the U.S. in terms of number of observations, we find Japan, China and U.K. Only firms from the U.S. and Japan account for more than 7.74% of the firm-year observations in our sample. Furthermore, 73% of the countries have a firm-year weight of less than 1% in our sample.

[Please place Table 4.2 about here]

Table 4.3 presents the correlations between the main variables. The first and second columns document the negative correlations between creditor rights and both measures of debt maturity, and the positive correlations between these maturity measures and the efficiency of contract enforcement. The correlation of 0.35 between the two measures of maturity suggests that it is high enough to infer that both variables refer to the same underlying variable but low enough to indicate that they are somewhat different measures. A determinant of contract enforcement and property rights, corruption, has a zero correlation with creditor rights, corroborating the former observation of independence between our measures of credit rights and contract enforcement. Consistent with the predictions of our model, corruption is positively related to both measures of maturity. The debt-maturity indexes are positively and significantly correlated with per capita GDP but not significantly correlated with inflation. The debt-maturity indexes are positively correlated with firm leverage, tangible assets and firm profitability, which is consistent with the findings of Barclays and Smith (1995) and Ozkan (2000, 2002).

[Please place Table 4.3 about here]

Figure 17 depicts the relative positions of the various countries according to their time-series mean corporate debt maturities. To plot this graph, we first take the means of the maturity index over time and across all firms in any given country and then sort countries based on their average maturities. We observe that the mean ratios of long-term to total liabilities tend to be higher for the more advanced economies. The United States has the largest debt maturity based on this measure, followed by Norway, New Zealand, and Ireland. In contrast, Zimbabwe has the lowest index for this measure with a ratio of 0.1, followed by China, Morocco and Thailand. In the middle maturity range, we find Portugal, Brazil, Croatia and Spain with index values near 0.6.

[Please place Figure 4.1 about here]

As depicted in Figure 18, the distinction between a country's level of development and debt maturity is not as evident in the Ave-debt-maturity index. Mexico, Japan, and Chile now join the U.S. as the four countries with the longest weighted-average maturities. The four countries at the bottom of the list still include Morocco but now also include India, Sweden and Finland. Sweden in these two graphs shows a remarkable behaviour where it has one of the largest ratios of long term to total debt, while its average debt maturity in years is one of the lowest. In the middle range, we find both developed and developing countries. To illustrate, 14 countries have an Ave-debt-maturity index of 1.5 years. The countries are Croatia, Zimbabwe, China, Greece, Poland, Argentina, Germany, France, Switzerland, Kenya, Australia, New Zealand, Belgium and Hungary.

[Please place Figure 4.2 about here]

Figure 19 plots the level of the creditor-rights index for the various countries. Similar to Figure 17, the different regions and levels of economic development are scattered in the graph. The four countries of the United Kingdom, New Zealand, Kenya and Zimbabwe with the highest creditor protections are either highly advanced or largely underdeveloped. This is also the case for the four bottom countries of France, Columbia, Peru and Mexico.

[Please place Figure 4.3 about here]

4.4 EMPIRICAL RESULTS

4.4.1 Estimation Method and Econometric Issues

In this section, we present the results of the tests designed to identify the legal and institutional determinants of debt maturity, and particularly the creditor-rights index. In studying the effect of the creditor rights index on debt maturity, we also study the effect of each of its four components as identified by Djankov et al. (2007). We use different specifications to address econometric issues associated with any unobserved heterogeneity and potential simultaneity induced by the omitted variable bias.

We account for possible omitted variable bias by controlling for a variety of macroeconomic, political and legal determinants and control for unobserved country heterogeneity by including country effects. If an unobserved heterogeneity problem is caused by observed and unobserved factors, the residuals become correlated so that OLS results become biased. In this case, an initial solution is to use fixed-effects specifications, which yield consistent estimates (Qian and Strahan, 2007; Fan, Titman, and Twite, 2012). However, many of our variables of interest either change very slowly over time or are time invariant, including the creditor-rights index, its components and the enforcement-efficiency index. The persistent natures of legal and institutional variables make it impossible for a fixed-effects specification to yield the desired results as the effects of these variables cannot be estimated.

A random-effects specification is defensible when the unobserved heterogeneity is independent of the regressors. However, if the true model is fixed effects, a random-effects model yields inconsistent estimates. Bae and Goyal (2009) examine the effect of the bundle of creditor rights and enforcement on bank loans using a random-effects specification by implicitly assuming that the true model is random effects due in large part to the inability of fixed-effects models to estimate time-invariant effects. Their finding that creditor rights are not associated with debt maturity differs from the fixed-effects findings of Qian et al. (2007) that stronger creditor rights are associated with longer debt maturities.

As an alternative to these two specifications, we use a correlated random effect (CRE) specification (Blundell and Powell, 2003; Altonji and Matzkin, 2005; Wooldridge, 2009) as our primary estimation specification due to its many advantages over fixed or random effects specifications. Most notably, the CRE specification allows for a fixed-effects estimation of the time-varying regressors while providing consistent estimates of the time-invariant regressors. Our default CRE specification is:

$$Maturity_{it} = a_t\, X_1 + b_i X_2 + c_{it}\, X_3 + d_i + u_{it}. \tag{4.13}$$

In (13), X_1 contains variables (such as the macro variables) that change only across time. X_2 contains the time-invariant variables (such institutional variables as the creditor rights index and its components, enforcement efficiency and legal origins) that change by country but not for firms in that country. X_3 contains those variables that change both over time and across firms such as a firm's size, market to book ratio, profitability, tangibility, cash flow volatility, and leverage. d_i captures the unobserved heterogeneity and u_{it} is the regression error term. We can also define the following composite error term that captures the serially correlated errors when there is a heterogeneity problem:

$$v_{it} = d_i + u_{it} \tag{4.14}$$

In (14), the unobserved heterogeneity is decomposed into a time-invariant component and a component that is a linear function of the observed regressors (Mundlak, 1978; Chamberlain, 1980, 1982). This allows us to rewrite the conditional expectation of the unobserved heterogeneity as:

$$E[d_i \mid X_{i,s}\,, s \in (1,t)\,] = \ E[d_i \mid \bar{X}_i\,] = \alpha_1 + \bar{X}_\iota \alpha_2 \tag{4.15}$$

The unobserved heterogeneity, d_i, can be decomposed into a constant component α_1, a linear function of the mean firm-specific variable $\bar{X}_\iota \alpha_2$, and a firm-specific effect given by:

$$d_i = \alpha_1 + \ \bar{X}_\iota \alpha_2 + f_i \tag{4.16}$$

The composite error term v_i is the sum of a firm fixed effect and the error term u_{it}, or:

$$v_i = f_i + u_{it} \tag{4.17}$$

Using Equations (23) and (24), we can rewrite the main specification as:

$$maturity_{it} = X_{it}\beta + \alpha_1 + \ \bar{X}_\iota \alpha_2 + v_i \tag{4.18}$$

Equation (25) can be estimated using a feasible GLS, with the following variance- covariance matrix:

$$Cov(f_i\,, u_{it}) = 0, \qquad \forall t \in T \tag{4.19}$$
$$Cov\,(u_{it}, u_{is}) = 0\,, \qquad t \neq s$$
$$Var\,(u_{it}) = \sigma_u^2\,, \qquad \forall t \in T$$

With v_i as a $T \times 1$ vector, the variance- covariance matrix can be rewritten as:

$$W = E(v_i\, v_i') = \begin{bmatrix} \sigma_f^2 + \sigma_u^2 & \cdots & \sigma_f^2 \\ \vdots & \ddots & \vdots \\ \sigma_f^2 & \cdots & \sigma_f^2 + \sigma_u^2 \end{bmatrix} \tag{4.20}$$

4.4.2 Does Level of Creditor Rights and Enforcement Influence Debt Maturity?

Figure 20 provides primary evidence on how creditor rights and efficiency of contract enforcement influence debt maturities. In both panels 5-a and 5-b, the vertical axis is the median debt maturity index in any given country, ranging from 0 to 100%. The horizontal axis is the strength of creditor rights for each country in figure 20-a and the efficiency of the contract enforcement index in figure 20-b. Both panels report estimated trend lines based on simple OLS regressions. As the graphs clearly suggest, the maturity index is significantly and negatively related with the strength of creditor rights and significantly and positively related with the efficiency of enforcement mechanisms.[23] Figures 20-c and 5-d reach similar conclusions when the weighted-average maturity index is used.

[Please place Figure 4.4 about here]

We then examine the following multivariate relationship between debt maturity and creditor rights, efficiency of contract enforcement and various control variables:

$$\begin{aligned} Maturity_{itj} = {} & \beta_0 + \beta_1 Creditor_j + \beta_2 Enforcement_j + \beta_3 Firm_{it-1} \\ & + \beta_4 Macro_{jt-1} + \beta_5 Institute_j + \beta_6 time + \beta_7\, Hetro_j + d_i \\ & + u_{ijt} \end{aligned} \tag{4.21}$$

[23] The estimated slope coefficient for creditor rights is -0.0724 (t-value of 156.39) and for contract enforcement is 0.004 (t-value of 215.33).

Subscripts i, j and k refer to firm, country and year, respectively. $Creditor$ is a matrix of the creditor rights index and its four components for each country j. $Enforcement$ is the efficiency of the contract enforcement index for each country j from Djankov et al. (2008). $Firm$ is a matrix of firm-specific variables including the natural logarithm of size, market to book ratio, profitability, tangibility, and cash flow volatility. $Macro$ is a matrix of country-level macroeconomic variables including inflation, GDP growth and the logarithm of per capita GDP. $Institute$ is a matrix of institutional variables including legal origins. $Time$ captures the time trend using time dummy variables. $Hetro$ captures any unobserved heterogeneity. d_i is the firm fixed effect and u_{ijt} is the error term. The time-varying explanatory variables are lagged one period, as in Bae and Goyal (2009). Variable construction is described in Appendix 3.

Our primary goal at this point is to investigate the relations between debt maturity as measured by the long-term debt ratio and the creditor rights index, its four components and the efficiency of contract enforcement. The components of the creditor-rights index are: (1) existence of restrictions on manager (debtor) when manager calls for reorganization, including the requirement of creditor consent, (2) whether creditors can seize collateral after reorganization is agreed upon, (3) if secured creditors have priority above other stakeholders or the government over liquidation proceeds, and (4) if control during a reorganization moves from the manager to a corporate administrator.

The CRE estimation results with standardized variables and robust t-statistics and year clustering are reported in Table 4.4. Due to the large number of observations and their effect on standard errors, we report significance levels up to a 0.001 p-value in all tables. To account for the effect of enforcement we include the efficiency of contract enforcement of Djankov et al. (2008) in the second row. Finally, columns 9 and 10 extend this study into two subsamples of developed and developing countries. As expected, long-term debt ratios are smaller with stronger creditor rights. Based on the first column of Table 4.4, a one standard deviation increase in the creditor-rights index translates into a 0.11 standard deviation decrease in the long-term debt ratio. This magnitude is similar after controlling for firm-specific determinants (column 2), macroeconomic determinants (column 3) and legal origin determinants (column 4). All four creditor rights components have similar directional associations with the long-term debt ratio. Consistent with Barclay and Smith (1995), increases in size or tangibility are associated with a higher long-term debt ratio. Higher long-term debt ratios also are associated with higher market to book ratios, profitabilities and leverages and with lower GDPs per capita and inflations. Based on columns 9 and 10 of Table 4.4, we find that the estimated coefficient for $Creditor$ and $Enforcement$ are significant for firms in the developed but not developing countries. This may in effect be the result of established institutions in the developed world compared to the fledgling or partially dysfunctional institutions in the developing sphere.

[Please place Table 4.4 about here]

4.4.3 Alternative Measure of Maturity as a Test of Robustness

Table 4.5 reports similar inferences based on the CRE results when the weighted-average maturity index is used instead of the long-term debt ratio. These new results indicate that weighted-average debt maturities generally increase with stronger creditor rights and weaker enforcement quality. Based on the first row of the first column of Table 4.5, a one standard deviation increase in the creditor-rights index is associated with an almost three times as large reduction in the average debt-maturity index as for the long-term debt ratio.[24] This strongly significant positive association is robust to the inclusion of firm-specific, macroeconomic and legal origin determinants. The coefficient estimates for the four components of the creditor-rights index are reported in columns (5) through (8) of Table 4.5. Except for the third component (i.e., debt-holder priority over liquidation proceedings), increases in each of the other components is associated with a shorter average-debt maturity that is almost as much as the index itself.

[Please place Table 4.5 about here]

The second row of Table 4.5 reports the estimated coefficients and their t-values for the efficiency of contract enforcement. Based on the first column of the second row, a one standard deviation increase in the efficiency of contract enforcement is associated with a 0.5 standard deviation increase in the weighted-average maturity index, which is considerably larger than its effect on the long-term debt ratio reported in the corresponding column of Table 4.4. Thus, the positive, large and significant association of the enforcement mechanism on both of our measures of debt maturity persists for all specifications with various sets of controls.

[24] Since the numbers of observations for our two measures of maturity are not similar, we conduct a test using the same observations. We find that these untabulated results for the long-term debt maturity index are consistent with those reported in Table 4.5.

4.5 *ROBUSTNESS TESTS*

The robustness of our results to alternative measures of contract enforcement, alternative subsamples, alternative estimation methods and the inclusion of additional country-level controls are now tested.

4.5.1 Alternative Measures of Contract Enforcement

In this section, we investigate the relations between alternative measures of enforcement with debt maturity. Property rights institutions differ inter-country and are closely related to the quality of contract enforcement. [25] Since creditor-rights provisions deal with the legal position of creditors over borrowers in a financial contract, they do not guarantee the legitimacy of legal enforcement procedures or how effectively legal enforcement procedures are implemented. If citizens are unable to enforce their property rights from expropriation, they may not be able to circumvent enforcement problems through contract design (Acemoglu and Johnson, 2005) or instituting additional laws. Acemoglu and Johnson (2005) find that property rights institutions have a more dominant effect on financial development and investment decisions across countries than contracting institutions.[26]

The various proxies used in the literature for property rights are closely related to the implementation rather than the nature and "design" of laws. Therefore, we use the terms 'strength of property-rights institutions" and 'enforcement' interchangeably (e.g., Bae and Goyal, 2009). As a robustness test of our results, we test if the seven measures of property rights discussed below have the same effect on debt maturity as the efficiency variable used earlier.

Corruption: The corruption index from ICRG (International Country Risk Guide) varies between zero and six (lowest corruption) and primarily assesses corruption in a country's political system. According to the ICRG methodology, more corrupt countries tend to wield laws and regulations much less effectively, since governmental procedures and bureaucratic red tape in such regimes can be violated by the use of bribes through networks of corrupt officials, particularly in the acquisition of licenses and loans. Individuals in high corruption regimes receive lower quality service if they refuse to provide bribes to the officials that require such (Laszlo et al., 2005).

[25] Property rights are the set of rules and regulations that are designed to protect citizens from seizure or confiscation of their assets by the elites and particularly governments.

[26] The importance of property rights for financial development and financial markets also is discussed by various other authors (e.g., Jones, 1981; De Long and Shleifer, 1993).

Corruption can reduce governmental efficiency when the elevation to power of officials and politicians is not based on merit. Corruption can increase financial risk if it results in unexpected scandals that destabilize country-wide political institutions and functions and even threatens law and order. Corruption can deteriorate the efficiency of law enforcement primarily due to higher enforcement costs in more corrupt countries. In the aggregate, corruption is costlier than a tax due to its inherent need for secrecy (Shleifer and Vishni, 1993).

Law and order: The ICRG "law and order" index used herein ranges between zero and six (highest law and order), with each of its two components ranging between zero and three. The first component, law, measures the impartiality and strength of a country's legal system. The second component, order, measures to what extent citizens are willing to resolve disputes through established legal systems and procedures (Demirgüç-Kunt and Maksimovic, 1999). Since law and order determines how well a legal institution functions (Knack and Keefer, 1995), this index is concerned more with the implementation and enforcement of laws rather than how laws are designed. Higher levels of this index indicate more willingness of citizens to accept a country's laws. The weak implementation of law and order or lack of effective sanctions can consequently lead to increases in crime rates and investment risk.

Bureaucracy quality: The ICRG index used herein for bureaucracy quality ranges between zero and four (highest quality). A higher value is assigned if a country's bureaucratic system is well developed, has its own hiring and training procedures and can act independently and autonomously from the center of political power. A lower rating is assigned if changes in political power affect the routines, policies and practices of a country's bureaucracy. Changes in government in these countries tend to adversely affect the administrative functions and destabilize long-term policies. The quality of the bureaucratic system is closely related to corruption (Bai and Wei, 2000) and to the speed and effectiveness of contract implementation (Bae and Goyal, 2009). By acting as a "shock absorbent" to changes in political power, the quality of a bureaucratic system affects the adjustment costs associated with changes in governmental processes and regulations.

Contract viability: The ICRG index used herein to measure contract viability ranges between 0 and 4 (highest contract viability). This index captures the risk of unilateral cancellations of contracts or governmental appropriations of assets (domestic and/or foreign). Lower contract viability weakens property rights institutions and increases the costs of law enforcement. This index also may capture some investment risk that is not already captured by other political or institutional determinants.

Constraint on executives: The index used herein is from the Polity IV database, and it ranges between 0 and 10 (most constrained). This index relates to the regulations and processes that monitor and limit the actions of a country's political executive power, while also capturing the link between political and property rights institutions (Acemoglu and Johnson, 2005). Executive constraints can be levied by different authorities across different countries such as lawmakers in the Western democracies or by ruling parties, monarchies, or the judiciary system in other countries.

Property rights index: The index of property rights used herein is from the Heritage Foundation. Index values that range between 0 and 100 (highest) are higher with increasing promptness and efficiency of the legal system in enforcing contracts, more effective punishment of any unlawful confiscation of land or other forms of private property, and lower corruption or risk of state confiscation of domestic or foreign assets. The index is closely related to contract enforcement (Acemoglu and Johnson, 2005). Since the index reflects the independence and corruption level of the judiciary system and how effectively individuals are able to enforce contracts, the index can also be interpreted as showing the extent to which private property rights are preserved and how effectively the government enforces these laws. Thus, the lowest values of this index are given to those countries with no legal provisions for private property (e.g., where the state owns all property), access to courts is extremely limited, filing for litigation is very difficult, and corruption is prevalent.

Strength of legal rights: The index used herein is drawn from the World Bank Doing Business database. Index values range from 0 to 12 (greatest strength). This index captures the protection mechanisms instituted by governments for both lenders and borrowers in order to facilitate financial contracting.

Since some of the property-rights variables are correlated by construction (e.g., corruption is embedded in the legal rights index), we report the regression (21) results for each property-rights variable separately (including the other controls) in columns 2 through 8 of Table 4.6. In all specifications, we include the creditor-rights index to ascertain the robustness of its directional association with debt maturity. Consistent with our predictions, lower corruption (higher corruption index) is associated with a higher long-term debt ratio (see column 2 of Table 4.6).[27] A one standard deviation increase in the corruption index is associated with a 0.13 standard deviation increase in the long-term debt ratio. As predicted, stronger property rights are associated with a higher long-term debt ratio (see column 3 of Table 4.6). We find similar positive and significant associations between long-term debt ratios and contract viability, executive constraints, law and order index, bureaucracy quality and strength of the legal system (columns 4 to 8, respectively). While all seven measures of property rights significantly increase maturity, the coefficient inferences for the creditor rights index remain unchanged.

[Please place Table 4.6 about here]

4.5.2 Tobit Estimations

In Panel A of Table 4.7, we report Tobit regression results with lower censoring to reflect the existence of zero-maturity debt structures in the database. The first and second columns report the results for the long-term debt ratio and the weighted-average debt maturity, respectively. The previously reported results are robust to the zero-maturity cut-off threshold with the exception of the estimated coefficient for legal-system efficiency when the long-term debt ratio is the dependent variable. This estimated coefficient remains significant but is now negative. Thus, both measures of maturity continue to decrease with stronger credit rights. However, the long-term debt ratio now decreases and the weighted-average maturity now increases with greater efficiency of the legal system.

[Please place Table 4.7 about here]

4.5.3 Alternative Subsamples

We now examine the effect of a greater representation of firms from some countries in our full sample. The CRE regression results for the long-term debt ratios with the removal of firms from the U.S., Japan, China separately and all three countries together are reported in columns (3) – (6), respectively, of Panel B of Table 4.7. Our previous full-sample results are robust to each of these exclusions. Long-term debt ratios are significantly lower with stronger creditor rights and poorer enforcement efficiency. The signs of the other coefficient estimates remain largely consistent with those presented earlier. Some notable exceptions are the estimated market-to-book ratio coefficients that are now significantly positive, the estimated profitability coefficients that remain

[27] We obtain the same inferences using the weighted-average maturity index as the dependent variable.

significant but are now negative instead of positive and the estimated inflation coefficients that are now insignificant.

4.5.4 Effect of Additional Country-level Variables

We now test if our results are robust to inclusion of additional country-level variables. The variables, which are more completely described in Appendix 3, include private credit to GDP, stocks traded to GDP, Fitch sovereign rating, information sharing dummies based on whether a country has private or public registries, public registry coverage ratio, private registry coverage ratio, check formalism (i.e., procedural efficiency for collecting a bounced check) and religion. Private credit to GDP is obtained from the World Bank database and is used by Qian and Strahan (2007). This variable is not only a well-documented measure of financial development (King and Levine, 1993; Beck, Demirguc-Kunt and Levine, 2010; Claessens and Laeven, 2003; Djankov *et al.*, 2007) but it also increases with the power of creditors (Djankov et al., 2007). Religion is captured by eight dummy variables where each dummy variable equals one if the majority of a country's population practices that particular religion (one religious category is excluded to avoid the dummy-variable trap). Religion is a proxy for culture (Qian and Strahan, 2007) and is correlated with both a country's' legal origins (Djankov, McLiesh, and Shleifer, 2007) and the strength of a country's creditor rights (Stulz and Williamson, 2003).

The CRE regression (21) results with the inclusion of these additional variables and the long-term debt ratio as the dependent variable are reported in Table 4.8. We find that the estimated coefficients for creditor rights and enforcement remain essentially unchanged. Of the seven additional non-religion variables with consistently significant estimated coefficients, we find that the estimated coefficients are consistently significant and positive for Fitch sovereign ratings, information sharing and public registry, and consistently significant and negative for private registry. We also find that the long-term debt ratio when a dummy variable for religion is included is significantly higher in countries where the major religion is Buddhism or significantly lower in countries where the major religion is Atheism, Catholicism, Islam or Orthodoxy.

[Please place Table 4.8 about here]

4.5.5 Controlling for Cross-listed Firms

In this section, we test whether our results are robust to the exclusion of cross-listed firms. Potential problems with the inclusion of cross-listed firms arise mostly due to the exposure of a cross-listed firm to two or more different country settings, including political, economic and legal rules and regulations. This makes the inference regarding the effect of institutional factors potentially more difficult. A well-documented example of this limitation can be due to the bonding effect where the cross-listing of a firm can act as a mechanism for bonding managers (Lel and Miller, 2008; Hope et al, 2004; Lichit and Chi, 2003). Similarly, cross-listing may result in better governance with more credible commitments to serving creditor demands if cross-listing subjects a firm to stricter enforcement mechanisms and tougher disclosure requirements, as is found for firms that cross-list in the U.S. market (Leuz, 2003).

To account for any possible cross-listing effects on our previous inferences, we test if our main results reported in Tables 4.4 and 4.5 are robust to the exclusion of cross-listed firms identified in Sarkissian and Schill (2014). Their sample consists of 3,589 firms from 73 home and 33 host markets. We redo our main CRE estimation tests after removing the 5,603 observations based on the matches between their and our samples of firms. Comparing the new Table 4.9 results when the long-term debt ratio is the dependent variable with those reported earlier in Table 4.4, we find that the effects of creditor rights and the other determinants remain essentially unchanged across all regressions with only some marginal changes in the estimated significance levels. Comparing the new Table 4.10 results when the weighted-average debt maturity is the dependent variable with those reported earlier in Table 4.5 yields similar inferences. In summary, these results indicate that our findings are not influenced materially by the inclusion of cross-listed firms in our original sample.

[Please place Tables 4.9 and 4.10 about here]

4.6 CONCLUSION

One strand of the literature posits that increased creditor rights and better enforcement result in cheaper credit and a further relaxation of financial constraints (Diamond, 2004; Qian and Strahan, 2007). An opposing strand of the literature asserts that increased creditor rights may lead to ex-post inefficiencies that increase the probability of liquidation (Vig, 2014). Thus, while the former predicts longer maturities with stronger creditor protection, the latter predicts the reverse.

We revisit this inferential difference by first proposing a theoretical model in which creditor rights and contract enforcement efficiencies influence debt maturity independently (following Hart and Moore, 1999; Jensen and Meckling, 1976; and Park, 2000). We show that the preference of borrowers for long-term debt is related to decreased rollover costs documented by He and Xiong (2012), and the preference of creditors for shorter-term debt is related to the higher effort of managers and the reduction in monitoring costs by creditors associated with short-term debt. In our model, creditors and borrowers enter a bargaining Nash game based on their bargaining power at the time of contract initiation.

We examine the different effects of creditor-rights institutions and contract enforcement mechanisms on the choice of debt maturity. This contrasts with most studies in law and financial economics that have either examined the joint effects of creditor rights and enforcement efficiency or have not sufficiently described the underlying mechanisms through which creditor rights and enforcement efficiency influence contracting features and debt maturity. We find that not only are these two variables not correlated but that they have opposite effects on debt maturity.

Consistent with the empirical predictions of our model, we find that increased creditor rights across 42 countries leads to shorter-term maturities while better contract enforcement lengthens maturity. Our findings for increased "creditor rights" are consistent with Vig, (2014) and Davydenko and Franks (2008) who report that the choice of secured debt is negatively influenced by increased creditor rights that increase the cautiousness of creditors and make creditors less willing to compromise. Our findings for the effect of enforcement mechanisms are consistent with the findings of Bae and Goyal (2009) who find that increased enforcement efficiency lengthens debt maturity.

CHAPTER 5:

Conclusion

In this thesis, we study corporate capital structure determinants from three interconnected perspectives, namely the leverage ratio, debt-type structure and finally, corporate debt maturity. We investigate the time-series stability of leverage ratios and debt structures and provide insights on the impact of credit ratings on such corporate behaviours. We find that the stability of leverage ratios is largely influenced by the tendency of firms to maintain stable credit ratings. Using treatment effect estimations on survival data, we show that assignment to better rating classes can lead firms to postpone leverage ratio changes significantly over a range between 1.8 to 3.5 years. We also document that across matched rated and unrated firms, being rated is associated with as much as 9 years longer wait before a material leverage variation.

We also study the stability in corporate debt structures. We document that there are large time-series variations in corporate debt structures. Firms change their selected debt types and their priorities frequently. However; they maintain the single main debt type highly stable over time. This result extends the findings of Colla et al. (2013) from a year-to-year to a long-run setting and sheds light on the time-series behaviour of debt structures. We confirm the finding of Rauh and Sufi (2010) that there are large variations in debt structures that can possibly compensate for the lack of variations in leverage ratios.

Finally, we study the optimal corporate debt maturities across different countries by investigating how the strength of creditor rights and contract enforcement mechanisms impact optimal maturity choice. Using a stylized model, we are able to disentangle the independent effects of better creditor rights and stronger contract enforcement on debt maturity. Our model predicts that stronger creditor rights shorten debt maturity and better contract enforcement lengthens it. Empirically, we test the model predictions across firms located in 42 countries and confirm the model predictions. Our results extend the literature on the inefficiency outcomes of stronger creditor protections. Moreover, our results imply that the large discrepancy in the literature regarding the effects of institutional settings on optimal debt maturity can be the result of the tendency to bundle creditor rights with enforcement efficiencies.

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Appendixes

Appendix 1. Description of variables and their computation for Chapter 2

This appendix lists the variables used in the paper and explains how they are computed. In Table A1, we report the variables used as determinants of market leverage in a selection of past papers and their estimated signs.

- *Book Leverage* (Lev^{ι}) is defined as total debt (long-term debt plus debt in current liabilities) divided by the book value of assets.
- *Cash flow volatility* (*CFVol*) is defined as in Kryzanowski and Mohsni (2013) as the volatility of $CF_{i,t} = E_{i,t} - A_{i,t}$ over the past six years where
- *Collateral*: is computed using Inventory (Compustat item #3) + net PPE (Compustat item #8)/ Total book assets
- *CAPX*: is from Compustat and shows funds, including property and equipment expenditures that are used in addition to plant, property and equipment. It excludes acquisition proceedings.
- $E_{i,t}$ is Income before extraordinary items (Compustat item #18), $A_{i,t}$ is the change in working capital (or ΔWC) minus Depreciation and Amortization (Compustat item #14).
- ΔWC is the change in current operating assets (Compustat item #4), net of cash and short-term investments (Compustat item #1), less the change in current operating liabilities (Compustat item #5), net of short-term debt (Compustat item #34).
- Dividend Payer (DivPay) is a dummy variable equal to 1 if the firm is a dividend payer.
- Lagged Leverage (Lev^{1}_{-10}) is the (market or book) leverage of the firm lagged ten years to capture an initial leverage that minimizes loss in the number of years in our time series since our data starts from 1985.
- Market Leverage (Levι) is defined as total debt divided by firm value, where firm value is defined as the book value of assets, minus the book value of common equity, plus the market value of equity, plus the book value of deferred taxes.
- *Market to Book* (*Mkt/Bk*) is defined as (market equity + total debt + preferred stock liquidating value (Compustat item #10) – deferred taxes and investment tax credits (Compustat item #35))/book assets.
- *Net Equity Issuance* is the split-adjusted change in shares outstanding $[\text{Compustat item } \#25_{t} - \text{Compustat item } \#25_{t-1} * (\text{Compustat item } \#27_{t-1}/ \text{Compustat item } \#27_{t})]$ times the split-adjusted average stock price $[\text{Compustat } item\ \#199_{t} + \text{Compustat item } \#199_{t-1} * (\text{Compustat item } \#27_{t}/\text{Compustat item } \#27_{t-1})]$ dividend by the end of year t−1 total assets.
- *Net Debt Issuance* is defined as the change in total debt from year t−1 to year t divided by the total assets at the end of year t−1.
- *Profitability* (*Profit*) is defined as earnings before interest and taxes given by operating income before depreciation (Compustat item #13), divided by the book value of assets.
- *Rating* is the S&P credit rating of the firm, where the value 1 corresponds to a Standard and Poor rating of AAA; 2 corresponds to AA+, and so on.
- *Rated* is a dummy variable equal to one if the firm has a Standard and Poor's credit rating.
- Size is the natural logarithm of total sales in millions of U.S. dollars.

- Tangibility (*Tang*) is defined as net PPE divided by book assets, where PPE is Property, Plant, and Equipment (Compustat item #8).
- Log (Size) is the natural logarithm of book assets (Compustat item #120).
- Log (Sales) is the natural logarithm of Sales (Compustat item #12).
- Industry Leverage: Is the average market (book) leverage of firms in the same industry with the same first two digits in their SIC codes.

Table A1. Coefficient signs for the independent variables used in previous studies

This table reports the leverage determinants used and the signs of their estimates reported in a selection of papers dated from 2006 to 2013. The table also reports if each paper has accounted for firm, time (year) and industry fixed effects.

Variables Used	Faulkender & Petersen (2006)	Frank & Goyal (2008)	Lemmon et al. (2008)	Fan, Titman, & Twite (2012)	Saretto & Tookes (2013)
Initial Lev		+	+		+
Size	-			+	-
Sales	-		+		
Market to Book	-	-	-	-	-
Profitability	-	-	-		+
Tangibility (or Fixed Assets)	+	+	+	-	+
Industry Lev			+		+
Cash flow volatility			-		
Dividend Payer		-	-		
Existence of Rating	+				+/-
Credit rating	+	+			+/-
Net debt issuance		yes	yes		
Net equity issuance		yes	yes		
Firm Fixed Effect			yes		yes
Year Fixed Effect			yes		yes
Industry Fixed Effect			yes		yes

Table A2. Size-adjusted critical t-values

The table reports critical t values adjusted for large sample size from $t^* = \sqrt{\left[c^{\frac{2}{T}}T^{\frac{1}{T}} - 1\right](T-k)}$ where t^* is the new critical t value; T and k denote the sample size and the number of regressors in the model; and c represents the ratio between the Bayes probabilities of the alternative and null hypotheses. Thus, for a 5% level of significance, c = 95%/5% = 19. This formula is derived from Leamer (1978), is a refinement of that that used by Connolly (1989) and Davidson and Faff (1999), and has been used by Frino and Oetomo (2005), amongst others. See Johnstone (2005) for derivation and further explanation.

Alternative	Null	T	c	K=							
				1	2	3	4	5	10	15	20
95.00%	5%	10,000	19	3.887	3.887	3.887	3.886	3.886	3.885	3.884	3.883
99.00%	1%	10,000	99	4.291	4.291	4.291	4.291	4.29	4.289	4.288	4.287
95.00%	5%	20,000	19	3.975	3.975	3.974	3.974	3.974	3.974	3.973	3.973
99.00%	1%	20,000	99	4.371	4.37	4.37	4.37	4.37	4.37	4.369	4.368
95.00%	5%	30,000	19	4.025	4.025	4.025	4.025	4.025	4.025	4.024	4.024
99.00%	1%	30,000	99	4.416	4.416	4.416	4.416	4.416	4.416	4.415	4.415
95.00%	5%	50,000	19	4.088	4.088	4.088	4.088	4.088	4.088	4.087	4.087
99.00%	1%	50,000	99	4.474	4.474	4.474	4.474	4.473	4.473	4.473	4.473
95.00%	5%	75,000	19	4.137	4.137	4.137	4.137	4.137	4.137	4.137	4.137
99.00%	1%	75,000	99	4.519	4.519	4.519	4.519	4.519	4.518	4.518	4.518
95.00%	5%	90,000	19	4.159	4.159	4.159	4.159	4.159	4.159	4.159	4.159
99.00%	1%	90,000	99	4.539	4.539	4.539	4.539	4.539	4.538	4.538	4.538
95.00%	5%	125,000	19	4.198	4.198	4.198	4.198	4.198	4.198	4.198	4.198
99.00%	1%	125,000	99	4.575	4.575	4.575	4.575	4.575	4.575	4.574	4.574
95.00%	5%	175,000	19	4.238	4.238	4.238	4.238	4.238	4.238	4.238	4.238
99.00%	1%	175,000	99	4.611	4.611	4.611	4.611	4.611	4.611	4.611	4.611

APPENDIX 2: VARIABLE CONSTRUCTION FOR CHAPTER 3

- Cash flow volatility (*CFVol*) is defined as in Kryzanowski and Mohsni (2013) as the volatility of $CF_{i,t} = E_{i,t} - A_{i,t}$ over the past six years where $E_{i,t}$ is Income before extraordinary items (Compustat item #18), $A_{i,t}$ is the change in working capital (or ΔWC) minus Depreciation and Amortization (Compustat item #14).
- Dividend Payer (DivPayer) is a dummy variable equal to 1 if the firm is a dividend payer, and zero otherwise.
- Heterogeneity index ($\mathrm{HHI}_{i,t}$) for firm i at time t is a normalized Herfindahl-Hirschman index (HHI) defined as the sum of squared ratios of each debt type from Capital IQ database to the total debt. The corresponding formula is from Colla et al. (2013).
- *Industry Maturity (IndMat)/ heterogeneity index (IndHet)* is the average maturity/ heterogeneity of firms in the same industry with the same first two digits in their SIC codes.
- Initial heterogeneity: For every firm, this variable refers to the first available debt heterogeneity observation.
- *Log* (*Sales*) is the natural logarithm of Sales (Compustat item #12).
- *Market to Book* (*MTB*) is defined as (market equity + total debt + preferred stock liquidating value (Compustat item #10) – deferred taxes and investment tax credits (Compustat item #35))/book assets.
- *Market Leverage* is total debt divided by firm value, where firm value is defined as the book value of assets, minus the book value of common equity, plus the market value of equity, plus the book value of deferred taxes.
- Maturity Index for firm *i* at time *t* (or $MI_{i,t}$) is defined as the ratio of long term debt to the total debt, according to Fan, Titman, and Twite (2010).
- *Profitability* (*Profit*) is earnings before interest and taxes given by operating income before depreciation (Compustat item #13), divided by the book value of assets.
- *Rated dummy* is a dummy variable equal to one if the firm has a Standard and Poor's credit rating. A firm has to report at least one rating report in any given year to be consider a rated firm in that year.
- *Sales* is the SALE variable from COMPUSTAT database.
- *Size* is the natural logarithm of total sales in millions of U.S. dollars.
- *Tangibility* (*Tang*) is defined as net *PPE* divided by book assets, where *PPE* is Property, Plant, and Equipment (Compustat item #8).
- *Tax rates* is the marginal tax rate from the Compustat marginal tax rate database.
- GDP, GDP growth and Inflation come from World Bank database
- Term spread is constructed using Federal Reserve database
- Idiosyncratic volatility is the moving average of daily stock prices from CRSP over the past 180 days.
- *Short interest volatility* is the volatility of the short-term interest rate over the past 180 days using data from the Fed database.

APPENDIX 3. VARIABLE CONSTRUCTION AND DATA SOURCES FOR CHAPTER 4

ICRG refers to the International Country Risk Guide database. Compustat refers to the Compustat Global and Compustat North America databases.

Variable	Description	Source
Country specific variables		
Bureaucratic quality	Higher bureaucratic quality index indicates that laws cannot be changed easily with the change of political power and hence such well-functioning institutions can act as shock absorbents to power transitions.	ICRG database
Constraint on Executives	This variable, according to the Polity IV methodology, refers to the institutionalized constraints on executive powers be it collective or individual. These limitations can be imposed by different forms of institutions in different societies, e.g., this role is played by legislatures in Western democracies. Elsewhere, a similar limiting role can be played by ruling parties, powerful advisors (in monarchies), or the military.	Polity IV
Contract viability	Contract viability measures the risk of unilateral contract cancellation or modification, as well as confiscation of foreign assets according to the reports in the ICRG database. Higher index levels state better contract viability.	ICRG database
Corruption	Corruption variable concerns a country's political system. Increased corruption has adverse effects on business and financial environment and increases the risk of foreign investment. This measure implies that power is transferred in other measures than ability and therefore can lead to long term destabilizing consequences. Corruption in our study is an index between 0 and 6 (highest level of corruption).	ICRG database
Country status (Developed/ Developing)	The measure comes from the World Bank's per capita GNI definition. In this measure, countries with per capita GNI of more than $12,276 are considered rich and those between $3,976 and $12,275 are considered as middle income. Our dataset does not contain poor countries due to unavailability of information.	World Bank, World Development Indicators
Creditor rights	Creditor rights index is the sum of four distinct dummy variables. The first dummy variable equals one if restrictions are in place in case a debtor needs to file for reorganization. The second dummy becomes one the secured creditors are able to seize collaterals in the case of reorganization. The third dummy becomes one if secured lenders are given priority over liquidation proceedings. The fourth dummy becomes one if the management cannot continue managing during the reorganization process.	Djankov et al. (2007)
Efficiency	This index measures the country-specific efficiency of debt enforcement, as in Djankov (2008)	Djankov (2008)
GDP Growth	Rate of growth in GDP of a country expressed in constant local currency. GDP is calculated without deduction of depreciations or depletion of natural resources.	World Bank, World Development Indicators
Inflation	According to the World Bank data definition, it is the annual rate of growth of the implicit GDP deflators, computed as GDP in terms of current currency to the GDP in the same local currency in 2003.	World Bank, World Development Ind.
Law and order	Index between 0 and 10 with 0 being the lowest levels of law and order in a country. The measure shows the traditional strength of law and order where, according to Knack and Keefer (1995), increases in this measure can be interpreted as reliable political institutions, smoother and ordered transition of political power, and better functioning legal system.	ICRG database
Legal origins	Four different legal origins are considered including English, French, German and Nordic. A dummy variable is assigned to each of these legal origins.	La Porta, Lopez-de-Silanes, Shleifer, and Vishny (1999)

Ln GDP per cap.	Natural logarithm of GDP per capita.	World Bank, World Development Ind.
Property rights index	Mainly considers the effectiveness of laws and institutions of a country to maintain and enforce the asset ownerships of private owners.	Heritage Foundation's database
Strength of legal rights index	This measure captures the extent to which the rights of both lenders and borrowers are preserved by the legal system, and includes eight "collateral law" aspects as well as two "bankruptcy law" aspects.	World Bank Doing Business database
	Firm Specific variables	
Ave-debt-maturity	Weighted average of the maturities of each of the available debt types.	Capital IQ debt structure database
Book leverage	Total debt (the sum of long term debt and debt in current liabilities) divided by total assets.	Compustat
Cash flow volatility	Standard deviation over past five years of the normalized operating income (i.e., operating income divided by total assets).	Compustat
Log of size	Natural logarithm of size, measured by a firm's total book assets (COMPUSTAT Item 6).	Compustat
Market to book	Market value of equity + total debt + preferred stock liquidating value less preferred taxes and investment tax credit, all divided by total book assets.	Securities Daily, Compustat
Maturity	The long-term debt ratio, which is long-term debt divided by total liabilities.	Compustat
Profitability	Earnings before interest and taxes (i.e., operating income before depreciation divided by total book assets).	Compustat
Tangibility	Net property, plant and equipment (PPE) divided by book assets	Compustat
	Robustness Variables	
Check formalism index	Index of formality that ranges from 1 to 7. Quantifies the "formal" procedures associated with collecting on a bounced check, worth 5 percent of the country's annual income per capita, when the defendant has no justification and avoids payment.	Legal formalism developed in Djankov et al. (2003)
Culture	Religion is used as a proxy for culture similar to Stulz and Williamson (2003). We recognize six distinct religions including Atheist, Buddhist, Catholic, Hindu, Muslim and Orthodox. A dummy for each of these religions equals one if majority of a country practice that certain religion.	Stulz and Williamson (2003) and the CIA Factbook (2003).
Information sharing	This dummy variable equals one if either a public registry or a private bureau operates in the country, zero otherwise.	World Bank Doing Business database
Private credit to GDP	Measures the financial resources that financial corporations provide for the private sector. These facilities can be loans, trade credits and other receivable accounts, according to the World Bank definition. Financial corporations may include monetary authorities and banks and other financial corporations conditional on the availability of data, and include leasing corporations, insurers, private lenders, pension funds and companies active in foreign exchange.	World Bank
Private registry	Percent of firms and adults that are covered by private registries.	World Bank Doing Business database
Public registry	Percent of firms and adults that are covered by public registries.	World Bank Doing Business database
Sovereign ratings	Captures the risk of government default and is interpreted as a general indicator of systematic risk.	Fitch Rating Agency
Stocks traded to GDP	Total value of stocks traded in a given year normalized by that year's GDP. Captures the annual stock market liquidity.	World Bank, World Development Indicators

Tables

Table 2.1. Descriptive statistics for the various variables

This table reports the summary statistics for the three main samples used in this paper. The All or left-most panel includes all firms in our sample regardless of whether or not they are rated. The Rated or middle panel and the Not-rated or right-most panel have firms with credit rating and no credit rating observations during our study period, respectively. The mean difference column reports the differences in the means of the rated and not-rated samples. The variables are described in Appendix 1. Initial market and book leverage (Lev) is their current counterparts lagged ten years. Data to compute the variables are obtained from the COMPUSTAT database for the period from 1985 to 2012. All financial firms (SIC codes 6000 to 6999) are excluded. Variable values are winsorized at the 0.1% level for the market (Mkt) and book leverage (Lev) ratios. N is the sample size. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

	All (N = 58,000)			Rated (N = 19,285)			Not-rated (N = 31,809)			Mean Difference
Variable	Mean	S.D.	Median	Mean	S.D.	Median	Mean	S.D.	Median	
Mkt Lev	0.3	0.23	0.25	0.34	0.22	0.31	0.27	0.24	0.21	0.07**
Book Lev	0.28	0.2	0.26	0.33	0.17	0.31	0.24	0.21	0.21	0.09***
Initial Market Lev	0.3	0.24	0.26	0.32	0.23	0.3	0.28	0.25	0.22	0.04***
Initial Book Lev	0.48	10.62	0.24	0.62	16.95	0.28	0.43	5.26	0.21	0.19**
Ln (Size)	4.79	2.26	4.86	6.73	1.55	6.71	3.52	1.85	3.57	3.21**
Ln (Sales)	5.72	2.38	5.83	7.79	1.55	7.76	4.37	1.96	4.46	3.42***
Market to Book	1.33	2.43	0.96	1.19	0.83	0.95	1.43	3.22	0.96	-0.24**
Profitability	0.09	0.28	0.12	0.14	0.07	0.13	0.06	0.37	0.11	0.08*
Tangibility	0.35	0.24	0.29	0.42	0.24	0.39	0.29	0.22	0.24	0.13**
Industry Lev	0.3	0.1	0.28	0.32	0.1	0.31	0.28	0.09	0.27	0.04
CF Volatility	4.13	231.56	0.7	2.81	84.24	1.05	1.86	68.42	0.51	0.95*
Net debt issuance	0.12	0.47	0.01	0.07	0.45	0.01	25.96	296.74	3.29	-25.89***
Net equity issuance	0.06	0.42	0	0.09	0.45	0.01	0.14	0.48	0.01	-0.05**

Table 2.2. Rating differences after formation of the quartiles based on credit ratings

This table reports average credit ratings at event years 0 (quartile formation date), 10 and 20, and tests of their differences for quartiles for the full sample of rated firms in Panel A and for the sample of rated firms with at least 20 years of observations in Panel B. The t-statistics are reported in the parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A: Average Rating, Regular Sample				
Event Year	Very Highly Rated	Highly Rated	Medium Rated	Lowly Rated
0	5.11	8.38	11.61	14.12
10	5.57	8.93	11.57	13.54
20	7.06	9.82	11.93	13.09
Difference				
0 and 10	0.45***	0.55***	-0.04	-0.57*
	(4.76)	(12.35)	(-0.24)	(-1.54)
10 and 20	1.49***	0.88***	0.35	-0.44***
	(8.5)	(24.72)	(1.2)	(-2.8)
0 and 20	1.95***	1.44***	0.31***	-1.02**
	(9.29)	(26.21)	(3.09)	(-2.76)

Panel B: Average Rating, Survived Sample				
Event Year	Very Highly Rated	Highly Rated	Medium Rated	Lowly Rated
0	3.87	6.11	8.1	11.06
10	5.28	7.4	9.32	12.19
20	6.23	8.2	9.71	12.33
Difference				
0 and 10	1.41***	1.28***	1.22***	1.12***
	(6.68)	(22.09)	(34.38)	(3.42)
10 and 20	0.94***	0.79***	0.38***	0.14*
	(23.39)	(20.75)	(13.14)	(1.56)
0 and 20	2.36***	2.08***	1.61***	1.26***
	(13.68)	(38.11)	(46.11)	(5.23)

Table 2.3. Average treatment effect for firms just above the investment-grade cut-off

This table measures the average treatment effect (ATE) and average treatment effect on the treated (ATT) for firms that have a credit rating just above the investment grade cut-off (BBB-) compared to firms with a credit rating just below the cut-off (BB+). Propensity score matching is performed based on a series of observables including classic capital structure determinants (Titman and Parsons, 2008) and credit-rating determinants used in Moody's KMV methodology (Duffie and Singleton, 2003). "Threshold" is the leverage threshold which takes arbitrary values of 10, 20 and 50. The second column, headed by "total" reports the number of total observations used in the study, and the third column shows the number of "treated" observations. The fourth column reports ATE and ATT, where the first row in each panel shows ATE and the second row in each panel shows the ATT. The fifth column "POM" shows the potential-outcome means. Weibull distribution is used to derive the results.

ATE and ATET for Leverage Survival						
Threshold	total	treatment	ATE/ ATT	POM	p	
50	400	20	3.55	9.15	0.00	ATE
	400	20	3.67	9.21	0.00	ATT
20	383	219	2.1	7.13	0.00	ATE
	383	219	2.12	6.85	0.00	ATT
10	307	271	1.83	3.27	0.00	ATE
	307	271	1.88	3.21	0.00	ATT

Table 2.4. Stability of rating classes and leverages

This table reports hazard ratio estimates for a sample confined to rated firms using an exponential hazard function. The variable of interest is the stability of the leverage ratios and the event occurs when the leverage diverts by more than 50% (left panel) and 20% (right panel) from its lagged value over the subsequent 27 years. Rating indicates the rating quality and equals the negative of our original rating indicator. Therefore, an increase in the rating variable indicates an improvement in rating quality and vice versa. All variables are standardized, except for the dummies. Rating, market leverage, size and sales are orthogonalized using the modified Gram-Schmidt procedure. The t-values are reported in the parentheses. *, ** and *** indicate significance at the 5%, 1% and 0.1% levels, respectively.

	Threshold = 50				Threshold = 20			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Rating	-0.81***	-0.97***	-0.88***	-0.93***	-0.73***	-0.76***	-0.71***	-0.72***
	(-16.10)	(-16.33)	(-13.13)	(-13.40)	(-22.12)	(-23.62)	(-19.43)	(-19.84)
Market Leverage		0.09	0.06	0.14	-0.04	-0.01	-0.03	-0.02
		-1.09	-0.67	-1.51	(-0.97)	(-0.29)	(-0.65)	(-0.52)
Ln(Sales)	-0.18***	-0.25***	-0.22***	-0.21***		0.11**	0.07	0.09*
	(-5.72)	(-6.89)	(-4.98)	(-4.39)		-3.06	-1.78	-2.16
Ln(Size)		-0.30***	-0.24**	-0.24**		-0.12**	-0.14***	-0.14***
		(-3.93)	(-2.87)	(-2.86)		(-3.18)	(-3.57)	(-3.69)
Profitability		83.19**	84.83**	90.81**		19.65	43.47	43.73
		-3.03	-2.71	-2.9		-1.26	-1.85	-1.86
Tangibility		0.01	0	0.08		-0.15***	-0.18***	-0.15***
		-0.11	-0.02	-0.84		(-3.81)	(-4.38)	(-3.55)
CF Volatility		0.06***	0.05***	0.06***		0.03***	0.03***	0.03***
		-20.67	-18.14	-18.15		-7.12	-6.59	-6.69
Dividend Payer			-1.48***	-1.45***			-0.36***	-0.35***
			(-4.16)	(-4.08)			(-4.19)	(-4.11)
Market to Book			-0.03	-0.06			-0.23***	-0.25***
			(-0.24)	(-0.50)			(-3.83)	(-4.05)
Industry				-2.77**				-0.77
				(-2.84)				(-1.76)
Constant	-5.33***	-7.29***	-7.02***	-6.34***	-2.67***	-3.08***	-3.26***	-3.02***
	(-65.08)	(-11.14)	(-10.19)	(-8.61)	(-83.85)	(-8.37)	(-6.25)	(-5.53)
Observations	2546	2527	2326	2326	2302	2286	2096	2096

Table 2.5. Market leverage differences after formation of the quartiles based on market leverage

This table reports average market leverages at event years 0 (quartile formation date), 10 and 20, and tests of their differences for quartiles of rated firms in Panel A and for not-rated firms in Panel B. The t-statistics are reported in the parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Panel A: Average Market Leverage, Rated Sample

Event Year	Very High Leverage	High Leverage	Medium Leverage	Low Leverage
0	0.49	0.4	0.32	0.23
10	0.5	0.4	0.31	0.23
20	0.47	0.38	0.29	0.23
Difference				
0 and 10	0.00	0.00	0.00**	0.00
	(0.23)	(0.05)	(-2.12)	(-1.11)
10 and 20	-0.02***	-0.02***	-0.02***	0.00
	(-4.06)	(-9.08)	(-6.43)	(-0.25)
0 and 20	-0.02	-0.02***	-0.02***	0.00
	(-1.00)	(-3.35)	(-6.05)	(-1.14)

Panel B: Average Market Leverage, Not-rated Sample

Event Year	Very High Leverage	High Leverage	Medium Leverage	Low Leverage
0	0.38	0.24	0.14	0.06
10	0.46	0.29	0.19	0.13
20	0.33	0.22	0.17	0.13
Difference				
0 and 10	0.07**	0.05***	0.05***	0.07***
	(2.81)	(7.28)	(19.47)	(10.07)
10 and 20	-0.12***	-0.07***	-0.01***	0.00
	(-13.59)	(-28.63)	(-3.87)	(0.25)
0 and 20	-0.05**	-0.01**	0.03***	0.07***
	(-1.99)	(-2.05)	(9.08)	(10.94)

Table 2.6. Rating effects on leverage stability

This table reports hazard ratio estimates using an exponential hazard function. The variable of interest is the stability of the leverage ratio and the event occurs when leverage diverts by more than 50% from its lagged value over a 27 year period. Rated dummy gets a value of 1 if a firm is rated, and zero otherwise. All variables are standardized, except for the dummies. Rated dummy, market leverage, size and sales are orthogonalized using the modified Gram-Schmidt procedure. The t-value are reported in the parentheses. *, ** and *** indicate significance at the 5%, 1% and 0.1% levels, respectively.

	Threshold = 50				Threshold = 20			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Rated dummy	-0.26***	-0.21***	-0.17***	-0.17***	-0.15***	-0.10***	-0.08***	-0.07***
	(-8.03)	(-6.37)	(-4.72)	(-4.64)	(-10.20)	(-7.26)	(-5.07)	(-4.93)
Market Lev.		0.47***	0.42***	0.42***		0.54***	0.51***	0.52***
		(-15.64)	(-13.59)	(-12.56)		(-38.13)	(-35.41)	(-33.19)
Ln(Size)		-0.52***	-0.49***	-0.49***		-0.27***	-0.25***	-0.25***
		(-15.88)	(-13.89)	(-13.79)		(-16.03)	(-13.39)	(-13.33)
Ln(Sales)		-0.10*	-0.08*	-0.08		0.00	0.03	0.04
		(-2.46)	(-1.98)	(-1.96)		(-0.21)	(-1.53)	(-1.62)
Profitability		-0.31***	-0.44***	-0.44***		0.86	0.80	0.80
		(-4.21)	(-3.65)	(-3.64)		(-1.66)	(-0.55)	(-0.55)
Tangibility		-0.11**	-0.09*	-0.09*		-0.13***	-0.13***	-0.12***
		(-2.82)	(-2.28)	(-2.11)		(-6.94)	(-6.41)	(-5.74)
CF Volatility		0.06***	0.05***	0.05***		0.02**	0.02***	0.02***
		(-29.42)	(-30.88)	(-30.88)		(-2.61)	(-3.49)	(-3.37)
Dividend Payer			-0.96***	-0.96***			-0.52***	-0.52***
			(-6.03)	(-6.03)			(-10.07)	(-9.99)
Market to Book			0.00	0.00			-0.01	-0.01
			(-1.18)	(-1.18)			(-1.02)	(-1.02)
Industry				-0.05				-0.23
				(-0.11)				(-1.22)
Constant	-4.63***	-4.67***	-4.56***	-4.55***	-2.50***	-2.44***	-2.35***	-2.28***
	(-140.12)	(-127.53)	(-114.14)	(-37.02)	(-156.98)	(-129.36)	(-51.46)	(-30.77)
Observations	13567	13405	12745	12745	11467	11330	10749	10749

Table 2.7. Leverage-ratio stability of firms with ratings starts or stops

This table provides the percentage of firms with leverage fluctuations that cross thresholds of 5%, 10%, 20%, 30% and 50% for firms whose credit ratings were started or stopped to be reported by S&P during the time period examined herein. The sample includes firms with at least 18 consecutive (annual) observations, at least seven consecutive observations in both their rated and their not-rated regimes, and whose ratio of observations in the rated period to the not-rated period is between 0.4 and 0.6. The method for calculating fluctuation differences is similar to that explained in Table 7. Since only a few firms have more than ten observations in both the rated and not-rated regimes, the maximum number of lags is restricted to ten. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Lag	Threshold	Not-rated Period	Rated Period	Difference	T-test Value
5	5%	19.85%	19.47%	0.38%***	11.18
10		3.74%	3.48%	0.27%***	5.07
5	10%	19.71%	19.32%	0.39%***	13.66
10		3.73%	3.47%	0.26%***	29.47
5	20%	19.37%	19.04%	0.33%***	6.87
10		3.71%	3.43%	0.28%***	9.44
5	30%	19.16%	18.77%	0.39%***	3.97
10		3.68%	3.40%	0.28%***	9.38
5	50%	19.85%	19.47%	0.38%***	3.63
10		3.73%	3.47%	0.26%***	7.15

Table 2.8. Fluctuations in leverage-ratios over time

This table reports the mean proportions of the rated (not-rated) firms whose market leverage ratios deviate by at least 5%, 10%, 20%, 30% and 50% from their base year ratios at different future points in event time (namely, leads of 5, 10, 15 and 20 years after the base or event year 0). The proportions are calculated for all the future points in event time beginning with the firms in the sample of (not-) rated firms in the 1985 base year, then for those in the 1986 base year, and ending with those in the 2005 base year. The last column reports the differences (Dif.) in the mean proportions for rated and not-rated firms and ratio tests of their statistical significance. *, ** and *** indicate significance at the 0.05, 0.01 and 0.001 levels, respectively, based on conventional critical t-values. Panel A reports the results for all firms in each sample. Panel B reports the results for samples of firms where each firm has at least 20 years of observations ending in 2012.

Lead	Minimum Deviation	Panel A: All firms in each sample			Panel B: Survived firms (Firm ≥ 20 annual observations ending in 2012)		
		Rated	Not-rated	Dif.	Rated	Not-rated	Dif.
5	5%	47.50%	54.49%	14%***	50.00%	58.00%	16%***
10		38.55%	46.65%	21%***	42.00%	51.00%	22%***
15		26.16%	33.84%	29%***	29.00%	39.00%	33%***
20		13.32%	16.10%	20%**	16.00%	23.00%	43%***
5	10%	47.21%	54.33%	15%***	50.00%	58.00%	16%***
10		38.39%	46.54%	21%***	41.00%	51.00%	22%***
15		26.07%	33.78%	29%***	29.00%	39.00%	33%***
20		13.28%	16.07%	21%***	16.00%	22.00%	43%***
5	20%	46.71%	54.01%	15%***	49.00%	57.00%	16%***
10		38.09%	46.32%	21%***	41.00%	50.00%	22%***
15		25.90%	33.66%	29%***	29.00%	39.00%	33%***
20		13.21%	16.02%	21%**	16.00%	22.00%	43%***
5	30%	46.27%	52.31%	13%***	49.00%	56.00%	14%**
10		37.79%	44.96%	18%***	41.00%	49.00%	20%***
15		25.73%	32.78%	27%***	29.00%	38.00%	31%***
20		13.13%	15.61%	18%***	16.00%	22.00%	40%***
5	50%	47.50%	54.49%	14%***	50.00%	58.00%	16%***
10		38.39%	46.54%	21%***	41.00%	51.00%	22%***
15		25.98%	32.85%	26%***	29.00%	38.00%	30%***
20		13.21%	16.02%	21%***	16.00%	22.00%	43%***

Table 2.9. Pooled regression results for leverage ratio determinants

This table presents the estimation results for the following pooled OLS regression model for samples of firms with reported book asset values:

$$Lev_{i,t}^{l} = \beta_0 + \beta_1 Lev_{i,t-10}^{l} + \beta_2 Log(Size_{i,t-1}) + \beta_3\ Log(Sales)_{i,t-1} + \beta_4 MTB_{i,t-1} + \beta_5\ Profit_{i,t-1} + \beta_6 Tang_{i,t-1} + \beta_7 IndLev_{i,t-1} + \beta_8 CFVol_{i,t-1} + \beta_9 DivPayer_i + \varepsilon_{i,t}$$

Mkt Lev and Book Lev are market and book leverage, respectively. The regressors are as defined in Appendix 1. Summary results for all firms, and those in the rated and not-rated subsamples are reported in Panels A, B and C, respectively. All variables are first winsorized at the upper and lower 0.1%, and then are standardized by dividing by their standard deviations. T-values based on clustered standard errors when so indicated in the last three rows of each panel are reported in the parentheses. Superscripts a, b and c indicate significance at the 0.05, 0.01 and 0.001 levels, respectively, based on conventional critical t-values. Superscript d and e indicate statistical significance at the 0.05 and 0.01 levels, respectively, based on size-adjusted critical t-values as reported in table A2.

Panel A: All firms	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables	Mkt Lev						Book Lev					
Mkt Lev at t-10	0.23 ^{c,e}	0.22 ^{c,e}	0.14 ^{c,e}		0.14 ^{c,e}	0.14 ^{c,e}						
	(58.35)	(33.14)	(24.26)		(39.2)	(24.41)						
Book Lev at t-10							0.00	0.00	0.00		0.00	0.00
							-0.26)	(0.38)	(0.29)		(0.13)	(0.21)
Log (Size)			-0.34 ^{c,e}	-0.36 ^{c,e}	-0.35 ^{c,e}	-0.35 ^{c,e}			-0.28 ^{c,e}	-0.29 ^{c,e}	-0.29 ^{c,e}	-0.29 ^{c,e}
			(-16.33)	(-17.16)	(-26.61)	(-16.66)			(-12.06)	(-12.25)	(-22.00)	(-12.25)
Log (Sales)			0.26 ^{c,e}	0.27 ^{c,e}	0.26 ^{c,e}	0.26 ^{c,e}			0.20 ^{c,e}	0.20 ^{c,e}	0.20 ^{c,e}	0.20 ^{c,e}
			(13.2)	(13.68)	(19.09)	(13.08)			(6.48)	(6.45)	(14.87)	(6.45)
Market to Book			-7.59	-7.86	-7.63 ^{c,e}	-7.61			3.04 ^{c,e}	3.03 ^{c,e}	3.08 ^{c,e}	3.03 ^{c,e}
			(-1.82)	(-1.81)	(-29.01)	(-1.82)			(4.89)	(4.85)	(11.68)	(4.85)
Profitability			-2.91 ^{a}	-2.96 ^{a}	-2.86 ^{c,e}	-2.87 ^{a}			-3.59 ^{b}	-3.57 ^{b}	-3.58 ^{c,e}	-3.57 ^{c,e}
			(-2.04)	(-2.03)	(-23.80)	(-2.03)			(-3.14)	(-3.12)	(-29.75)	(-3.12)
Tangibility			0.04 ^{c,e}	0.06 ^{c,e}	0.04 ^{c,e}	0.04 ^{c,e}			0.10 ^{c,e}	0.10 ^{c,e}	0.10 ^{c,e}	0.10 ^{c,e}
			(7.08)	(10.01)	(9.89)	(7.14)			(19.89)	(19.80)	(23.15)	(19.80)
Industry Lev			0.29 ^{c,e}	0.32 ^{c,e}	0.30 ^{c,e}	0.29 ^{c,e}			0.18 ^{c,e}	0.18 ^{c,e}	0.17 ^{c,e}	0.18 ^{c,e}
			(40.26)	(44.49)	(73.19)	(-40.73)			(20.19)	(20.29)	(42.24)	(20.29)
CF Volatility				0.05 ^{c,e}	0.04 ^{c,e}	0.05 ^{c,e}				0.03 ^{c,e}	0.03 ^{c,e}	0.03 ^{c,e}
				(9.47)	(9.64)	(9.67)				(6.84)	(5.90)	(6.81)
Dividend Payer				-0.00 ^{c,e}	-0.00 ^{c,d}	-0.00 ^{c,e}				-0.00 ^{b}	-0.00 ^{a}	-0.00 ^{b}
				(-5.44)	(-4.21)	(-4.65)				(-2.93)	(-2.15)	(-2.90)
Constant	0.04 ^{c,e}	0.04 ^{c,e}	0.00	0.00	0.01	0.01	-0.03 ^{c,e}	-0.03 ^{c,e}	0.06 ^{c}	0.06 ^{c}	0.06 ^{c,e}	0.06 ^{c}
	(11.02)	(>100.00)	(0.08)	(0.08)	(1.42)	(0.21)	(-6.68)	(>-100.00)	(3.59)	(3.69)	(13.71)	(3.69)
Observations	58,000	58,000	57,998	57,998	57,998	57,998	58,000	58,000	57,998	57,998	57,998	57,998
R-squared	0.06	0.08	0.2	0.18	0.2	0.2	0	0.01	0.11	0.11	0.11	0.11
Year Fixed Effect	NO	YES	YES	YES	NO	YES	NO	YES	YES	YES	NO	YES
Firm Fixed Effect	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
Year Clusters	NO	YES	YES	YES	NO	YES	NO	YES	YES	YES	NO	YES

Panel B: Rated	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables			Mkt Lev						Book Lev			
Mkt Lev at t-10	0.30 [c,e]	0.29 [c,e]	0.11 [c,e]		0.10 [c,e]	0.11 [c,e]						
	(45.42)	(24.62)	(11.14)		(17.73)	(11.31)						
Book Lev at t-10							-0.01	-0.01 [a]	0.01		0.00	0.00
							(-1.00)	(-2.03)	(1.72)		(0.69)	(1.53)
Log (Size)			-0.30 [c,e]	-0.34 [c,e]	-0.33 [c,e]	-0.33 [c,e]			-0.41 [c,e]	-0.45 [c,e]	-0.45 [c,e]	-0.45 [c,e]
			(-10.47)	(-11.36)	(-18.70)	(-11.18)			(-14.98)	(-15.74)	(-22.26)	(-15.74)
Log (Sales)			0.08 [c]	0.07 [b]	0.09 [c,e]	0.08 [c]			0.07 [b]	0.07 [b]	0.09 [c,e]	0.07 [b]
			(3.51)	(3.21)	(5.06)	(3.34)			(2.8)	(2.56)	(4.77)	(2.56)
Market to Book			-0.27[c,e]	-0.29 [c,e]	-0.26 [c,e]	-0.27 [c,e]			0.06 [b]	0.06 [b]	0.07 [c,e]	0.06 [b]
			(-12.20)	(-12.46)	(-39.50)	(-12.24)			-2.77	-2.89	-9.38	-2.89
Profitability			-0.25 [c,e]	-0.25 [c,e]	-0.25 [c,e]	-0.25 [c,e]			-0.14 [c,e]	-0.14 [c,e]	-0.15 [c,e]	-0.14 [c,e]
			(-14.34)	(-14.15)	(-35.48)	(-14.38)			(-6.30)	(-6.36)	(-18.50)	(-6.36)
Tangibility			-0.02	-0.02	-0.04 [c,e]	-0.03 [a]			0.01	0.00	-0.01	0.00
			(-1.83)	(-1.23)	(-6.41)	(-2.15)			(0.55)	(0.27)	(-1.67)	(0.27)
Industry Lev			0.21 [c,e]	0.23 [c,e]	0.23 [c,e]	0.21 [c,e]			0.16 [c,e]	0.16 [c,e]	0.16 [c,e]	0.16 [c,e]
			(17.71)	(24.66)	(35.91)	(18.43)			(8.88)	(9.13)	(22.42)	(9.12)
CF Volatility				0.07 [c,e]	0.07 [c,e]	0.07 [c,e]				0.04 [c,e]	0.04 [c,e]	0.04 [c,e]
				(10.07)	(8.53)	(9.98)				(6.40)	(4.74)	(6.50)
Dividend Payer				0.00	0.00	0.00				0.00 [c,e]	0.00 [c,e]	0.00 [c,e]
				(1.05)	(1.54)	(1.46)				(4.43)	(5.32)	(4.40)
Constant	-0.09 [c,e]	-0.09 [c,e]	-0.06 [c,e]	-0.06 [c,e]	-0.06 [c,e]	-0.06 [c,e]	-0.13 [c,e]	-0.13 [c,e]	-0.10 [c,e]	-0.11 [c,e]	-0.11 [c,e]	-0.11 [c,e]
	(-13.27)	(>-100.00)	(-34.15)	(-25.62)	(-11.05)	(-23.94)	(-20.07)	(>-100.00)	(-80.89)	(-32.61)	(-16.94)	(-32.57)
Observations	19,285	19,285	19,285	19,285	19,285	19,285	19,285	19,285	19,285	19,285	19,285	19,285
R-squared	0.1	0.12	0.44	0.43	0.44	0.44	0.00	0.01	0.21	0.21	0.2	0.21
Year Fixed Effect	NO	YES	YES	YES	NO	YES	NO	YES	YES	YES	NO	YES
Firm Fixed Effect	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
Year Clusters	NO	YES	YES	YES	NO	YES	NO	YES	YES	YES	NO	YES

Panel C: Not-rated	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables				Mkt Lev					Book Lev			
Mkt Lev at t-10	0.17 [c,e]	0.15 [c,e]	0.12 [c,e]		0.12 [c,e]	0.12 [c,e]						
	(31.63)	(20.04)	(16.56)		(23.40)	(16.49)						
Book Lev at t-10							0.00	0.00	0.00		0.00	0.00
							(0.20)	(0.22)	(0.39)		(0.28)	(0.39)
Log (Size)			-0.40 [c,e]	-0.42 [c,e]	-0.41 [c,e]	-0.41 [c,e]			-0.36 [c,e]	-0.37 [c,e]	-0.37 [c,e]	-0.37 [c,e]
			(-20.87)	(-22.28)	(-29.42)	(-21.50)			(-16.86)	(-17.68)	(-27.64)	(-17.61)
Log (Sales)			0.26 [c,e]	0.27 [c,e]	0.25 [c,e]	0.26 [c,e]			0.15 [c,e]	0.15 [c,e]	0.15 [c,e]	0.15 [c,e]
			(14.00)	(14.32)	(17.67)	(13.99)			(5.19)	(5.19)	(11.19)	(5.17)
Market to Book			-6.38 [a]	-6.47 [a]	-6.54 [c,e]	-6.40 [a]			3.30 [c,d]	3.27 [c,d]	3.27 [c,e]	3.27 [c,d]
			(-1.96)	(-1.96)	(-19.13)	(-1.97)			(4.01)	(3.99)	(9.9)2	(3.98)
Profitability			-2.15 [a]	-2.15 [a]	-2.05 [c,e]	-2.13 [a]			-3.56 [b]	-3.52 [b]	-3.52 [c,e]	-3.52 [b]
			(-1.93)	(-1.94)	(-13.05)	(-1.92)			(-3.11)	(-3.10)	(-23.17)	(-3.10)
Tangibility			0.05 [c,e]	0.06 [c,e]	0.05 [c,e]	0.05 [c,e]			0.08 [c,e]	0.08 [c,e]	0.08 [c,e]	0.08 [c,e]
			(6.23)	(6.73)	(8.76)	(6.24)			(13.62)	(12.68)	(13.76)	(12.68)
Industry Lev			0.23 [c,e]	0.25 [c,e]	0.25 [c,e]	0.23 [c,e]			0.13 [c,e]	0.13 [c,e]	0.13 [c,e]	0.13 [c,e]
			(39.17)	(37.05)	(45.11)	(39.05)			(17.64)	(17.65)	(23.88)	(17.57)
CF Volatility				0.07 [c,e]	0.06 [c,e]	0.07 [c,e]				0.08 [c,e]	0.08 [c,e]	0.08 [c,e]
				(5.02)	(5.24)	(4.95)				(4.80)	(6.63)	(4.80)
Dividend Payer				-0.00 [c,d]	-0.00 [c]	-0.00 [c,d]				-0.00 [a]	-0.00 [b]	-0.00 [a]
				(-3.94)	(-3.67)	(-4.01)				(-2.44)	(-3.20)	(-2.44)
Constant	0.04 [c,e]	0.04 [c,e]	0.01	0.02	0.02 [b]	0.02	-0.04 [c,e]	-0.04 [c,e]	0.09 [c,e]	0.09 [c]	0.09 [c,e]	0.09 [c]
	(8.17)	(>-100.00)	(0.5)	(0.6)	(2.58)	(0.64)	(-8.27)	(>-100.00)	(3.74)	(3.88)	(14.15)	(3.88)
Observations	31,809	31,809	31,807	31,807	31,807	31,807	31,809	31,809	31,807	31,807	31,807	31,807
R-squared	0.03	0.06	0.17	0.16	0.17	0.17	0	0.01	0.14	0.14	0.14	0.14
Year Fixed Effect	NO	YES	YES	YES	NO	YES	NO	YES	YES	YES	NO	YES
Firm Fixed Effect	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
Year Clusters	NO	YES	YES	YES	NO	YES	NO	YES	YES	YES	NO	YES

Table 2.10. Fixed effects regression results for leverage ratio determinants

This table reports the estimation results for regression model (1) as specified in table 2 without the initial leverage ($Lev_{i,t-10}^{l}$) regressor and with and without firm fixed effects for all firms and those in the rated and not-rated subsamples. Mkt Lev and Book Lev are market and book leverage, respectively. The regressors are as defined in Appendix 1. All variables are first winsorized at the upper and lower 0.1%, and then are standardized by dividing by their standard deviations. The t-values based on clustered standard errors when so indicated in the last two rows of each column are reported in the parentheses. Superscripts a, b and c indicate significance at the 0.05, 0.01 and 0.001 levels, respectively, based on conventional critical t-values. Superscript d and e indicate statistical significance at the 0.05 and 0.01 levels, respectively, based on size-adjusted critical t-values as reported in table A2. N is the number of observations. All the regressions reflect firm and year clustering.

	Panel A: All firms (N=57,998)				**Panel B**: Rated firms (N=19,285)				**Panel C**: Not-rated firms (N=31,807)			
Variables	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Mkt Lev		Book Lev		Mkt Lev		Book Lev		Mkt Lev		Book Lev	
Log (Size)	-0.36 ^{c,e}	-0.17 ^{c,e}	-0.29 ^{c,e}	-0.30 ^{c,e}	-0.34 ^{c,e}	-0.20 ^{c,e}	-0.45 ^{c,e}	-0.27 ^{c,e}	-0.42 ^{c,e}	-0.19 ^{c,e}	-0.37 ^{c,e}	-0.30 ^{c,e}
	(-11.82)	(-3.46)	(-8.04)	(-5.92)	(-7.56)	(-3.59)	(-7.56)	(-4.00)	(-14.78)	(-4.05)	(-11.10)	(-5.87)
Log (Sales)	0.27 ^{c,e}	0.22 ^{c,e}	0.20 ^{c,e}	0.22 ^{c,e}	0.07	0.17 ^{b}	0.07	0.07	0.27 ^{c,e}	0.15 ^{c,e}	0.15 ^{c,e}	0.16 ^{b,e}
	(8.66)	(4.77)	(5.19)	(4.37)	(1.68)	(3.07)	(1.18)	(1.14)	(9.62)	(3.70)	(4.47)	(3.26)
Market to Book	-7.86 ^{a}	-14.40 ^{c,e}	3.03	-1.56	-0.29 ^{c,e}	-0.21 ^{c,e}	0.06 ^{b}	0.03 ^{a}	-6.47 ^{a}	-12.05 ^{c,e}	3.27	-1.01
	(-2.09)	(-4.58)	(1.47)	(-1.40)	(-12.37)	(-8.17)	(3.18)	(1.69)	(-2.27)	(-4.09)	(1.55)	(-0.75)
Profitability	-2.96 ^{a}	-5.67 ^{c,e}	-3.57 ^{c,e}	-4.44 ^{c,e}	-0.25 ^{c,e}	-0.25 ^{c,e}	-0.14 ^{c,e}	-0.17 ^{c,e}	-2.15 ^{a}	-4.56 ^{c,e}	-3.52 ^{c,e}	-4.34 ^{c,e}
	(-2.13)	(-6.19)	(-4.01)	(-5.93)	(-13.53)	(-10.97)	(-6.64)	(-8.62)	(-2.00)	(-5.31)	(-3.82)	(-5.31)
Tangibility	0.06 ^{c,e}	0.13 ^{c,e}	0.10 ^{c,e}	0.09 ^{c,e}	-0.02	0.03	0.00	-0.03	0.06 ^{c,e}	0.18 ^{c,e}	0.08 ^{c,e}	0.14 ^{c,e}
	(5.13)	(6.20)	(9.03)	(4.05)	(-0.97)	(1.05)	(0.15)	(-0.64)	(3.99)	(6.61)	(5.60)	(4.92)
Industry Lev	0.32 ^{c,e}	0.30 ^{c,e}	0.18 ^{c,e}	0.16 ^{c,e}	0.23 ^{c,e}	0.25 ^{c,e}	0.16 ^{c,e}	0.13 ^{c,e}	0.25 ^{c,e}	0.26 ^{c,e}	0.13 ^{c,e}	0.16 ^{c,e}
	(26.46)	(21.07)	(17.25)	(13.09)	(13.16)	(12.95	(8.35)	(6.11)	(16.49)	(12.83)	(10.17)	(9.71)
CF Volatility	0.05 ^{c,e}	0.02 ^{c,e}	0.03 ^{c,e}	0.01	0.07 ^{c,e}	0.04 ^{b}	0.04 ^{a}	0.01	0.07 ^{b}	-0.02	0.08 ^{b}	-0.02
	(4.42)	(3.49)	(3.41)	(0.71)	(3.47)	(2.86)	(2.27)	(0.83)	(2.97)	(-0.43)	(2.57)	(0.52)
Dividend Payer	-0.00 ^{a}	-0.00	0.00	0.00	0.00	-0.00 ^{a}	0.00 ^{a}	0.00	-0.00 ^{a}	0.00 ^{a}	0.00	0.00 ^{a}
	(-2.44)	(-0.67)	(-1.43)	(-0.74)	(0.46)	(-2.19)	(2.47)	(1.10)	(-2.47)	(1.65)	(1.45)	(1.76)
Constant	0.00	0.00	0.06 ^{a}	0.08 ^{a}	-0.06 ^{c,e}	-0.05	-0.11 ^{c,e}	-0.03	0.02	0.04	0.09 ^{a}	0.07
	(0.08)	(0.10)	(2.14)	(2.38)	(-4.09)	(-1.62)	(-6.36)	(-0.75)	(0.63)	(0.86)	(2.45)	(1.59)
R-squared	0.18	0.71	0.11	0.7	0.43	0.8	0.21	0.75	0.16	0.7	0.14	0.71
Year Fixed Effect	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm Fixed Effect	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES

Table 2.11. Variance decomposition

This table reports the contributions of each traditional variable (as described in Appendix 1) and fixed-effect factors to the explanatory power of the regression models for market and book leverages whose results are reported in tables 2 and 3. The contribution of each factor in explaining the total variation in the dependent variable (market or book leverage) is calculated by dividing the Type III sum of squares of that variable by the total sum of squares of all variables. For example, in col. (4) for market leverage, 4.7% of the "explained sum of squares" comes from the market to book (M/B) ratio. Panels A, B and C report the contribution for the full sample and the rated and not-rated samples, respectively. Firm FE is the firm-fixed effect, Year FE is the year fixed effect and Industry FE (based on the two-digit SIC code) is the industry fixed effect. N is the number of observations. The t-values are reported in the parentheses. Superscripts a, b and c indicate significance at the 10%, 5% and 1% levels, respectively. Superscripts d and e indicate the sample-size adjusted levels of significance for 5% and 1%, respectively, as calculated in Table 2.

Panel A: All firms	Mkt Lev (N = 58,000)								Book Lev (N = 58,000)							
Parameter	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Firm FE	1 ^{c,e}		0.983 ^{c,e}		0.959 ^{c,e}		0.951 ^{c,e}	0.951 ^{c,e}	1 ^{c,e}		0.956 ^{c,e}		0.912 ^{c,e}		0.894 ^{c,e}	0.893 ^{c,e}
	(21.14)		(21.49)		(19.47)		(19.03)	(18.91)	(23.73)		(24.91)		(21.37)		(19.04)	(18.99)
Year FE		1 ^{c,e}	0.017 ^{c,e}	0.113 ^{c,e}	0.016 ^{c,e}	0.107 ^{c,e}	0.006 ^{c,e}	0.006 ^{c,e}		1 ^{c,e}	0.044 ^{c,e}	0.166 ^{c,e}	0.045 ^{c,e}	0.068 ^{c,e}	0.005 ^{c}	0.005 ^{c}
		(06.61)	(13.79)	(06.60)	(12.40)	(07.05)	(04.32)	(04.32)		(20.88)	(43.02)	(19.21)	(39.65)	(11.15)	(03.89)	(03.89)
M/B				0.047 ^{c,e}	0.002 ^{c,e}	0.053 ^{c,e}	0.002 ^{c,e}	0.002 ^{c,e}				0.314 ^{c,e}	0.022 ^{c,e}	0.224 ^{c,e}	0.027 ^{c,e}	0.027 ^{c,e}
				(70.87)	(41.14)	(90.89)	(40.05)	(40.03)				(45.60)	(05.56)	(55.35)	(59.60)	(59.42)
Profitability				0.153 ^{c,e}	0.011 ^{c,e}	0.107 ^{c,e}	0.01 ^{c,e}	0.01 ^{c,e}				0.129 ^{c,e}	0.012 ^{c,e}	0.097 ^{c,e}	0.015 ^{c,e}	0.015 ^{c,e}
				(33.28)	(09.49)	(83.90)	(82.30)	(82.32)				(87.86)	(74.68)	(14.65)	(06.56)	(06.48)
Tangibility				0.565 ^{c,e}	0.003 ^{c,e}	0.266 ^{c,e}	0.003 ^{c,e}	0.003 ^{c,e}				0.279 ^{c,e}	0.003 ^{c,e}	0.057 ^{c,e}	0.005 ^{c,e}	0.005 ^{c,e}
				(59.90)	(52.68)	(56.22)	(63.87)	(63.94)				(40.53)	(67.14)	(42.83)	(95.56)	(95.24)
Log(Sale)				0.049 ^{c,e}	0.004 ^{c,e}	0.008 ^{c,e}	0.004 ^{c,e}	0.004 ^{c,e}				0.053 ^{c,e}	0.004 ^{c,e}	0.007 ^{c,e}	0.003 ^{c,e}	0.003 ^{c,e}
				(74.01)	(81.99)	(14.31)	(74.78)	(74.76)				(59.00)	(79.77)	(30.58)	(64.61)	(64.63)
Log(Size)				0.074 ^{c,e}	0.005 ^{c,e}	0.014 ^{c,e}	0.004 ^{c,e}	0.004 ^{c,e}				0.059 ^{c,e}	0.002 ^{c,e}	0.007 ^{c,e}	0.001 ^{c,e}	0.001 ^{c,e}
				(13.23)	(02.84)	(24.15)	(82.66)	(82.62)				(76.60)	(41.55)	(29.08)	(24.29)	(24.32)
CF Volatility						0.008 ^{c,e}	0.000	0.000						0.017 ^{c,e}	0.000 ^{c,e}	0.000 ^{c,e}
						(13.47)	(00.13)	(00.13)						(70.83)	(08.69)	(08.69)
Dividend Payer						0.101 ^{c,e}	0.000	0.000						0.106 ^{c,e}	0.003 ^{c,e}	0.003 ^{c,e}
						(72.28)	(00.36)	(00.35)						(53.09)	(58.15)	(57.93)
Mkt Lev Mean						0.297 ^{c,e}	0.02 ^{c,e}	0.02 ^{c,e}						0.41 ^{c,e}	0.047 ^{c,e}	0.047 ^{c,e}
						(08.71)	(80.40)	(79.74)						(48.40)	(56.46)	(56.54)
Industry FE						0.038 ^{c,e}		0.000						0.006 ^{c,e}		0.000
						(65.27)		(00.09)						(27.31)		(00.25)
R Square	0.47	0.01	0.48	0.08	0.50	0.11	0.51	0.51	0.50	0.02	0.52	0.13	0.54	0.22	0.57	0.57

Panel B: Rated firms	Mkt Lev (N = 19,285)								Book Lev (N = 19,285)							
Parameter	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Firm FE	1 [c,e]		0.980 [c,e]		0.952 [c,e]		0.954 [c,e]	0.954 [c,e]	1 [c,e]		0.961 [c,e]		0.829 [c,e]		0.824 [c,e]	0.824 [c,e]
	(33.09)		(33.89)		(27.00)		(25.82)	(25.93)	(40.91)		(43.87)		(25.57)		(22.46)	(22.52)
Year FE		1 [b]	0.02 [c,e]	0.214 [c,e]	0.02 [c,e]	0.314 [c,e]	0.007	0.007		1 [c,e]	0.039 [c,e]	0.099 [c,e]	0.048 [c,e]	0.153 [c,e]	0.008[a]	0.008[a]
		(02.86)	(06.45)	(04.47)	(05.32)	(08.86)	(01.77)	(01.77)		(05.74)	(16.44)	(06.30)	(13.51)	(11.53)	(02.10)	(02.10)
M/B				0.00	0.002 [c,e]	0.003 [a]	0.002 [c,e]	0.002 [c,e]				0.253 [c,e]	0.035 [c,e]	0.187 [c,e]	0.035 [c,e]	0.035 [c,e]
				(00.01)	(10.36)	(02.24)	(14.30)	(14.30)				(20.19)	(56.67)	(65.45)	(28.10)	(28.10)
Profitability				0.155 [c,e]	0.019 [c,e]	0.064 [c,e]	0.018 [c,e]	0.018 [c,e]				0.413 [c,e]	0.086 [c,e]	0.264 [c,e]	0.092 [c,e]	0.092 [c,e]
				(84.27)	(28.35)	(46.99)	(15.90)	(15.90)				(84.47)	(33.06)	(17.27)	(94.32)	(94.32)
Tangibility				0.055 [c,e]	0.005 [c,e]	0.006 [c,e]	0.003 [c,e]	0.003 [c,e]				0.061	0.001 [c,e]	0.011 [c,e]	0.00	0.00
				(29.59)	(32.52)	(04.58)	(19.25)	(19.25)				(00.82)	(05.44)	(21.78)	(00.03)	(00.03)
Log(Sale)				0.139 [c,e]	0.00	0.073 [c,e]	0.00	0.00				0.059 [c,e]	0.00	0.031 [c,e]	0.00	0.00
				(75.53)	(00.98)	(53.31)	(01.78)	(01.78)				(97.94)	(02.56)	(59.96)	(01.85)	(01.85)
Log(Size)				0.437 [c,e]	0.002 [c,e]	0.23 [c,e]	0.001 [c,e]	0.001 [c,e]				0.115 [c,e]	0.00	0.054 [c,e]	0.00	0.00
				(36.87)	(10.71)	(68.51)	(07.30)	(07.30)				(90.32)	(02.39)	(06.47)	(00.51)	(00.51)
CF Volatility						0.003 [a]	0.000	0.000						0.033 [c,e]	0.002 [c,e]	0.002 [c,e]
						(02.50)	(00.08)	(00.08)						(64.59)	(12.68)	(12.68)
Dividend Payer						0.186 [c,e]	0.00	0.00						0.136 [c,e]	0.004 [c,e]	0.004 [c,e]
						(36.58)	(00.64)	(00.64)						(66.66)	(27.80)	(27.80)
Mkt Lev Mean						0.121 [c,e]	0.014 [c,e]	0.014 [c,e]						0.128 [c,e]	0.033 [c,e]	0.033 [c,e]
						(88.98)	(87.15)	(87.15)						(50.94)	(15.48)	(15.48)
Industry FE						0.000								0.002		
						(00.00)								(04.62)		
R Square	0.58	0.01	0.59	0.17	0.61	0.21	0.62	0.62	0.63	0.02	0.66	0.46	0.74	0.52	0.75	0.75

Panel C: Not-rated firms	Mkt Lev (N = 31,809)								Book Lev (N = 31,809)							
Parameter	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Firm FE	1 [c,e]		0.976 [c,e]		0.916 [c,e]		0.909 [c,e]	0.909 [c,e]	1 [c,e]		0.944 [c,e]		0.883 [c,e]		0.881 [c,e]	0.881 [c,e]
	(17.29)		(17.63)		(14.85)		(15.39)	(15.38)	(17.73)		(18.55)		(16.94)		(16.58)	(16.62)
Year FE		1 [c]	0.024 [c,e]	0.115 [b]	0.02 [c,e]	0.077	0.01	0.01		1 [c,e]	0.056 [c,e]	0.2 [c,e]	0.049 [c,e]	0.064 [b]	0.007 [a]	0.007 [a]
		(03.76)	(07.33)	(03.02)	(05.57)	(01.94)	(02.71)	(02.71)		(10.58)	(18.58)	(08.83)	(15.86)	(03.14)	(02.28)	(02.28)
M/B				0.136 [c,e]	0.007 [c,e]	0.14 [c,e]	0.007 [c,e]	0.007 [c,e]				0.218 [c,e]	0.022 [c,e]	0.21 [c,e]	0.025 [c,e]	0.025 [c,e]
				(93.53)	(51.64)	(90.96)	(49.91)	(49.91)				(50.17)	(81.42)	(67.48)	(03.96)	(03.96)
Profitability				0.166 [c,e]	0.018 [c,e]	0.149 [c,e]	0.015 [c,e]	0.015 [c,e]				0.102 [c,e]	0.015 [c,e]	0.111 [c,e]	0.017 [c,e]	0.017 [c,e]
				(14.06)	(30.37)	(96.78)	(10.23)	(10.23)				(17.17)	(24.55)	(41.66)	(38.20)	(38.20)
Tangibility				0.298 [c,e]	0.011 [c,e]	0.245 [c,e]	0.011 [c,e]	0.011 [c,e]				0.125 [c,e]	0.013 [c,e]	0.065 [c,e]	0.014 [c,e]	0.014 [c,e]
				(04.15)	(81.44)	(59.35)	(78.65)	(78.65)				(43.32)	(10.90)	(83.41)	(14.98)	(14.98)
Log(Sale)				0.044 [c,e]	0.01 [c,e]	0.013 [c,e]	0.009 [c,e]	0.009 [c,e]				0.133 [c,e]	0.009 [c,e]	0.057 [c,e]	0.008 [c,e]	0.008 [c,e]
				(29.87)	(72.09)	(08.15)	(62.65)	(62.65)				(51.88)	(79.46)	(73.32)	(63.69)	(63.69)
Log(Size)				0.241 [c,e]	0.016 [c,e]	0.135 [c,e]	0.013 [c,e]	0.013 [c,e]				0.222 [c,e]	0.009 [c,e]	0.102 [c,e]	0.007 [c,e]	0.007 [c,e]
				(65.37)	(13.98)	(88.18)	(95.01)	(95.01)				(54.14)	(71.99)	(29.88)	(53.92)	(53.92)
CF Volatility						0.047 [c,e]	0.002 [c,e]	0.002 [c,e]						0.033 [c,e]	0.001 [c,e]	0.001 [c,e]
						(30.89)	(14.35)	(14.35)						(42.08)	(07.40)	(07.40)
Dividend Payer						0.048 [c,e]	0.000	0.000						0.106 [c,e]	0.005 [c,e]	0.005 [c,e]
						(31.01)	(00.11)	(00.11)						(34.85)	(38.11)	(38.11)
Mkt Lev Mean						0.131 [c,e]	0.025 [c,e]	0.025 [c,e]						0.252 [c,e]	0.035 [c,e]	0.035 [c,e]
						(85.31)	(85.74)	(85.74)						(21.95)	(87.83)	(87.83)
Industry FE						0.015 [c,e]								0.000		
						(10.06)								(00.19)		
R Square	0.43	0.01	0.44	0.13	0.47	0.14	0.48	0.48	0.44	0.03	0.46	0.11	0.49	0.15	0.51	0.51

Table 3.1. Summary statistics

This table reports the summary statistics (mean, median and standard deviation) for firms in our samples. Variable construction is explained in detail in Appendix 1. N is the number of observations.

	Full Sample (N = 32053)			**Survived Sample (N = 24880)**		
	Mean	S.D.	Median	Mean	S.D.	Median
Heterogeneity	0.68	0.27	0.66	0.65	0.27	0.61
Initial heterogeneity	0.69	0.27	0.7	0.66	0.27	0.65
Market leverage	0.26	0.25	0.19	0.27	0.25	0.2
Market to book ratio	2.14	10.43	1.16	1.76	7.17	1.11
Firm size	4.53	2.43	4.71	4.89	2.32	5.06
Sales	5.37	2.64	5.63	5.79	2.49	6.04
Cash flow volatility	1.29	2.63	0.61	1.4	2.75	0.68
Profitability	0.01	0.32	0.1	0.06	0.24	0.11
Tangibility	0.26	0.24	0.18	0.28	0.23	0.2
Rating dummy	0.29	0.45	0	0.34	0.47	0
Dividend payer	0.26	0.44	0	0.31	0.46	0
Tax rate	0.21	0.13	0.24	0.22	0.13	0.28
Maturity	0.68	0.36	0.85	0.72	0.34	0.88
Idiosyncratic volatility	0.14	0.33	0.03	0.14	0.29	0.03
Industry heterogeneity	0	1	0.2	0	1	0.2
Term spread	0.15	0.01	0.02	0.15	0.01	0.02
Inflation	0.02	0.01	0.03	0.02	0.01	0.03
GDP per capita	45096	4193	46443	44869	4220	46443
GDP growth	0.02	0.17	0.02	0.02	0.17	0.02
Short interest rate vol.	0.25	0.18	0.23	0.25	0.18	0.23

Table 3.2. Determinants of the stability of debt structures

This table reports the hazard regression results where the dependent variable shows the survival of different measures of debt-type structures. The hazard distribution used in this table is exponential. The variable construction is explained in Appendix 1. All variables are standardized, except for the dummies. T-values are reported in the parentheses. *, ** and *** indicate significance at the 5%, 1% and 0.1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Heterogeneity	Heterogeneity	Largest	Ranks	Ranks All	Kendall's	Kendall's	Spearman's	Spearman's rho
Market Leverage	-0.32**	-0.05	-0.31***	-0.24*	0.13	-0.56***	0.22	-0.51***	-0.00
	(-2.46)	(-0.39)	(-3.03)	(-1.96)	(1.06)	(-2.95)	(1.19)	(-2.69)	(-0.02)
Market to Book	-0.03	-0.01	-0.02	-0.02	-0.03	0.03	-0.03	0.05	0.01
	(-1.33)	(-0.59)	(-1.03)	(-0.89)	(-1.03)	(0.82)	(-0.60)	(1.37)	(0.37)
Log(Size)	-0.07*	-0.07*	-0.11***	-0.11***	-0.07*	-0.04	-0.01	0.00	0.00
	(-1.86)	(-1.74)	(-3.61)	(-2.92)	(-1.81)	(-0.65)	(-0.10)	(0.06)	(0.01)
Log(Sales)	0.01	0.07*	0.05*	0.05	0.08**	0.05	0.03	0.01	0.03
	(0.38)	(1.78)	(1.86)	(1.56)	(2.15)	(1.00)	(0.61)	(0.12)	(0.53)
CF Volatility	0.03***	0.02**	0.02**	0.02***	0.02**	0.01	0.01	0.01	-0.01
	(2.64)	(2.17)	(2.21)	(3.38)	(2.55)	(1.10)	(0.87)	(0.89)	(-0.71)
Profitability	0.27**	0.06	0.28***	0.25**	0.13	0.24	0.44**	0.41**	0.31*
	(2.01)	(0.44)	(2.67)	(2.17)	(1.12)	(1.48)	(2.23)	(2.22)	(1.75)
Tangibility	-0.04	-0.04	-0.40***	-0.09	-0.16	-0.19	-0.07	-0.17	-0.17
	(-0.35)	(-0.35)	(-3.67)	(-0.78)	(-1.27)	(-1.04)	(-0.47)	(-0.91)	(-0.97)
Dividend Payer	-0.05	0.04	-0.13**	-0.04	-0.02	-0.12	-0.05	-0.09	-0.10
	(-0.80)	(0.64)	(-2.30)	(-0.63)	(-0.32)	(-1.27)	(-0.55)	(-0.98)	(-1.17)
Rated Dummy	0.16**	0.32***	0.07	0.20***	0.21***	0.13	0.32***	0.08	0.13
	(2.17)	(4.39)	(1.10)	(2.77)	(2.78)	(1.25)	(3.17)	(0.70)	(1.26)
Marginal Tax Rate	-0.30	-0.19	-1.10***	-0.59*	-0.41	-1.20**	-0.50	-1.71***	-1.07**
	(-1.01)	(-0.65)	(-4.49)	(-1.92)	(-1.27)	(-2.45)	(-1.03)	(-3.43)	(-2.23)
Maturity	0.07	0.04	-0.01	0.07	0.08	0.05	0.03	0.09	0.08
	(0.92)	(0.48)	(-0.22)	(0.85)	(0.95)	(0.40)	(0.26)	(0.72)	(0.67)
Idio. Volatility	0.06	0.21*	-0.49***	-0.24*	-0.09	-0.08	-0.02	-0.08	-0.16
	(0.40)	(1.82)	(-4.72)	(-1.66)	(-0.63)	(-0.41)	(-0.11)	(-0.42)	(-0.78)
Industry	-0.01	-0.07*	0.06*	0.01	-0.09**	-0.07	-0.03	0.02	-0.04
	(-0.26)	(-1.67)	(1.81)	(0.22)	(-1.96)	(-1.07)	(-0.45)	(0.36)	(-0.64)
Term spread	-0.03	-0.04	0.29***	-0.06	-0.09**	-0.06	-0.15**	-0.08	-0.10
	(-0.61)	(-0.81)	(7.92)	(-1.30)	(-2.01)	(-0.88)	(-2.28)	(-1.29)	(-1.49)
Inflation	4.26	-0.34	6.32**	7.88**	0.96	5.89	1.35	7.18	-0.96
	(1.13)	(-0.09)	(2.22)	(2.10)	(0.23)	(1.09)	(0.25)	(1.35)	(-0.18)
GDP per Capita	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
	(4.15)	(5.92)	(6.79)	(4.72)	(4.86)	(3.73)	(5.87)	(2.92)	(4.90)

GDP Growth	-0.06***	-0.01	0.02	-0.04**	-0.02	-0.04	-0.03	-0.05	-0.01
	(-2.81)	(-0.45)	(0.96)	(-2.06)	(-0.73)	(-1.28)	(-1.01)	(-1.53)	(-0.42)
Constant	-2.93***	-3.70***	-3.15***	-2.44***	-2.65***	-2.99***	-3.85***	-2.58***	-3.36***
	(-7.27)	(-9.14)	(-11.82)	(-6.32)	(-6.63)	(-5.62)	(-7.23)	(-4.99)	(-6.39)
Observations	2914	2378	3259	1663	1663	2914	2378	1427	1266

Table 3.3. Clustering results

This table reports the clustering results for firm-1year (upper panel) and firm-12year (lower panel) samples. The Stata command *kmeans* is used to do the clustering, where the Calinski/Harabasz stopping rule determines the optimal number of clusters. The reported percentages are the means for each of the clusters of the ratio of the value of each debt type to the total value of a firm's debt. Variable definitions are provided in Appendix 1.

Panel A: Clustering results for Firm-1Year

Cluster	Commercial Paper	Capital Lease	Lines of Credit	Notes	Term Loans	Trust	Other Debt
1	2.30%	2.10%	*42.90%*	*44.60%*	4.80%	0.50%	2.60%
2	0.00%	91.40%	1.90%	3.10%	2.60%	0.00%	1.10%
3	1.50%	3.40%	6.00%	12.70%	9.80%	0.20%	66.50%
4	0.10%	2.20%	9.40%	3.60%	83.30%	0.00%	1.40%
5	0.10%	2.00%	84.50%	4.40%	7.70%	0.00%	1.30%
6	3.60%	2.50%	7.90%	*43.80%*	*38.70%*	0.30%	3.40%
7	0.90%	1.90%	3.30%	89.40%	2.50%	0.10%	1.80%

Panel B: Clustering results for Firm-12Year

Cluster	Commercial Paper	Capital Lease	Lines of Credit	Notes	Term Loans	Trust	Other Debt
1	0.40%	2.10%	3.40%	87.90%	4.00%	0.10%	2.30%
2	2.20%	2.90%	%23.80	50.80%	15.30%	0.30%	4.70%
3	0.00%	84.30%	3.10%	*5.40%*	5.30%	0.00%	1.90%
4	0.20%	2.50%	81.80%	8.20%	*5.50%*	0.00%	1.80%
5	0.00%	2.00%	4.20%	7.80%	83.70%	0.00%	2.40%
6	0.70%	3.90%	5.80%	12.20%	11.70%	0.10%	65.60%
7	0.40%	3.20%	39.30%	10.00%	43.30%	0.30%	3.40%

Table 3.4. Determinants of the main debt type

This table reports the results of logit regressions for various potential determinants of the selection of each of the seven debt types as the main debt type in a firm's debt structure. Each of the seven dependent variables is a binary variable that is equal to one if the specific debt type is the largest debt type for the firm in any given year, and is equal to zero otherwise. The logistic specification uses firm fixed-effects and year dummies. Variable construction is explained in Appendix 1. $^{+}$, * , ** and *** indicate significance at the 10%, 5%, 1% and 0.1% levels, respectively, based on t-tests.

	(1) Commercial	(2) Credit	(3) Term loan	(4) Notes	(5) Capital lease	(6) Trust	(7) Other
Market Leverage	0.46*	0.49***	0.77***	1.01***	0.13*	1.46**	0.24***
	(2.01)	(9.22)	(15.98)	(16.26)	(2.46)	(2.95)	(4.86)
Market to Book	-3.84^{+}	0.11	0.02	1.16***	0.73*	-19.9	0.29
	(-1.85)	(0.33)	(0.05)	(3.55)	(2.25)	(-1.24)	(0.86)
Log (Size)	-3.90***	-1.84***	0.38*	0.79***	0.96***	2.89	0.79***
	(-4.20)	(-8.95)	(2.31)	(4.09)	(4.97)	(1.44)	(4.38)
Log (Sales)	7.83***	2.45***	-0.02	0.19	-0.02	0.17	0.60***
	(6.53)	(10.73)	(-0.12)	(1.08)	(-0.11)	(0.07)	(3.53)
CF Volatility	-0.03	-0.08	0.03	-0.14^{+}	-0.14	-0.36	0.03**
	(-1.35)	(0.00)	(1.36)	(-2.66)	(-1.17)	(-1.14)	(2.35)
Profitability	-0.86	0.00	0.09	-0.18**	-0.08	2.23	-0.17*
	(-1.35)	(0.00)	(1.36)	(-2.66)	(-1.17)	(-1.14)	(-2.35)
Tangibility	0.00	0.03	0.36***	-0.26*	0.53***	0.97	0.25**
	(0.01)	(0.32)	(4.02)	(-2.33)	(5.15)	(0.94)	(2.58)
Rated dummy	1.88*	-0.40**	-0.03	1.77***	0.31*	-1.14	-0.27^{+}
	(2.57)	(-2.71)	(-0.24)	(9.51)	(2.14)	(-0.42)	(-1.89)
Dividend Payer	0.23	-0.03	-0.32**	-0.13	-0.06	-1.59	0.07
	-0.61	(-0.22)	(-3.16)	(-1.02)	(-0.51)	(-1.57)	-0.61
Tax rate	0.82**	0.17**	0.11*	-0.09	-0.14*	-0.09	-0.10^{+}
	(2.87	-3.04	-2.18	(-1.37)	(-2.41)	(-0.18)	(-1.76)
Maturity index	-0.42**	-0.27***	0.09**	0.32***	0.07^{+}	1.06^{+}	0.03
	(-2.84)	(-7.72)	-2.68	-8.76	-1.87	-1.79	-0.69
Idio. Volatility	0.05	0.11**	-0.04	0.01	0.03	-0.26	0.07^{+}
	(0.17	(2.93)	(-1.06)	-0.32	-0.82	(-1.06)	-1.92
Industry Heterogeneity	-0.21	-0.25***	-0.24***	0.02	-0.02	-1.77***	-0.11*
	(-1.51)	(-5.53)	(-5.63)	-0.25	(-0.30)	(-4.05)	(-2.37)
Term Spread	0.60	0.05	0.00	0.71**	0.76***	-8.55^{+}	0.87***
	(1.16)	(0.23)	(0.01)	(2.96)	(3.77)	(-1.68)	(4.36)
Inflation Rate	0.27	0.44***	0.04	0.09	0.17^{+}	1.42	-0.15^{+}
	(1.18)	(4.11)	(0.47)	(0.81)	(1.81)	(1.17)	(-1.79)

GDP per cap	-0.04	-1.08***	-0.77**	-0.32	-0.48+	-14.05+	-0.08
	(-0.05)	(-3.62)	(-2.82)	(-0.91)	(-1.66)	(-1.74)	(-0.28)
GDP growth	-0.07	-0.02	0.11*	0.05	0.09	0.52	-0.02
	(-0.47)	(-0.29)	(1.98)	(0.65)	(1.46)	(0.56)	(-0.29)
Short interest Vol.	0.31	-0.25	-0.14	0.00	0.34+	-1.71	-0.48**
	(0.66)	(-1.15)	(-0.80)	(0.01)	(1.81)	(-0.54)	(-2.72)
Observations	1630	12091	12130	8553	9617	443	10781
Pseudo R^2	0.07	0.16	0.05	0.13	0.03	0.21	0.03

Table 3.5. Percent of firms with debt structures with more than x% in one debt type

This table reports the percent of sample firms with more than x% of one debt-type in their debt structures. The first column presents the different levels of x using firm-1year and firm-12year observations. The Base case columns report the results for all firms and the columns headed by ML>10%, ML>20% and ML>50% report the results when firms with less than 10, 20 and 50 percent market leverage have been removed, respectively. For example, in the third row of the firm-1year panel, 90% of the firms have more than 50% of their debt structure consisting of one single debt type based on firm-1year observations. Based on the corresponding number in the firm-12year sample, we observe that 87% of the firms have more than 50% of their debt structure in one single debt type.

Percent of sample firms with more than x% of one debt-type in their debt-type structures								
	Firm-1year				Firm-12year			
>x%	Base case	ML > 10%	ML > 20%	ML > 50%	Base case	ML > 10%	ML > 20%	ML > 50%
20%	100%	100%	100%	100%	100%	100%	100%	100%
30%	100%	100%	100%	100%	100%	100%	100%	100%
50%	90%	89%	88%	90%	87%	85%	85%	88%
70%	64%	58%	57%	63%	57%	51%	50%	57%
90%	42%	34%	32%	38%	33%	25%	24%	30%
Observations	32053	22853	16586	6184	5903	3822	2933	1316

Table 3.6. Treatment effects estimates

This table reports the average treatment effect (ATE) and average treatment effect on the treated (ATT) using a Weibull distribution for a matched sample of firms with and without credit ratings. Firms are matched using propensity score matching using a series of observables including classic capital structure determinants (Titman and Parsons, 2008) and credit-rating determinants used in Moody's KMV methodology (Duffie and Singleton, 2003). "POM" reports the potential-outcome means. The p-values are reported in the parentheses.

Variable	Observations	Treatment	ATE	ATT	POM
Debt Heterogeneity, 20%	3795	1910	-0.52		4.08
			(-0.05)		(0.00)
				-1.18	5.44
				(-0.34)	(0.00)
Debt Heterogeneity, 10%	3057	1789	-0.9		3.42
			(0.00)		(0.00)
				-1.1	3.95
				(0.00)	(0.00)
Largest Debt Type	8392	2740	-2.11		12.6
			(0.00)		-0.09
				-0.64	4.95
				(-0.28)	(0.00)
Debt Type Ranks - All seven	2165	1407	-0.64		2.6
			(0.00)		(0.00)
				-0.94	3.18
				(-0.09)	(0.00)
Debt Type Ranks - First two	2165	1407	-0.64		2.6
			(0.00)		(0.00)
				-0.94	3.18
				(-0.09)	(0.00)

Table 3.7. Summary Statistics

This table reports the summary statistics for a sample of firms in 42 countries. Variables of interest are selected from three broad categories including institutional, macroeconomic and firm-specific determinants. Column 1 shows the number of observations and column 2 reports the mean for each variable. Columns 3-6 report the variable values in the 5th, 50th, 95th and 100th percentiles, respectively, and the last column reports the standard deviation. The first row measures maturity as the ratio of long term to total debt similar to Fan et al (2012) and therefore varies between 0 and 1. The second row measures maturity similar to Saretto et al (2013) as the weighted-average maturity over different types of debt. The creditor rights index is a measure between 0 and 4 where 4 stands for the strongest creditor rights. Construction of each variable is described in Appendix 1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	N	Mean	P5	Median	P95	Max	Std. Dev.
Maturity	206575	0.52	0.00	0.56	1.00	5.67	0.35
Ave-debt-maturity	128070	3.01	0.00	2.13	8.81	153.44	3.24
Creditor rights	206575	1.86	1.00	2.00	4.00	4.00	0.99
Efficiency	206575	75.71	39.80	85.80	95.90	96.10	22.15
Log (GDP per capita)	206564	10.06	7.88	10.50	10.87	11.52	0.99
Inflation	204879	2.16	-0.72	2.12	5.41	22.56	2.03
GDP growth	206575	2.89	-2.62	2.45	9.30	15.24	3.30
Public registry	135210	6.56	0.00	0.00	42.40	96.00	14.25
Private Bureau	135210	63.86	0.00	76.20	100.00	100.00	39.23
Information sharing	206575	1.00	1.00	1.00	1.00	1.00	0.03
Corruption	206575	3.74	2.00	4.00	5.00	6.00	1.05
Private cred. To GDP	187866	142.62	46.12	157.83	199.87	232.10	47.70
Stocks trad. to GDP	191942	118.67	13.72	90.58	309.65	434.87	90.42
Log (Size)	179602	5.38	2.04	5.34	8.88	11.94	2.05
MtB	206575	1.02	0.04	0.63	2.64	124.26	3.15
Profitability	206131	0.06	-0.19	0.08	0.24	2.27	0.20
Tangibility	206513	0.32	0.02	0.27	0.79	1.00	0.24
CF Volatility	206363	0.06	0.00	0.03	0.19	2.13	0.11
Book Leverage	206575	0.24	0.01	0.22	0.59	0.85	0.18

Table 3.8. Number of firms and firm-years by country

Columns 1 to 3 report the number of firms, firm-year observations and percent of firm-years as a fraction of total sample firms for each of the sample countries.

	(1)	(2)	(3)
Country	Number of firms	Number of firm-years	Percent of firm-year in the total sample
Argentina	69	700	0.34%
Australia	1596	9082	4.40%
Austria	109	866	0.42%
Belgium	134	1227	0.59%
Brazil	306	1963	0.95%
Canada	2117	11235	5.44%
Chile	150	1317	0.64%
China	2283	15995	7.74%
Colombia	35	238	0.12%
Croatia	37	246	0.12%
Denmark	172	1345	0.65%
Finland	147	1457	0.71%
France	875	7319	3.54%
Germany	903	6683	3.24%
Greece	235	2247	1.09%
Hungary	28	207	0.10%
Indonesia	345	2612	1.26%
Ireland	116	796	0.39%
Italy	319	2774	1.34%
Japan	3695	35810	17.34%
Malaysia	985	8881	4.30%
Mexico	117	1027	0.50%
Netherland	215	1655	0.80%
New	144	1031	0.50%
Norway	286	1763	0.85%
Peru	82	664	0.32%
Philippine	167	1336	0.65%
Poland	442	2642	1.28%
Portugal	62	588	0.28%
Romania	44	132	0.06%
Singapore	714	5802	2.81%
South Africa	323	2676	1.30%
Spain	159	1428	0.69%
Sri Lanka	181	1226	0.59%
Sweden	466	3136	1.52%
Switzerland	248	2333	1.13%
Thailand	487	4235	2.05%
Turkey	192	1196	0.58%
United Kin	2122	13321	6.45%
United	8065	46937	22.72%
Sum	29231	206575	

Table 3.9. Correlation matrix

This table reports the Pearson correlations for the main variables of interest. The first row (maturity) is the ratio of long term to total debt similar to Fan et al. (2012) and therefore varies between 0 and 1. The second row is for weighted-average maturity over different types of debt. The creditor rights index ranges between 0 and 4 where higher levels of the index indicate stronger creditor protection provisions. Efficiency is the efficiency of debt contracts. Log of per capita GDP is the logarithm of per capita GDP. Inflation captures annual changes in the consumer prices index. Public and private registry variables are percentages of adults and firms covered by public and private registries, respectively. Log of size is the logarithm of total book assets. Market to book (MtB) is market value of equity divided by total book assets. Profitability is earnings before interest and taxes divided by total book assets. Tangibility is net property, plant and equipment divided by total book assets. Cash flow (CF) volatility is the standard deviation over past five years of operating income divided by total assets. Book leverage is the sum of short and long-term debt divided by total assets. Construction of each variable is described in Appendix 1.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Maturity	1.00																			
Ave-debt-maturity	0.35	1.00																		
Creditor rights	-0.15	-0.17	1.00																	
Efficiency- Debt Enforcement	0.18	0.17	0.05	1.00																
Log (GDP per capita)	0.27	0.19	-0.07	0.87	1.00															
Inflation	-0.01	-0.10	0.05	-0.53	-0.44	1.00														
GDP growth	-0.21	-0.18	0.07	-0.54	-0.61	0.39	1.00													
Legal origins	0.23	0.08	0.18	0.26	0.30	0.20	-0.15	1.00												
Public registry	-0.16	-0.12	0.20	-0.60	-0.51	0.16	0.33	-0.03	1.00											
Private Bureau	0.32	0.19	-0.15	0.72	0.82	-0.26	-0.58	0.45	-0.45	1.00										
Information	-0.01	0.02	-0.04	0.05	0.02	-0.01	0.03	0.04	0.02	0.00	1.00									
Corruption	0.27	0.10	0.00	0.72	0.84	-0.27	-0.38	0.35	-0.47	0.70	0.04	1.00								
Private cred. To GDP	0.20	0.23	-0.06	0.67	0.68	-0.46	-0.50	0.23	-0.40	0.57	0.06	0.45	1.00							
Stocks trad. to GDP	0.21	0.19	-0.23	0.33	0.42	-0.06	-0.20	0.37	-0.32	0.38	0.05	0.28	0.58	1.00						
Log (Size)	0.31	0.35	-0.16	0.02	0.06	-0.10	-0.04	-0.18	-0.07	0.02	-0.01	-0.02	0.14	0.08	1.00					
MtB	-0.06	-0.06	0.08	-0.14	-0.13	0.07	0.12	-0.11	0.05	-0.13	0.00	-0.09	-0.15	-0.09	-0.08	1.00				
Profitability	0.13	0.08	-0.01	-0.07	-0.07	0.02	0.03	-0.06	0.02	-0.07	0.00	-0.07	-0.05	-0.05	0.35	-0.02	1.00			
Tangibility	0.18	0.15	-0.04	-0.09	-0.11	0.04	0.05	-0.01	0.05	-0.08	-0.02	-0.07	-0.12	-0.09	0.14	0.00	0.07	1.00		
CF Volatility	-0.07	-0.10	0.01	0.05	0.08	0.05	-0.03	0.16	-0.05	0.11	0.01	0.12	0.02	0.08	-0.34	0.04	-0.44	-0.07	1.00	
Book Leverage	0.21	0.18	-0.06	-0.03	-0.03	0.02	-0.01	0.01	0.01	-0.01	-0.01	-0.02	0.00	0.03	0.14	0.00	-0.05	0.24	-0.02	1.00

Table 3.10. Maturity index, creditor rights and contract enforcement

This table reports regression results using a correlated random effects (CRE) specification where the dependent variable is maturity as measured by the ratio of long term debt to total debt. This table provides the relationship of creditor rights and its four components (CR1 to CR4) and the efficiency of contract enforcement on the maturity structure of corporate debt. The last two columns are for firms in developed and developing countries, respectively, based on the World Bank's GNI thresholds for 2013. Significance at the 10, 5, 1 and 0.1 percent levels are represented using +, *, **, and ***, respectively. The t-values reported in the parentheses are based on clustered standard errors at the firm-level and year dummies, and are heteroscedasticity consistent. Construction of each variable is described in Appendix 1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
									Developed	**Developing**
Creditor rights	-0.11***	-0.09***	-0.07***	-0.08***					-0.09***	-0.04
	(-24.27)	(-19.61)	(-13.64)	(-16.51)					(-17.63)	(-1.63)
Efficiency	0.17***	0.17***	0.03**	0.08***	0.04**	0.06***	0.07***	0.11***	0.07***	0.01
	(35.66)	(36.15)	(2.67)	(7.35)	(3.23)	(5.64)	(6.31)	(9.19)	(4.81)	(0.28)
cr1					-0.06***					
					(-10.82)					
cr2						-0.07***				
						(-14.44)				
cr3							-0.06***			
							(-8.35)			
cr4								-0.06***		
								(-10.83)		
Log Size		0.29***	0.26***	0.26***	0.26***	0.26***	0.26***	0.26***	0.26***	0.29***
		(23.11)	(19.72)	(20.27)	(20.25)	(19.88)	(20.19)	(20.29)	(18.35)	(8.98)
Market to book		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01*	0.00
		(1.41)	(1.19)	(1.14)	(1.16)	(1.18)	(1.20)	(1.13)	(2.31)	(0.11)
Profitability		0.04***	0.04***	0.04***	0.04***	0.04***	0.04***	0.04***	0.04***	0.05**
		(9.03)	(9.79)	(9.58)	(9.59)	(9.66)	(9.60)	(9.59)	(8.97)	(3.16)
Tangibility		0.08***	0.09***	0.08***	0.08***	0.08***	0.08***	0.08***	0.09***	0.06***
		(10.37)	(11.49)	(11.02)	(11.02)	(11.13)	(11.04)	(11.03)	(10.85)	(3.75)
Cash flow volatility		-0.01	-0.01	-0.01^{+}	-0.01^{+}	-0.01^{+}	-0.01^{+}	-0.01^{+}	-0.01^{+}	-0.00
		(-1.35)	(-1.60)	(-1.93)	(-1.82)	(-1.94)	(-1.78)	(-1.85)	(-1.92)	(-0.27)
Book leverage		0.12***	0.12***	0.12***	0.12***	0.12***	0.12***	0.12***	0.12***	0.10***
		(22.72)	(22.52)	(22.84)	(22.79)	(22.84)	(22.76)	(22.81)	(21.26)	(8.68)
Log GDP per cap			0.22***	0.10***	0.11***	0.13***	0.12***	0.10***	0.02	0.13***
			(18.45)	(7.52)	(8.43)	(10.14)	(9.66)	(7.31)	(1.20)	(4.49)
Inflation			0.07***	0.02***	0.02***	0.02***	0.02***	0.02***	0.04***	0.03***
			(14.95)	(4.26)	(4.66)	(4.06)	(3.72)	(4.95)	(4.01)	(5.50)
GDP growth			-0.04***	-0.03***	-0.03***	-0.03***	-0.03***	-0.03***	-0.02***	-0.04***
			(-9.32)	(-7.27)	(-6.83)	(-6.84)	(-7.27)	(-8.31)	(-3.38)	(-3.98)
English legal origin				-0.14***	-0.18***	-0.13***	-0.16***	-0.14***	-0.16***	-0.08
				(-5.70)	(-6.92)	(-5.09)	(-6.41)	(-5.71)	(-6.32)	(-1.36)
French legal origin				-0.22***	-0.30***	-0.14***	-0.26***	-0.09**	-0.44***	0.00
				(-6.85)	(-8.63)	(-4.37)	(-7.50)	(-2.82)	(-10.33)	(.)
German legal origin				-0.72***	-0.75***	-0.75***	-0.73***	-0.67***	-0.68***	-0.48***
				(-27.33)	(-27.61)	(-28.37)	(-27.45)	(-24.96)	(-24.79)	(-10.29)
Constant	-0.12**	-0.09*	-0.15***	0.19***	0.22***	0.17***	0.21***	0.16***	0.23***	-0.08
	(-2.81)	(-2.14)	(-3.55)	(3.96)	(4.63)	(3.64)	(4.25)	(3.36)	(4.22)	(-0.75)
Observations	206575	179134	177432	177432	177432	177432	177432	177432	145215	31989
Within R^2	0.00	0.03	0.02	0.03	0.03	0.03	0.03	0.03	0.03	0.04
Between R^2	0.12	0.27	0.31	0.36	0.36	0.36	0.36	0.36	0.31	0.38
Overall R^2	0.11	0.21	0.25	0.30	0.30	0.30	0.30	0.30	0.26	0.30

Table 3.11. Alternative- maturity index, creditor rights and contract enforcement

This table reports the CRE regression results using the weighted-average maturity index in years of Saretto et al. (2013) as the dependent variable. This table also includes the effect of creditor rights and its four components (CR1 to CR4). Significance at the 10, 5, 1 and 0.1 percent levels are represented using +, *, **, and ***, respectively. The t-values reported in the parentheses are based on clustered standard errors at the firm-level and year dummies. The estimates are heteroskedasticity consistent. Construction of each variable is described in Appendix 1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9) **Developed**	(10) **Developing**
	-0.32***	-0.29***	-0.25***	-0.29***					-0.32***	0.09
Creditor rights	(-20.97)	(-17.69)	(-15.17)	(-16.34)					(-17.66)	(0.67)
	0.54***	0.49***	0.25***	0.23***	0.05	0.13**	0.15***	0.37***	0.33***	0.10
Efficiency	(33.23)	(29.05)	(6.60)	(5.85)	(1.32)	(3.28)	(3.86)	(8.21)	(6.61)	(0.84)
					-0.25***					
cr1					(-12.12)					
						-0.33***				
cr2						(-18.78)				
							0.07**			
cr3							(2.77)			
								-0.23***		
cr4								(-11.20)		
		0.73***	0.69***	0.68***	0.67***	0.66***	0.66***	0.68***	0.70***	0.45***
Log Size		(14.51)	(13.62)	(13.31)	(13.26)	(12.89)	(13.06)	(13.34)	(11.88)	(4.86)
		0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01
			(0.01)							
Market to book		(0.62)	0.24)	(0.29)	(0.30)	(0.38)	(0.30)	(0.22)	(0.87)	(0.42)
		-0.04**	-0.04**	-0.04**	-0.03**	-0.03**	-0.03*	-0.03**	-0.04**	0.00
Profitability		(-3.12)	(-2.78)	(-2.70)	(-2.63)	(-2.60)	(-2.57)	(-2.68)	(-2.76)	(0.04)
		0.13***	0.14***	0.14***	0.14***	0.14***	0.14***	0.14***	0.14***	0.18***
Tangibility		(4.51)	(4.78)	(4.84)	(4.83)	(4.92)	(4.91)	(4.89)	(4.09)	(3.41)
Cash flow		-0.02	-0.02	-0.02	-0.02	-0.02+	-0.01	-0.02	-0.01	-0.05+
volatility		(-1.58)	(-1.45)	(-1.61)	(-1.43)	(-1.70)	(-1.35)	(-1.46)	(-1.18)	(-1.83)
		0.24***	0.24***	0.24***	0.24***	0.24***	0.24***	0.24***	0.24***	0.24***
Book leverage		(12.41)	(12.39)	(12.39)	(12.37)	(12.44)	(12.32)	(12.31)	(11.04)	(5.15)
Log GDP per			0.23***	0.18***	0.22***	0.35***	0.31***	0.16**	-0.11+	0.15
cap			(5.06)	(3.61)	(4.59)	(7.14)	(6.31)	(3.07)	(-1.66)	(1.45)
			0.05**	-0.01	0.00	-0.01	0.00	0.00	-0.06+	0.06**
inflation			(3.26)	(-0.42)	(0.11)	(-0.73)	(0.03)	(0.09)	(-1.80)	(2.87)
			-0.16***	-0.16***	-0.15***	-0.14***	-0.16***	-0.17***	-0.12***	0.01
GDP growth			(-12.98)	(-12.75)	(-12.37)	(-11.52)	(-13.17)	(-14.04)	(-7.78)	(0.27)
English legal				1.41***	1.26***	1.53***	1.33***	1.40***	1.32***	2.04***
origin				(17.58)	(15.91)	(18.64)	(16.95)	(17.46)	(15.74)	(9.35)
French legal				1.06***	0.69***	1.42***	1.36***	1.55***	1.09***	2.06***
origin				(8.61)	(5.34)	(11.65)	(9.86)	(12.71)	(6.26)	(4.52)
German legal				0.87***	0.76***	0.77***	0.89***	1.06***	0.77***	1.58***
origin				(9.82)	(8.54)	(8.68)	(10.13)	(11.79)	(8.28)	(7.02)
	2.28***	2.16***	2.10***	0.94***	1.07***	0.82***	0.89***	0.83***	1.15***	0.00
Constant	(16.71)	(18.64)	(17.73)	(6.52)	(7.40)	(5.69)	(6.18)	(5.75)	(6.61)	(0.11)
Observations	128047	110604	109471	109471	109471	109471	109471	109471	90129	19342
Within R^2	0.01	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.03	0.02
Between R^2	0.11	0.26	0.26	0.27	0.27	0.28	0.27	0.27	0.28	0.12
Overall R^2	0.11	0.22	0.23	0.24	0.24	0.24	0.23	0.24	0.25	0.09

Table 3.12. Alternative measures of contract enforcement

This table presents the CRE regression results using alternative measures of enforcement quality on the dependent variable, debt maturity structure, as proxied by the long-term to total debt ratio. The seven additional variables are "corruption", "law and order", "bureaucracy quality", "contract viability"; "constraints on executives"; "property rights" index, and "strength of legal rights". Significance at the 10, 5, 1 and 0.1 percent levels are represented using +, *, **, and ***, respectively. The t-values reported in the parentheses are based on clustered standard errors at the firm-level and year dummies. The estimates are heteroskedasticity consistent. Construction of each variable is described in Appendix 1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Creditor rights	-0.07***	-0.08***	-0.08***	-0.06***	-0.07***	-0.08***	-0.09***	-0.15***
	(-13.64)	(-16.81)	(-17.60)	(-13.44)	(-14.49)	(-16.47)	(-18.24)	(-26.77)
Efficiency	0.03**							
	(2.67)							
Corruption (lack of)		0.12***						
		(23.39)						
Property rights			0.27***					
			(36.98)					
Contract viability				0.18***				
				(22.60)				
Constraint on Executives					0.04***			
					(6.05)			
Law and order						0.07***		
						(10.92)		
Bureaucracy quality							0.40***	
							(8.42)	
Strength of legal rights index								0.23***
								(37.94)
Log Size	0.26***	0.27***	0.28***	0.27***	0.26***	0.26***	0.28***	0.31***
	(19.72)	(21.62)	(22.06)	(21.13)	(20.33)	(20.90)	(22.13)	(19.28)
Market to book	0.00	0.00	0.01+	0.00	0.01+	0.01+	0.00	0.01***
	(1.19)	(1.45)	(1.70)	(1.05)	(1.69)	(1.82)	(1.53)	(3.83)
Profitability	0.04***	0.04***	0.04***	0.04***	0.04***	0.04***	0.04***	0.05***
	(9.79)	(9.94)	(9.51)	(9.93)	(10.04)	(10.06)	(9.66)	(8.10)
Tangibility	0.09***	0.09***	0.09***	0.09***	0.09***	0.09***	0.09***	0.09***
	(11.49)	(12.26)	(11.99)	(12.57)	(12.79)	(12.44)	(12.14)	(10.73)
Cash flow volatility	-0.01	-0.01+	-0.01+	-0.01+	-0.01	-0.01	-0.01	0.00
	(-1.60)	(-1.77)	(-1.94)	(-1.74)	(-1.61)	(-1.51)	(-1.52)	(0.51)
Book leverage	0.12***	0.12***	0.11***	0.11***	0.11***	0.11***	0.11***	0.11***
	(22.52)	(23.53)	(22.69)	(23.15)	(23.09)	(23.15)	(23.18)	(19.18)
Log Gdp per cap	0.22***	0.02**	-0.07***	0.06***	0.10***	0.07***	-0.09***	0.03***
	(18.45)	(2.70)	(-8.61)	(9.40)	(16.81)	(10.59)	(-9.59)	(4.42)
Inflation	0.07***	0.02***	0.03***	0.03***	0.02***	0.03***	0.02***	0.00
	(14.95)	(5.75)	(6.84)	(8.47)	(6.13)	(7.70)	(6.72)	(1.04)
Gdp growth	-0.04***	-0.04***	-0.01*	-0.02***	-0.02***	-0.03***	0.00	0.01*
	(-9.32)	(-10.43)	(-2.40)	(-6.37)	(-4.77)	(-7.64)	(0.59)	(2.46)
Constant	-0.15***	-0.13**	-0.07+	-0.74***	-0.14**	-0.43***	-1.46***	-0.19***
	(-3.55)	(-3.11)	(-1.68)	(-14.61)	(-3.18)	(-8.54)	(-25.64)	(-3.83)
Observations	177432	193766	192438	193766	193766	193766	193766	131041
Within R^2	0.02	0.02	0.02	0.03	0.02	0.02	0.03	0.02
Between R^2	0.31	0.28	0.31	0.27	0.26	0.26	0.28	0.30
Overall R^2	0.25	0.22	0.25	0.22	0.21	0.21	0.23	0.25

Table 3.13. Tobit and CRE sub-sample regression results

The dependent variable is the weighted-average maturity in column 2, and the ratio of long term debt to total debt in all other columns. Tobit estimations are reported in columns 1 and 2 to rule out the possibility of biased estimates due to existence of zero maturity ratios. Remaining columns are for CRE regressions for subsamples that exclude three countries with the highest number of observations to assess the possible effect of their over-representation in the total sample. The firms from the U.S., Japan, and China separately, and the three countries together, are excluded in columns 3, 4, 5 and 6, respectively. Significance at the 10, 5, 1 and 0.1 percent levels are indicated using +, *, **, and ***, respectively. The t-values reported in the parentheses are based on clustered standard errors at the firm-level and year dummies. The estimates are heteroskedasticity consistent. Construction of each variable is described in Appendix 1.

	Panel A: Tobit		Panel B: CRE Regressions			
	(1)	(2)	(3) Ex US	(4) Ex Japan	(5) Ex China	(6) Ex. the
	Maturity	Ave-debt-maturity	Maturity	Maturity	Maturity	Maturity
Creditor rights	-0.12***	-0.13***	-0.04***	-0.06***	-0.08***	-0.02*
	(-21.54)	(-20.50)	(-6.76)	(-12.75)	(-17.22)	(-2.31)
Efficiency	-0.04***	0.18***	0.08***	0.09***	0.06***	0.09***
	(-3.41)	(9.91)	(6.54)	(7.09)	(5.26)	(6.73)
Log Size	0.33***	0.24***	0.09***	0.14***	0.06***	0.07***
	(58.59)	(31.17)	(6.73)	(10.82)	(4.00)	(4.41)
Market to book	0.02***	-0.00	0.02***	0.02**	0.03***	0.02***
	(4.82)	(-0.55)	(4.20)	(3.15)	(5.23)	(3.76)
Profitability	0.06***	-0.01*	-0.03***	-0.05***	-0.02***	-0.03***
	(16.16)	(-2.55)	(-6.91)	(-10.81)	(-3.87)	(-5.17)
Tangibility	0.12***	0.00	0.25***	0.28***	0.26***	0.28***
	(20.18)	(0.62)	(15.64)	(20.66)	(18.83)	(14.53)
Cash flow volatility	-0.01*	-0.02***	0.00	0.00	0.00	0.00
	(-1.99)	(-4.33)	(1.01)	(0.86)	(0.69)	(0.17)
Book leverage	0.16***	0.17***	0.04***	0.04***	0.04***	0.04***
	(32.71)	(26.85)	(7.36)	(9.25)	(9.29)	(6.44)
Log Gdp per cap	0.27***	-0.16***	0.08***	0.08***	0.09***	0.08***
	(19.58)	(-7.33)	(9.63)	(9.86)	(11.12)	(7.94)
inflation	0.08***	-0.04***	-0.01	-0.01*	-0.01*	-0.01^{+}
	(11.12)	(-3.95)	(-1.64)	(-2.10)	(-1.99)	(-1.88)
Gdp growth	-0.07***	-0.06***	0.10***	0.13***	0.12***	0.12***
	(-10.34)	(-8.13)	(16.13)	(22.86)	(22.23)	(14.97)
English legal origin	0.03	0.77***	-0.23***	-0.12***	-0.16***	-0.25***
	(0.88)	(24.17)	(-8.30)	(-4.97)	(-6.52)	(-9.03)
French legal origin	-0.28***	0.70***	-0.20***	-0.09*	-0.36***	-0.17***
	(-7.39)	(14.77)	(-6.16)	(-2.45)	(-10.22)	(-4.57)
German legal origin	-0.64***	0.77***	-0.69***	-0.53***	-0.68***	-0.18***
	(-20.64)	(21.32)	(-25.80)	(-16.72)	(-25.32)	(-5.19)
Constant	0.07	0.67***	0.20***	0.11*	0.21***	0.14*
	(1.34)	(9.74)	(3.83)	(2.11)	(4.22)	(2.07)
Observations	177432	109471	130677	141638	161447	78898
Within R^2			0.02	0.03	0.03	0.03
Between R^2			0.31	0.38	0.31	0.28
Overall R^2			0.24	0.31	0.26	0.22
Pseudo R^2	0.10	0.04				

Table 3.14. Additional country-level controls

This table examines the robustness of our CRE regression results for long-term debt to total debt as the dependent variable with the inclusion of additional country-level institutional and macroeconomic variables. These variables are: private credit to GDP, stocks traded to GDP, Fitch sovereign ratings, Information sharing dummy that reflects whether a country has public or private registry bureaus, public registry and private bureau's coverage ratios that determine the percentage of individuals and firms covered by each type of institution, and check formalism as a measure of the well-functioning of courts that addresses the procedural efficiencies for collecting a bounced check, dummies for English, French and German legal origins (Nordic dummy omitted), and dummies for Atheism, Buddhism, Catholicism, Hinduism, Islam and Orthodoxy. Significance at the 10, 5, 1 and 0.1 percent levels are represented using +, *, **, and ***, respectively. The t-values reported in the parentheses are based on clustered standard errors at the firm-level and year dummies. The estimates are heteroskedasticity consistent. Construction of each variable is described in Appendix 1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Creditor rights	-0.08***	-0.07***	-0.08***	-0.08***	-0.08***	-0.08***	-0.04***	-0.05***
	(-16.33)	(-14.08)	(-17.57)	(-16.74)	(-14.12)	(-13.61)	(-6.79)	(-10.77)
Efficiency	0.04***	0.06***	0.08***	0.09***	0.01	0.01	0.08***	0.09***
	(3.70)	(5.58)	(7.44)	(7.73)	(0.64)	(0.67)	(6.20)	(7.32)
Log Size	0.25***	0.26***	0.27***	0.26***	0.32***	0.33***	0.25***	0.28***
	(18.55)	(19.29)	(20.56)	(20.31)	(19.16)	(19.46)	(15.59)	(21.53)
Market to book	0.00	0.00	0.00	0.00	0.01**	0.01**	0.00	0.00
	(0.12)	(0.38)	(1.08)	(1.14)	(3.15)	(3.23)	(1.01)	(1.00)
Profitability	0.04***	0.04***	0.04***	0.04***	0.04***	0.04***	0.04***	0.04***
	(9.14)	(9.05)	(9.60)	(9.57)	(7.33)	(7.32)	(7.35)	(9.26)
Tangibility	0.08***	0.08***	0.08***	0.08***	0.07***	0.07***	0.08***	0.08***
	(10.43)	(10.64)	(11.03)	(11.00)	(8.17)	(8.17)	(9.61)	(10.54)
Cash flow	-0.01	-0.01	-0.01^{+}	-0.01^{+}	0.00	0.00	-0.01	-0.01^{+}
	(-1.51)	(-1.55)	(-1.89)	(-1.93)	(0.44)	(0.42)	(-1.63)	(-1.91)
Book leverage	0.12***	0.11***	0.12***	0.12***	0.12***	0.12***	0.10***	0.12***
	(21.52)	(21.58)	(23.00)	(22.84)	(18.53)	(18.60)	(16.13)	(22.99)
Log GDP per cap	0.04**	0.03*	0.04**	0.04**	-0.03	-0.03	-0.00	0.02^{+}
	(3.03)	(2.29)	(2.84)	(2.67)	(-1.39)	(-1.64)	(-0.18)	(1.66)
inflation	0.03***	0.03***	0.03***	0.03***	0.02**	0.02**	0.02**	0.02**
	(3.51)	(3.51)	(3.76)	(3.82)	(2.80)	(2.74)	(2.76)	(3.07)
Gdp growth	0.00	0.01	0.00	0.01	-0.00	-0.00	0.01	0.01
	(0.25)	(1.02)	(0.43)	(0.91)	(-0.45)	(-0.45)	(0.57)	(0.87)
Private credit to	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.02*
	(1.44)	(1.32)	(0.61)	(0.88)	(1.38)	(1.46)	(1.55)	(2.55)
Stocks traded	0.00	0.00	0.01	0.01	-0.00	-0.00	0.02*	0.00
	(0.48)	(0.72)	(1.47)	(1.39)	(-0.40)	(-0.38)	(2.18)	(0.21)
Sovereign ratings	0.04***	0.04***	0.04***	0.04***	0.05***	0.05***	0.03**	0.04***
	(5.48)	(5.51)	(5.13)	(5.20)	(5.55)	(5.47)	(2.96)	(5.04)
Information	0.15***	0.10***	0.16***	0.09***	0.19***	0.16***	0.09***	-0.03*
	(11.08)	(7.81)	(11.04)	(7.25)	(13.86)	(11.21)	(5.64)	(-2.41)
Public registry	0.01*	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.01**
	(2.26)	(3.51)	(3.47)	(4.24)	(3.67)	(3.47)	(4.18)	(3.02)
Private registry	-0.04***	-0.03***	-0.02***	-0.03***	-0.02***	-0.02***	-0.03***	-0.00
	(-10.10)	(-8.36)	(-5.96)	(-6.96)	(-4.65)	(-4.46)	(-6.89)	(-0.87)
Check formalism	-0.07***							
	(-7.57)							
English legal		0.02***						
		(5.20)						
French legal origin			0.09***					
			(9.19)					
German legal origin				-0.54***				
				(-5.84)				

Table 4.8- Cont'd

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Religion, Atheism					-0.03***			
					(-3.86)			
Religion, Buddhism						0.06***		
						(7.43)		
Religion, Catholicism							-0.01	
							(-0.65)	
Religion, Islam	-0.11***	-0.18***	-0.14***	-0.14***	-0.02	-0.05+	-0.23***	-0.10***
	(-3.98)	(-6.85)	(-5.50)	(-5.73)	(-0.72)	(-1.71)	(-7.76)	(-4.10)
Religion, Orthodoxy	-0.36***	-0.25***	-0.30***	-0.22***	-0.10**	-0.11**	-0.19***	-0.20***
	(-9.93)	(-7.53)	(-8.93)	(-6.68)	(-2.73)	(-3.18)	(-5.62)	(-5.55)
Constant	-0.68***	-0.74***	-0.78***	-0.72***	-0.55***	-0.54***	-0.69***	-0.20***
	(-23.41)	(-27.56)	(-28.70)	(-27.48)	(-18.28)	(-18.03)	(-25.85)	(-6.63)
Observations	160516	164584	177432	177432	116733	116733	130677	177432
Within R^2	0.02	0.03	0.03	0.03	0.02	0.03	0.02	0.03
Between R^2	0.36	0.36	0.36	0.36	0.37	0.37	0.31	0.38
Overall R^2	0.30	0.30	0.30	0.30	0.31	0.31	0.24	0.32

Table 3.15. Main maturity results for a sample without cross-listed firms

This table reports the CRE regression estimates when the dependent variable is the ratio of long term to total debt for a subsample that excludes cross-listed firms. This table provides estimates of the effect of creditor rights and its four components (CR1 to CR4) and the efficiency of contract enforcement on the maturity structure of corporate debt. Columns 9 and 10 use samples of developed and developing countries, respectively, based on the World Bank's GNI thresholds of 2013. Significance at the 10, 5, 1 and 0.1 percent levels are represented using +, *, **, and ***, respectively. The t-values reported in the parentheses are based on clustered standard errors at the firm-level and year dummies. The estimates are heteroskedasticity consistent. Construction of the each variable is described in Appendix 1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9) Developed	(10) Developing
Creditor rights	-0.11***	-0.09***	-0.07***	-0.08***					-0.09***	-0.04^{+}
	(-24.34)	(-19.59)	(-13.61)	(-16.41)					(-17.53)	(-1.74)
Efficiency	0.17***	0.18***	0.03**	0.08***	0.04**	0.06***	0.07***	0.11***	0.07***	0.00
	(35.89)	(36.16)	(2.70)	(7.37)	(3.23)	(5.65)	(6.33)	(9.19)	(4.82)	(0.11)
cr1					-0.06***					
					(-10.73)					
cr2						-0.07***				
						(-14.37)				
cr3							-0.06***			
							(-8.30)			
cr4								-0.06***		
								(-10.80)		
Log Size		0.30***	0.26***	0.26***	0.26***	0.26***	0.26***	0.26***	0.26***	0.29***
		(23.31)	(19.81)	(20.37)	(20.35)	(19.98)	(20.29)	(20.39)	(18.50)	(8.95)
Market to book		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01*	0.00
		(1.41)	(1.19)	(1.14)	(1.16)	(1.18)	(1.20)	(1.13)	(2.38)	(0.04)
Profitability		0.04***	0.04***	0.04***	0.04***	0.04***	0.04***	0.04***	0.04***	0.05**
		(8.91)	(9.73)	(9.51)	(9.53)	(9.59)	(9.54)	(9.53)	(8.96)	(3.01)
Tangibility		0.08***	0.09***	0.08***	0.08***	0.08***	0.08***	0.08***	0.09***	0.06***
		(10.26)	(11.36)	(10.90)	(10.90)	(11.01)	(10.92)	(10.91)	(10.83)	(3.62)
Cash flow volatility		-0.00	-0.01	-0.01^{+}	-0.01^{+}	-0.01^{+}	-0.01^{+}	-0.01^{+}	-0.01^{+}	-0.00
		(-1.29)	(-1.54)	(-1.87)	(-1.76)	(-1.88)	(-1.72)	(-1.79)	(-1.84)	(-0.27)
Book leverage		0.12***	0.12***	0.12***	0.12***	0.12***	0.12***	0.12***	0.12***	0.10***
		(22.69)	(22.51)	(22.82)	(22.77)	(22.82)	(22.74)	(22.80)	(21.31)	(8.50)
Log GDP per cap			0.22***	0.10***	0.11***	0.13***	0.12***	0.10***	0.02	0.13***
			(18.40)	(7.47)	(8.42)	(10.07)	(9.61)	(7.23)	(1.17)	(4.53)
Inflation			0.07***	0.02***	0.02***	0.02***	0.02***	0.02***	0.04***	0.03***
			(14.84)	(4.21)	(4.61)	(4.01)	(3.68)	(4.91)	(3.96)	(5.47)
GDP growth			-0.04***	-0.03***	-0.03***	-0.03***	-0.03***	-0.03***	-0.02***	-0.04***
			(-9.37)	(-7.28)	(-6.86)	(-6.87)	(-7.29)	(-8.32)	(-3.38)	(-4.03)
English				-0.14***	-0.18***	-0.13***	-0.16***	-0.14***	-0.16***	-0.08
				(-5.68)	(-6.88)	(-5.08)	(-6.38)	(-5.69)	(-6.31)	(-1.30)
French				-0.22***	-0.30***	-0.14***	-0.26***	-0.09**	-0.44***	0.00
				(-6.66)	(-8.47)	(-4.27)	(-7.34)	(-2.64)	(-10.12)	(.)
German				-0.72***	-0.75***	-0.75***	-0.73***	-0.66***	-0.68***	-0.47***
				(-27.11)	(-27.38)	(-28.15)	(-27.23)	(-24.76)	(-24.59)	(-9.94)
Constant	-0.12**	-0.09*	-0.15***	0.19***	0.23***	0.17***	0.21***	0.16***	0.23***	-0.10
	(-2.86)	(-2.18)	(-3.57)	(3.95)	(4.61)	(3.65)	(4.23)	(3.37)	(4.29)	(-0.91)
Observations	203656	177511	175896	175896	175896	175896	175896	175896	144091	31581
Within R^2	0.00	0.03	0.02	0.03	0.03	0.03	0.03	0.03	0.03	0.04
Between R^2	0.12	0.27	0.31	0.35	0.35	0.36	0.36	0.36	0.30	0.36
Overall R^2	0.11	0.20	0.25	0.28	0.29	0.29	0.30	0.30	0.24	0.28

Table 3.16. Alternative maturity results for a sample without cross-listed firms

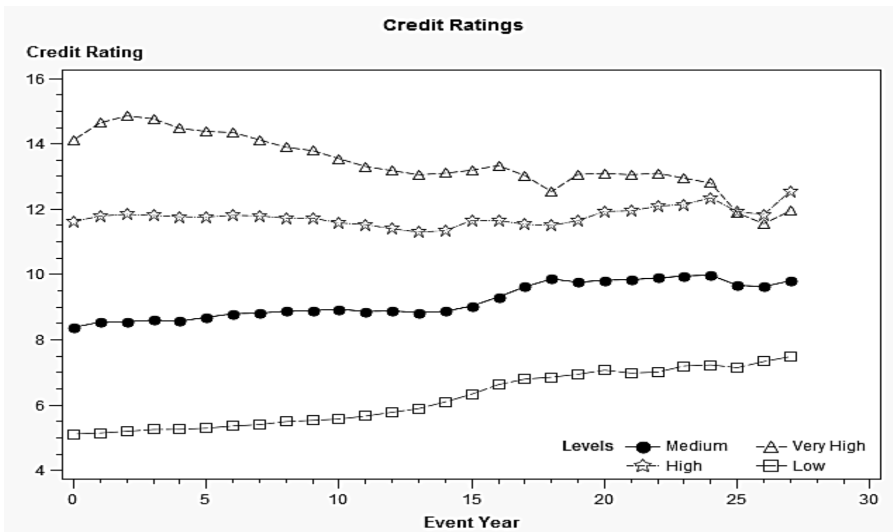
This table reports the CRE regression estimates when the dependent variable is the weighted-average debt maturity for a sample that excludes cross-listed firms. This table provides estimates of the effect of creditor rights and its four components (CR1 to CR4) and the efficiency of contract enforcement on the maturity structure of corporate debt. Columns 12 and 13 examine developed and developing countries, respectively, based on the World Bank's GNI thresholds of 2013. Significance at the 10, 5, 1 and 0.1 percent levels are represented using +, *, **, and ***, respectively. The t-values reported in the parentheses are based on clustered standard errors at the firm-level and year dummies. The estimates are heteroskedasticity consistent. Construction of each variable is described in Appendix 1.

	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(12)	(13)
									Developed	Developing
Creditor rights	-0.32***	-0.29***	-0.25***	-0.29***					-0.33***	0.10
	(-21.16)	(-17.87)	(-15.32)	(-16.51)					(-17.82)	(0.71)
Efficiency	0.54***	0.49***	0.25***	0.23***	0.05	0.13**	0.15***	0.38***	0.33***	0.10
	(33.23)	(28.80)	(6.58)	(5.82)	(1.21)	(3.23)	(3.80)	(8.21)	(6.66)	(0.84)
cr1					-0.25***					
					(-12.28)					
cr2						-0.33***				
						(-18.86)				
cr3							0.07**			
							(2.76)			
cr4								-0.23***		
								(-11.27)		
Log Size		0.72***	0.69***	0.67***	0.67***	0.65***	0.66***	0.67***	0.69***	0.44***
		(14.38)	(13.50)	(13.19)	(13.13)	(12.77)	(12.93)	(13.22)	(11.79)	(4.74)
Market to book		0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00
		(0.57)	(0.19)	(0.23)	(0.24)	(0.33)	(0.25)	(0.17)	(0.85)	(0.37)
Profitability		-0.04**	-0.04**	-0.03**	-0.03*	-0.03*	-0.03*	-0.03**	-0.04**	0.00
		(-3.07)	(-2.72)	(-2.64)	(-2.57)	(-2.54)	(-2.51)	(-2.62)	(-2.67)	(0.03)
Tangibility		0.13***	0.13***	0.14***	0.14***	0.14***	0.14***	0.14***	0.13***	0.18***
		(4.36)	(4.63)	(4.69)	(4.68)	(4.77)	(4.76)	(4.74)	(4.00)	(3.30)
Cash flow		-0.02	-0.02	-0.02^{+}	-0.02	-0.02^{+}	-0.01	-0.02	-0.01	-0.06^{+}
volatility		(-1.62)	(-1.49)	(-1.65)	(-1.47)	(-1.74)	(-1.39)	(-1.50)	(-1.20)	(-1.93)
Book leverage		0.24***	0.24***	0.24***	0.24***	0.24***	0.24***	0.24***	0.24***	0.25***
		(12.43)	(12.39)	(12.39)	(12.36)	(12.44)	(12.31)	(12.31)	(11.06)	(5.11)
Ln GDP per cap			0.22***	0.17***	0.22***	0.34***	0.30***	0.15**	-0.12^{+}	0.14
			(4.96)	(3.48)	(4.51)	(7.01)	(6.21)	(2.93)	(-1.74)	(1.38)
inflation			0.06***	-0.00	0.01	-0.01	0.00	0.01	-0.05^{+}	0.07**
			(3.49)	(-0.21)	(0.32)	(-0.51)	(0.24)	(0.31)	(-1.69)	(3.11)
GDP growth			-0.16***	-0.16***	-0.15***	-0.14***	-0.16***	-0.18***	-0.12***	0.00
			(-13.07)	(-12.85)	(-12.49)	(-11.64)	(-13.28)	(-14.14)	(-7.75)	(0.08)
English				1.41***	1.26***	1.52***	1.33***	1.40***	1.32***	2.00***
				(17.36)	(15.70)	(18.43)	(16.73)	(17.25)	(15.54)	(8.97)
French				1.04***	0.66***	1.41***	1.35***	1.55***	1.08***	2.02***
				(8.42)	(5.09)	(11.38)	(9.65)	(12.53)	(6.14)	(4.38)
German				0.86***	0.75***	0.75***	0.88***	1.05***	0.76***	1.56***
				(9.61)	(8.34)	(8.46)	(9.91)	(11.58)	(8.08)	(6.83)
Constant	2.26***	2.15***	2.09***	0.93***	1.07***	0.82***	0.89***	0.83***	1.15***	0.00
	(16.39)	(18.25)	(17.40)	(6.41)	(7.30)	(5.61)	(6.12)	(5.67)	(6.54)	(.)

Figures

Figure 2.1. Evolution of the average credit ratings of firm quartiles over event time

The evolution of average credit ratings in event time are depicted for the full sample of rated firms in the upper figure and for the sample of firms with at least 20 consecutive annual observations in the lower figure. The figures are obtained by first categorizing the rated and not-rated firms into four quartiles based on their starting-year (event year 0) credit ratings, and then producing time-series paths for their mean credit ratings from the starting date of 1985 (event year 0) until 2012 (event year 27) for this starting date. The same procedure then is repeated but starting a year forward in time, and is continued until the starting year (or event year 0) is 2004. The cross-sectional average is then calculated for each event year based on the resulting average credit ratings for each of the four quartiles for each sample of rated firms. This results in the credit-rating paths over event time for quartiles having very high, high, medium and low leverage ratios for both samples of rated firms. The credit ratings represented are converted from S&P's alphabetical format to numerical values based on the equivalent methodology of Hotchkiss Strömberg and Smith. (2014).



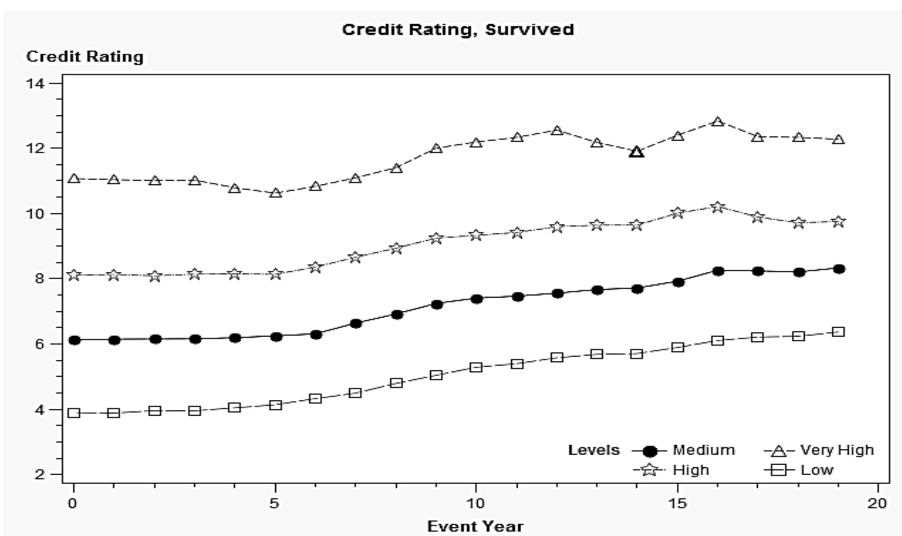


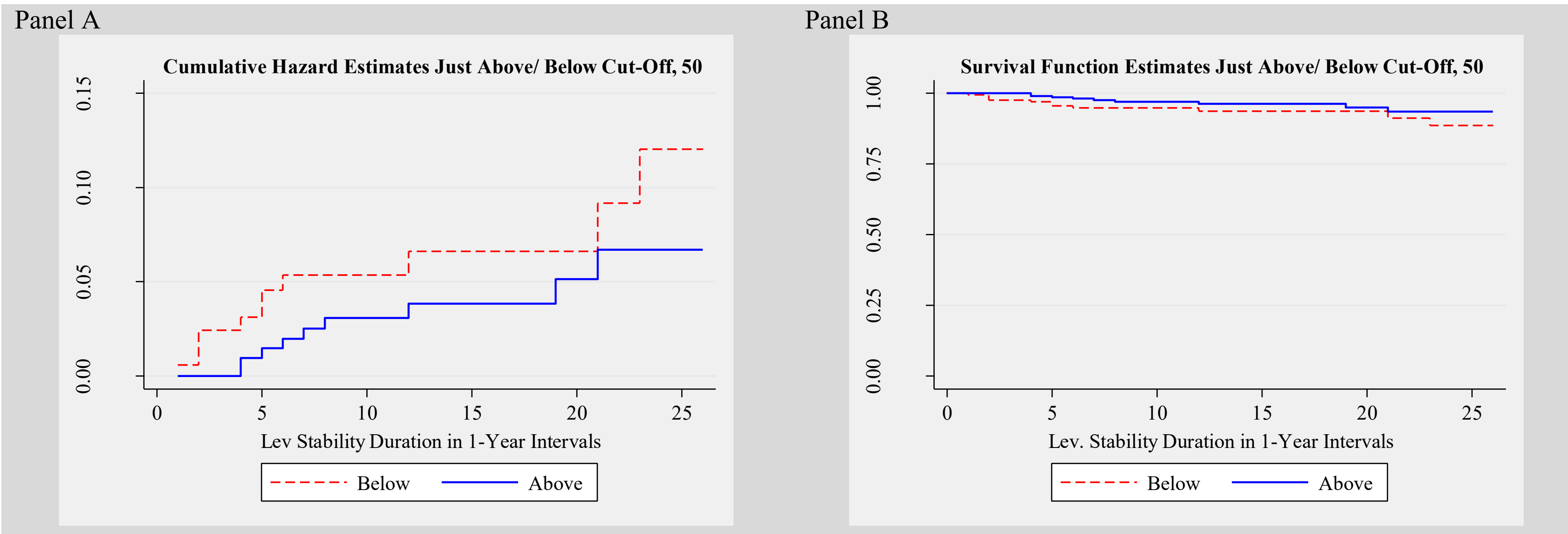
Figure 2.2. Rating transition matrix

This figure is an excerpt from "Introducing Moody's Credit Transition Model, (2007)" special comment by Moody's Analytics. The figure shows a typical one-year transition matrix. The diagonal figures show the probability that a firm maintains its current rating over the next year.

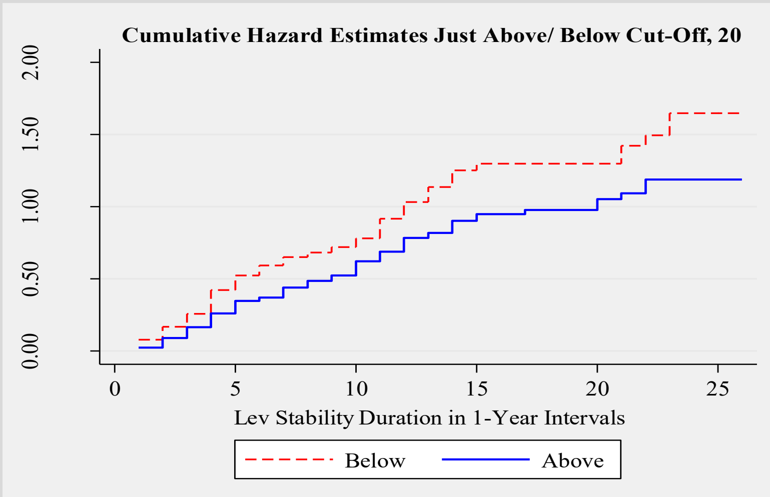
Current Rating \ One Year Later	Aaa	Aa1	Aa2	Aa3	A1	A2	A3	Baa1	Baa2	Baa3	Ba1	Ba2	Ba3	B1	B2	B3	Caa1	Caa2	Caa3	Ca-C	WR	DEF
Aaa	**89**	3	3	0		0															5	
Aa1	3	**82**	5	5	0	0	0	0													5	
Aa2	1	3	**79**	8	2	1	0		0	0											7	
Aa3	0	1	3	**79**	7	2	1	0	0		0			0							6	
A1	0	0	0	5	**80**	7	2	1	0	0	0	0	0								5	
A2	0	0	0	1	5	**79**	7	3	1	0	0	0	0		0			0	0		4	0
A3	0	0	0	0	1	8	**74**	7	3	1	0	0	0	0	0	0		0	0	0	4	0
Baa1	0	0	0	0	0	2	6	**75**	8	3	1	0	0	0	0	0	0	0		0	4	0
Baa2	0	0	0	0	0	1	2	6	**76**	7	1	1	1	1	0	0	0	0	0	0	5	0
Baa3	0	0		0	0	0	1	2	8	**73**	5	3	1	1	0	0	0	0	0	0	5	0
Ba1			0	0	0	0	0	1	2	9	**65**	5	4	1	1	1	0	0	0	0	8	0
Ba2			0	0	0	0	0	0	1	3	8	**63**	6	4	2	1	1	0	0	0	9	1
Ba3			0	0	0	0	0	0	0	1	3	7	**65**	5	5	2	0	0	0	0	10	2
B1	0	0		0	0	0	0	0	0	0	1	2	6	**66**	6	4	1	1	0	0	9	3
B2	0		0	0	0	0	0	0	0	0	0	0	2	5	**67**	7	3	1	1	0	9	4
B3		0	0		0		0	0		0	0	0	0	2	5	**61**	5	4	1	1	11	9
Caa1						0				0		0	0	1	2	5	**59**	5	4	3	11	10
Caa2						0			0	0	0	0	0	1	1	2	3	**54**	3	4	13	18
Caa3											0		0	1	1	2	3	3	**45**	6	13	25
Ca-C														0		0	1	1	1	**35**	13	20

Figure 2.3. Cumulative hazard and survival functions for firms above/ below the Investment grade cut-off

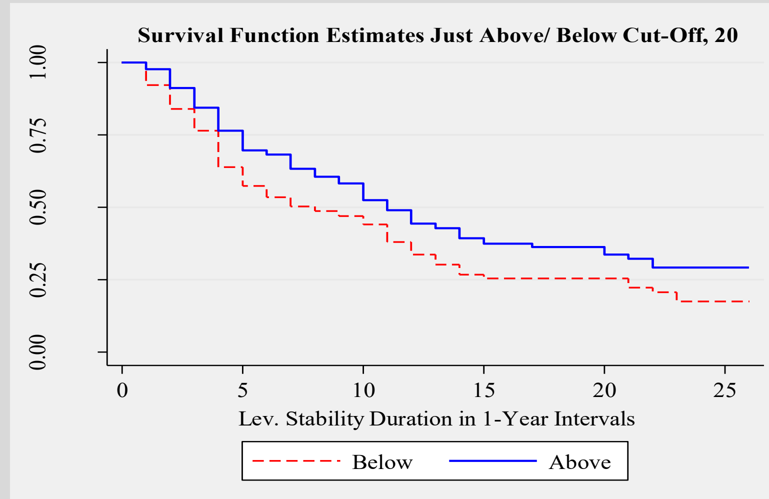
This figure plots the hazard and survival rates over time for the rated and not-rated firms. The event in these graphs are instances when a firm crosses a given leverage threshold. These thresholds are 50%, 20% and 10% of the lagged leverage values and are used in the top, middle and bottom panels respectively. Graphs on the left-hand-side depict the hazard ratios and right panels depict the survival estimates. Solid blue lines show firms just above the investment grade cut-off (BBB-) and the dashed red lines show firms just below the cut-off point (BB+). For ease of interpretation, the left panels are scaled to the range of the vertical axes, while the right axes are scaled at the fixed interval of zero to one. The horizontal axis represents the annual intervals over 27 years.



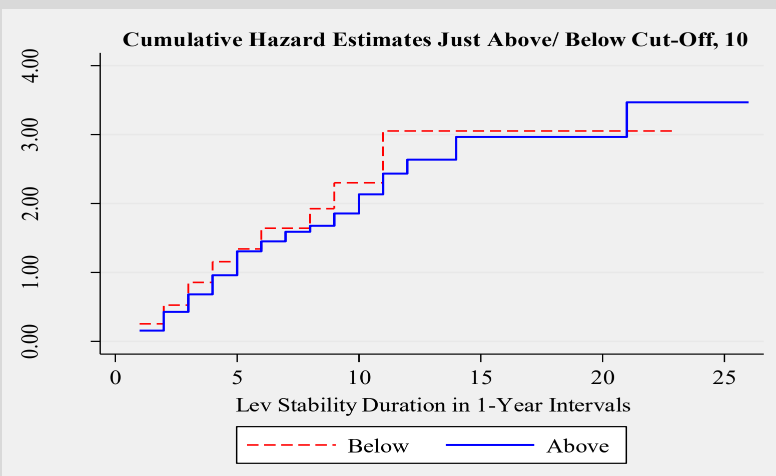
Panel C



Panel D



Panel E



Panel F

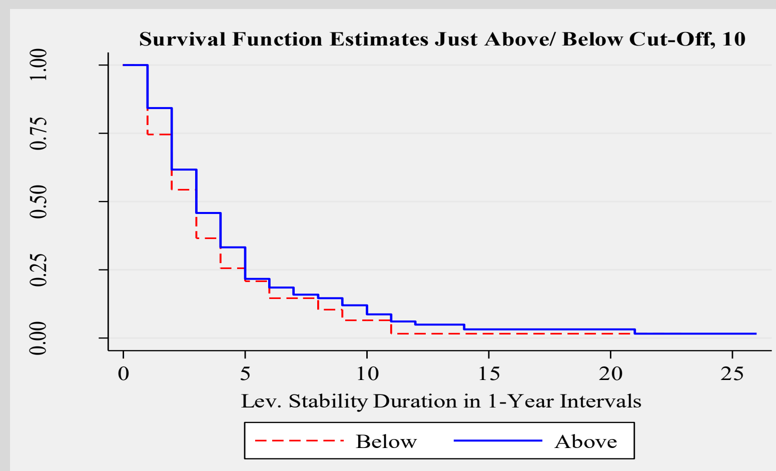
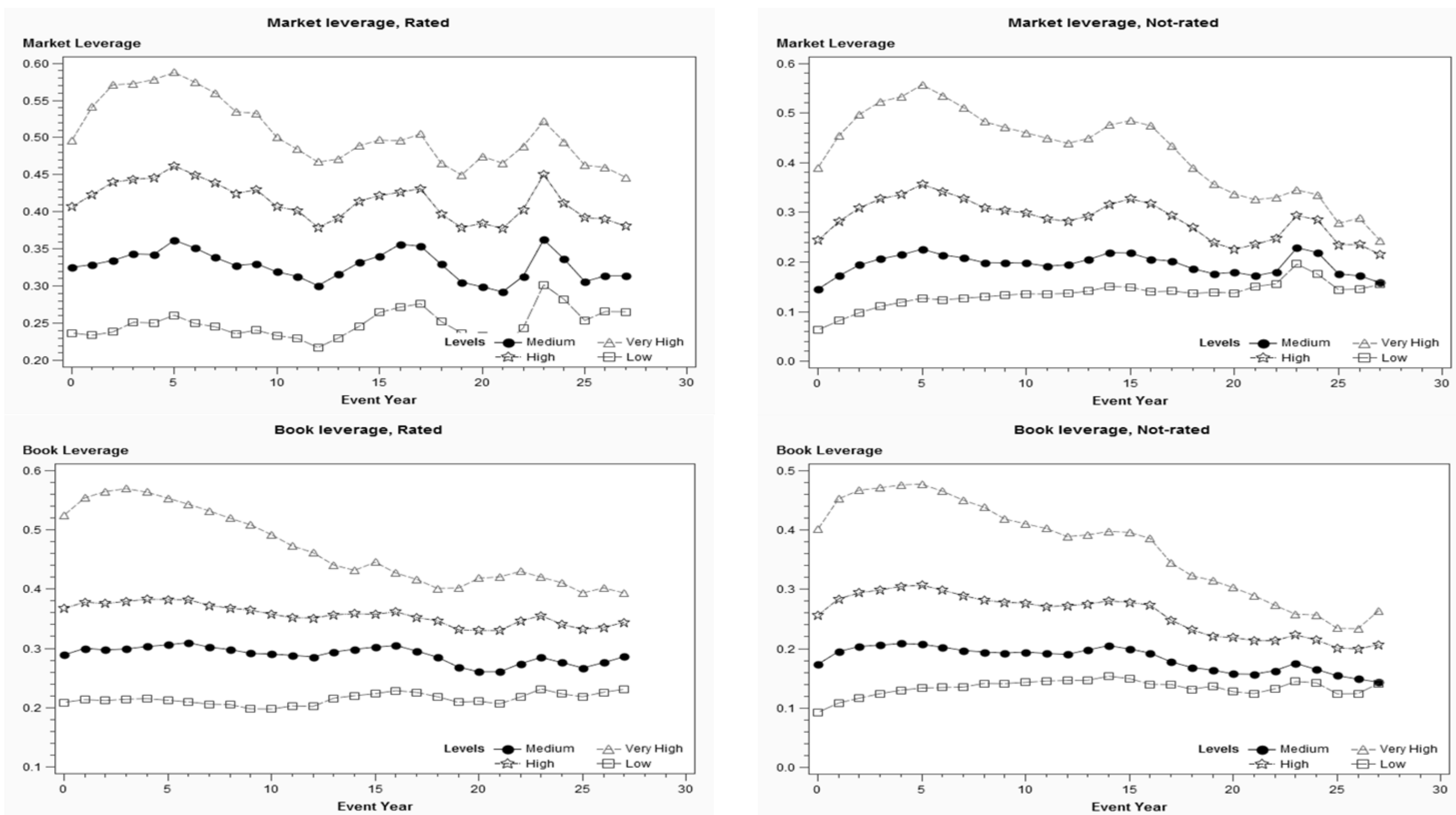


Figure 2.4. Evolution of market leverage ratios in event time

The evolution of average leverage ratios in event time are depicted in the following two panels. Panel A uses the base dataset of rated and not-rated firms while Panel B uses the sample of firms with at least 20 consecutive annual observations. In both panels, the first (second) row consists of two graphs for the mean market (book) leverage of rated and not-rated firms on the left- and right-hand sides (LHS & RHS), respectively. Graphs are obtained by first categorizing the rated and not-rated firms into four quartiles based on their starting-year (event year 0) leverage ratios (book, market), and then producing time-series paths for the mean leverage ratios for the quartiles from the starting date of 1985 (event year 0) until 2012 (event year 27) for this starting date. The same procedure then is repeated but starting a year forward in time, and is continued until the starting year (or event year 0) is 2004. The cross-sectional average is then calculated for each event year based on the resulting average leverage ratios for each of the quartiles for the rated and not-rated firms. This results in the leverage paths over event time for quartiles having very high, high, medium and low leverage ratios for both the rated and not–rated quartiles of firms.

Panel A. Evolution of market leverage ratios for quartiles for the full sample of rated and not-rated firms



Panel B. Evolution of market leverage ratios for the quartiles of samples of rated and not-rated firms in the "survived sample" (with at least 20 annual observations)

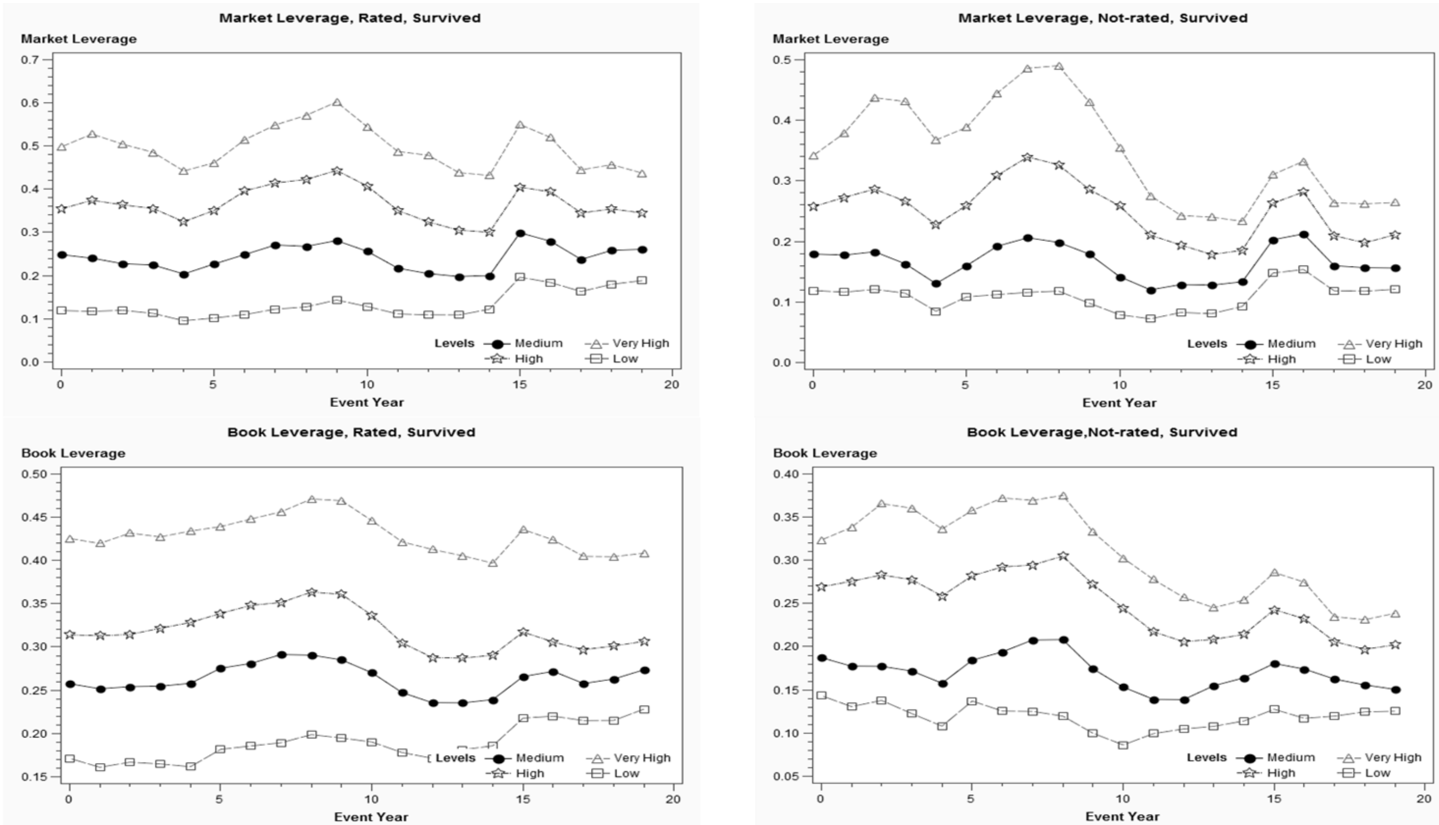
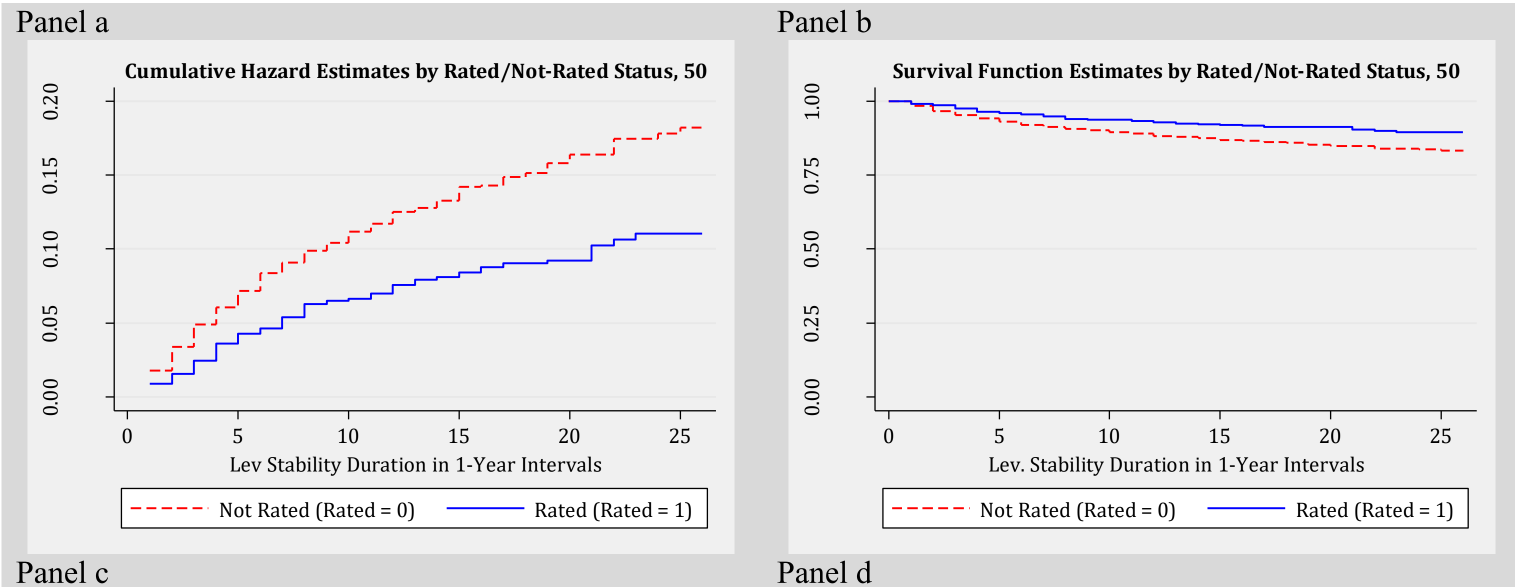
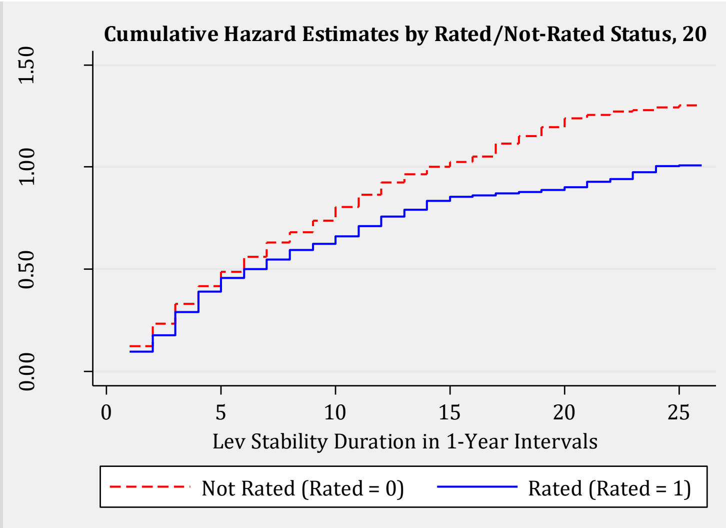
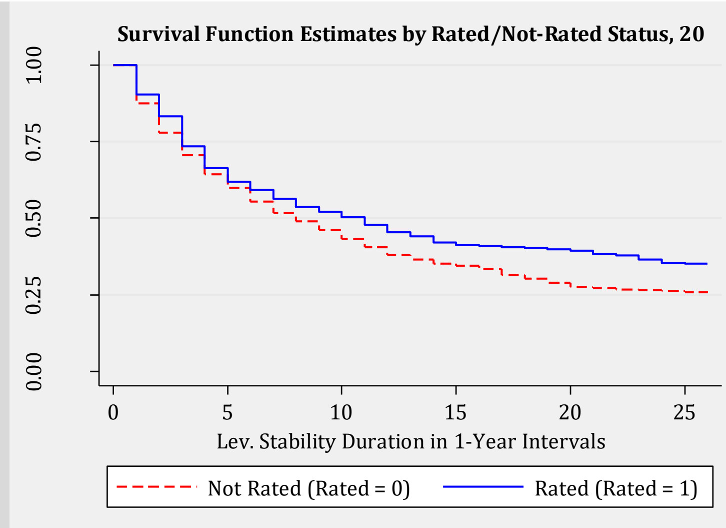


Figure 2.5. Cumulative hazard and hurvival functions across rated and not-rated firms

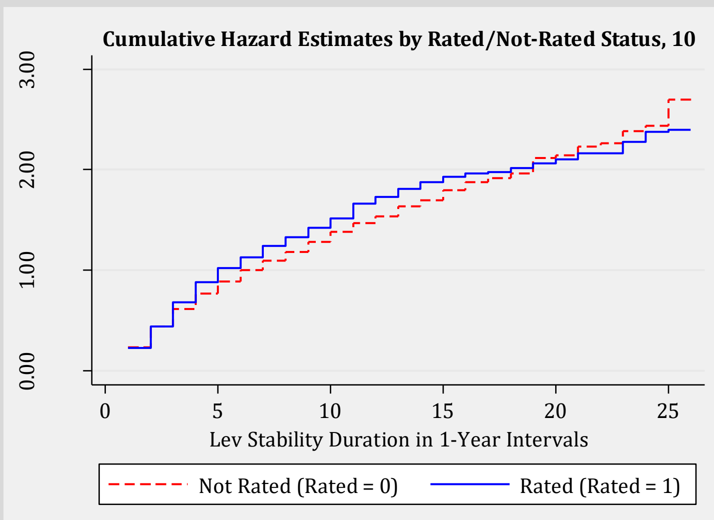
This figure plots the hazard and survival rates over time for the rated and not-rated firms. The event in these graphs are instances when a firm crosses a given leverage threshold. These thresholds are 50%, 20% and 10% of the lagged leverage values and are used in the top, middle and bottom panels respectively. Graphs on the left-hand-side depict the hazard ratios and right panels depict the survival estimates. Solid blue lines are for rated firms and dashed red lines for not-rated firms. For ease of interpretation, the left panels are scaled to the range of the vertical axes, while the right axes are scaled at the fixed interval of zero to one. The horizontal axis represents the annual intervals over 27 years.







Panel e



Panel f

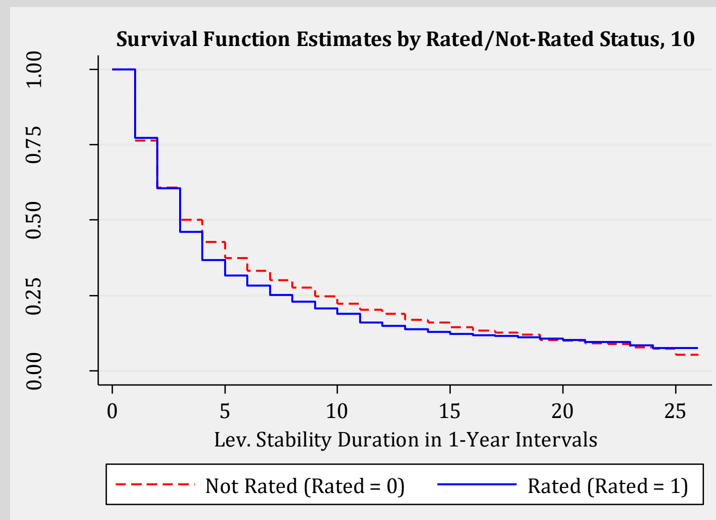


Figure 2.6. Effect of net debt issuance on subsequent market leverage ratios

This figure depicts the effects of active leverage management through net debt issuance (NDI) and net equity issuance (NEI) on the evolution of market leverage over 27 years. The upper and lower panels show the not-rated and rated sample, respectively. Left-hand (right-hand) graphs show market leverage using "NDI-based" (NDE-based) quartile formation methods. For each year, we form quartiles by ranking firms based on their net debt or net equity issuance and calculate the average leverages of the firms in each quartile. The construction of NDI and NEI is explained in Appendix 1. The first quartiles are fixed for 27 years. Similar to Figure 1, we repeat this quartile-formation method for subsequent years in the sample. After this step, we average the market leverage averages for the quartiles in event time.

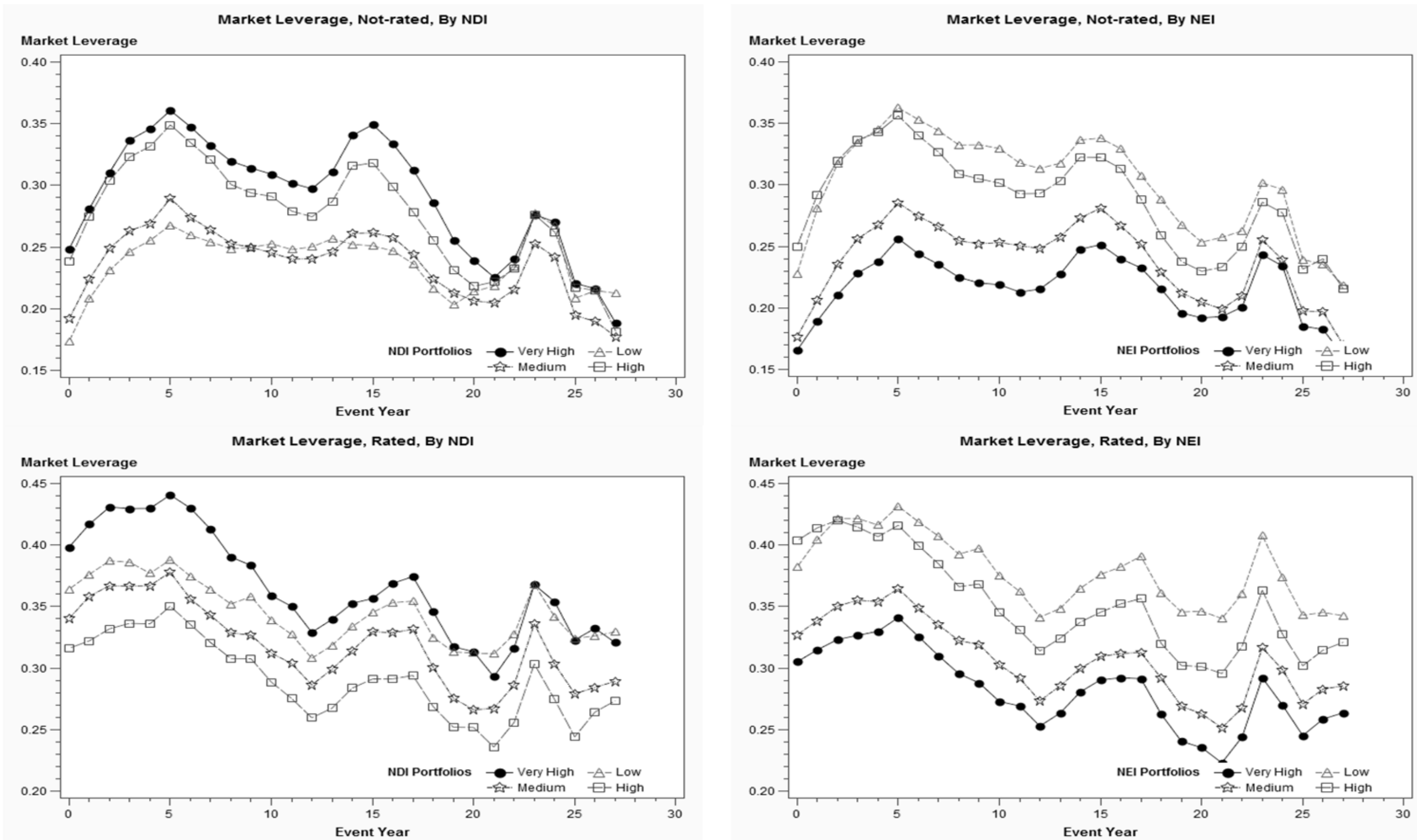
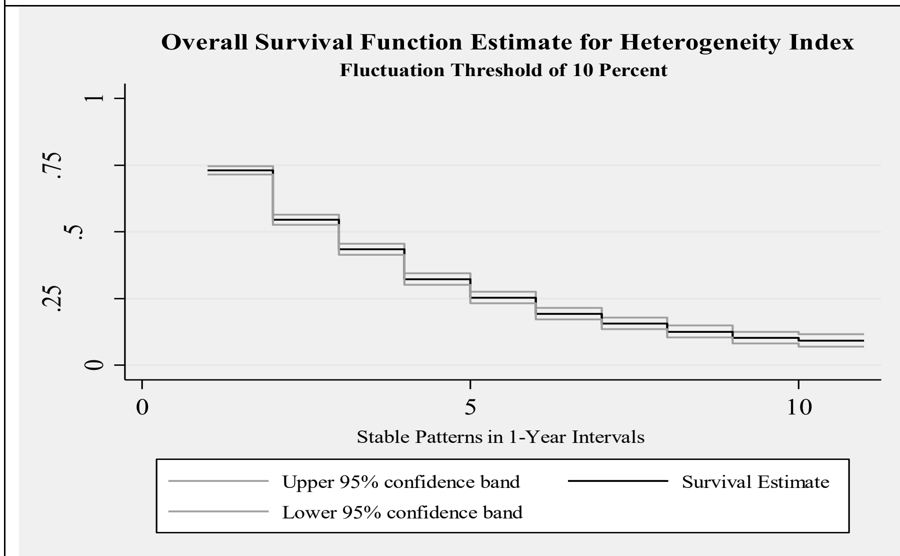


Figure 3.1. Survival analysis with two variation thresholds

This graph reports the Kaplan-Meier survival estimates for the debt heterogeneity index (HHI). In Panel A (B), the survival probabilities are based on the variation of the debt heterogeneity index being less than 10% (20%) of its base value. A non-survival event occurs when a firm changes its debt heterogeneity type in any given year by more than the indicated threshold. Solid lines show the survival estimates and the two grey lines show the 95% confidence intervals.

Panel A: Survival function for debt heterogeneity index, 10% variation threshold



Panel B: Survival function for debt heterogeneity index, 20% variation threshold

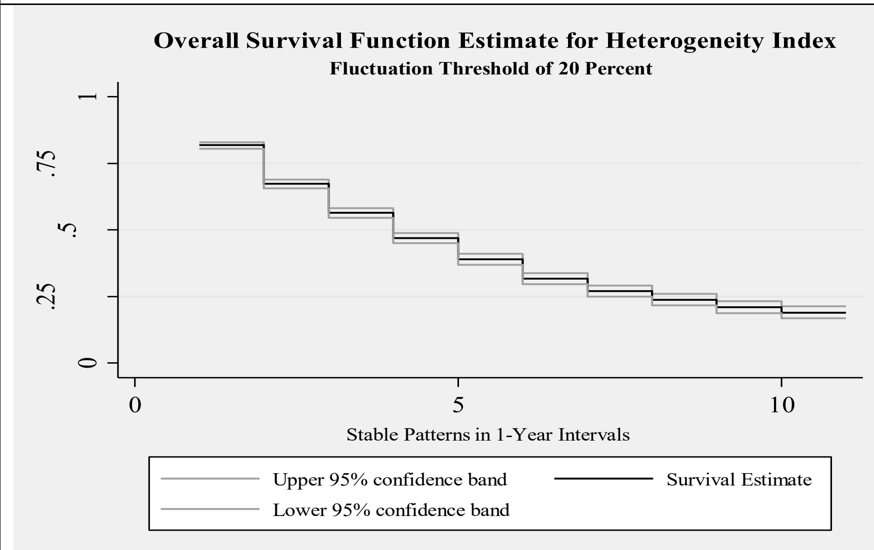


Figure 3.2. Survival analysis of the largest debt type

This graph reports the Kaplan-Meier survival estimates for the main (largest) debt type. The non-survival event occurs in time when a firm changes its main debt type. Solid lines show the survival estimates and the two grey lines show 95% confidence intervals.

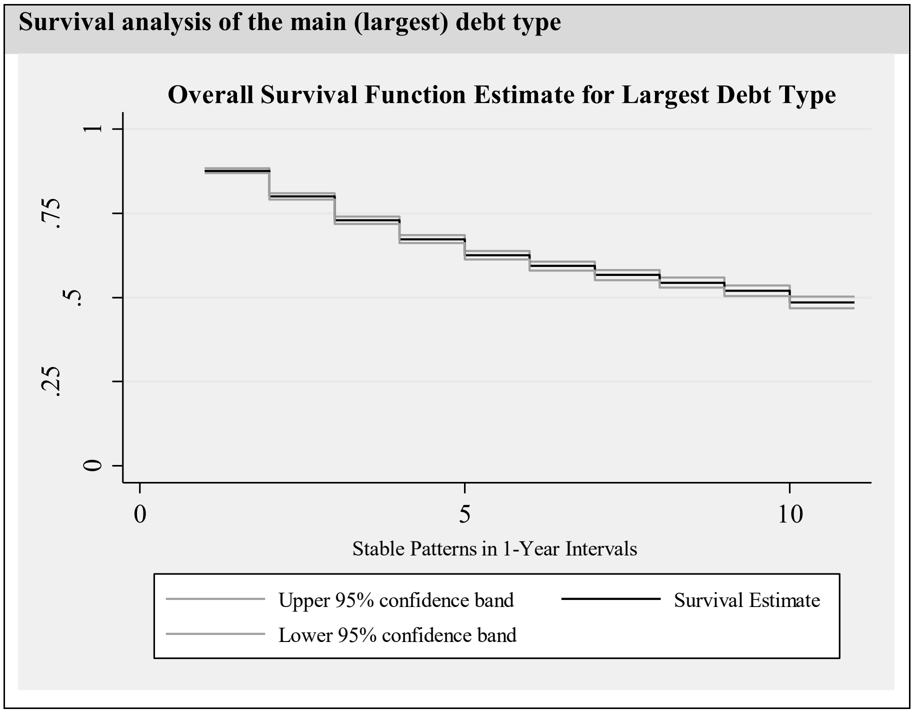
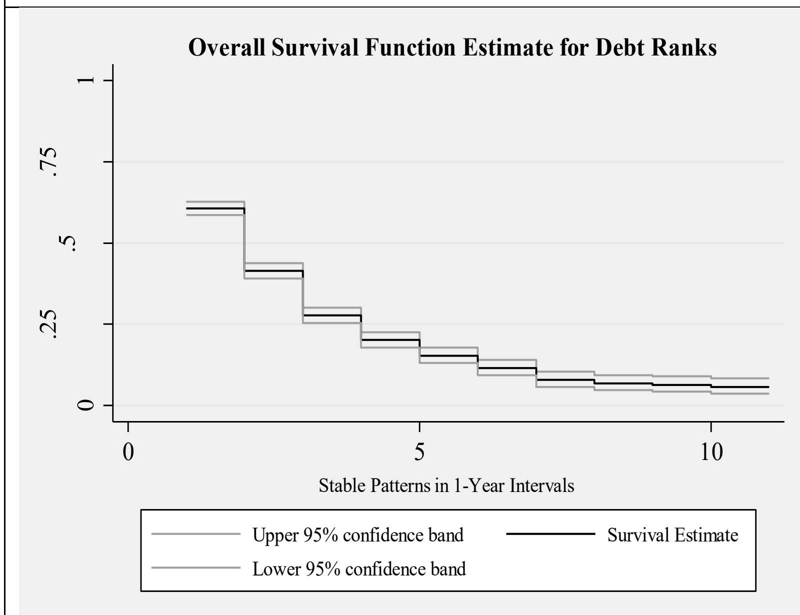


Figure 3.3. Survival analysis of debt type ranks

This graph reports the Kaplan-Meier survival estimates for the various *debt-type rank-ordered index*. The non-survival event occurs when there is a change in the order of different debt types or discontinuation or introduction of any of them. Panel A (B) considers a change threshold in the debt rank index of 10% (20%). Solid lines show the survival estimates and the two grey lines show 95% confidence intervals.

Panel A: Survival function for ranks of all 7 debt types



Panel B: Survival function for ranks of only the first two debt types

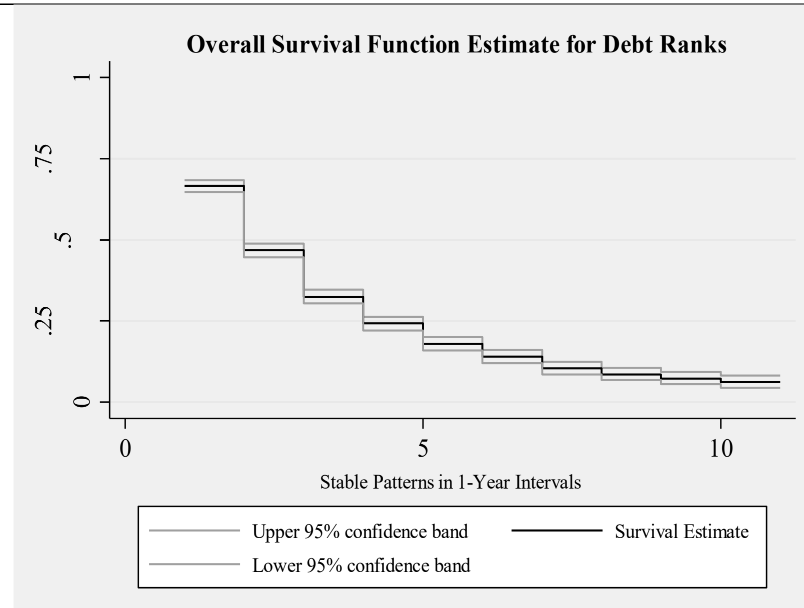


Figure 3.4. Survival analysis of debt type ranks

This graph reports the Kaplan-Meier survival estimates for the 7*debt-type rank-ordered index* using Kendall’s tau-b measure of similarity. The non-survival event occurs when Kendal’s tau-b index changes more than 10% (20%) in Panel A (B). Solid lines show the survival estimates and the two grey lines show 95% confidence intervals.

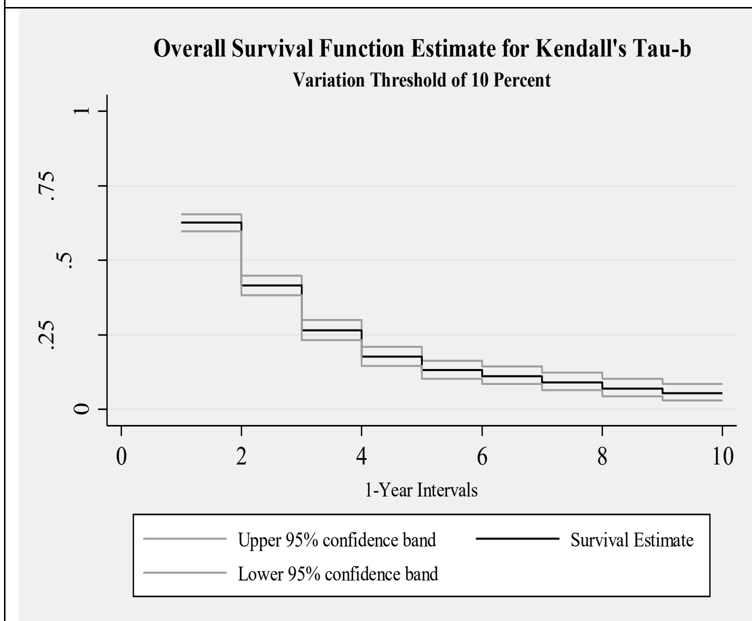
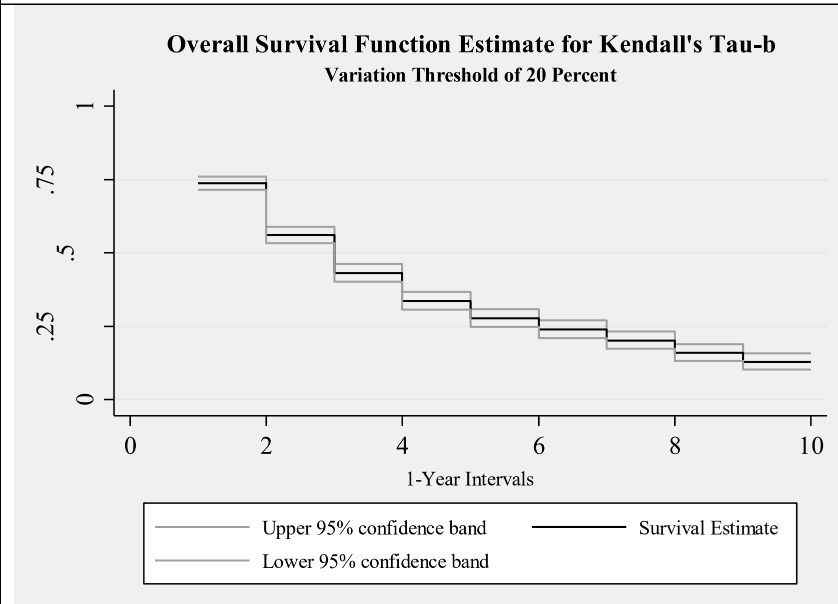
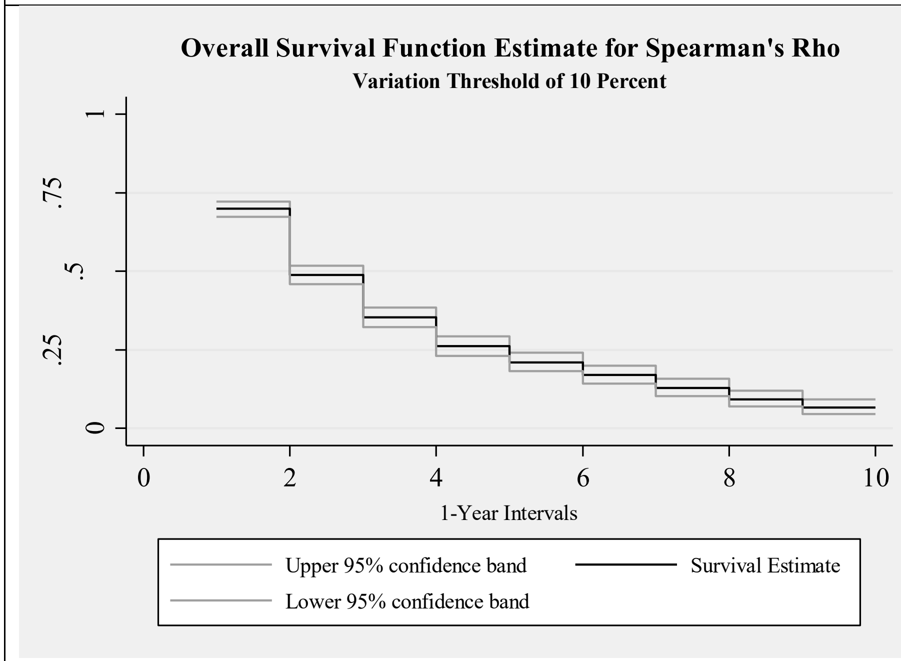
Panel A- Survival function for Kendall’s Tau-b, 10% change	**Panel B- Survival function for Kendall’s Tau-b, 20% change**
	

Figure 3.5. Survival analysis of debt type ranks, Spearman's rho

This graph reports the Kaplan-Meier survival estimates for the 7*debt-type rank-ordered index* using the Spearman's rho measure of similarity. The non-survival event occurs when Spearman's rho index changes more than 10% (20%) in the Panel A (B). Solid lines show the survival estimates and the two grey lines show 95% confidence intervals.

Panel A: Survival function, Spearman's rho, 10% change



Panel B: Survival function, Spearman's rho, 20% change

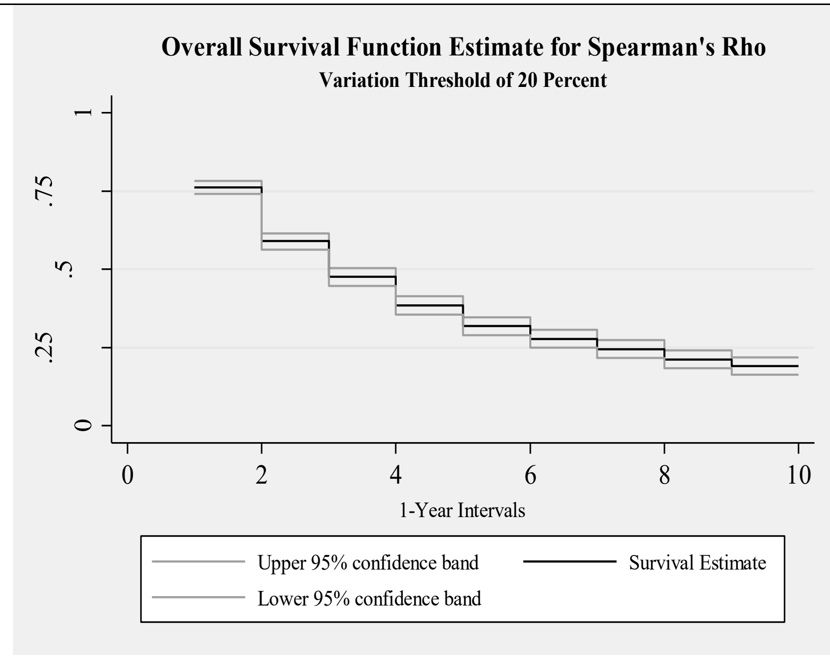
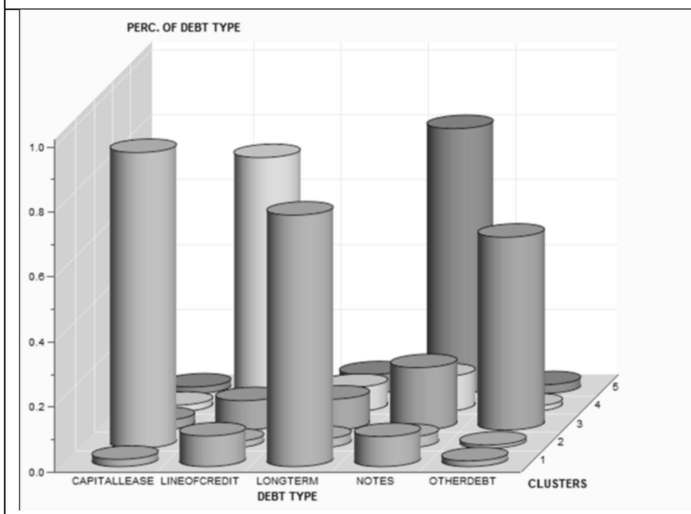
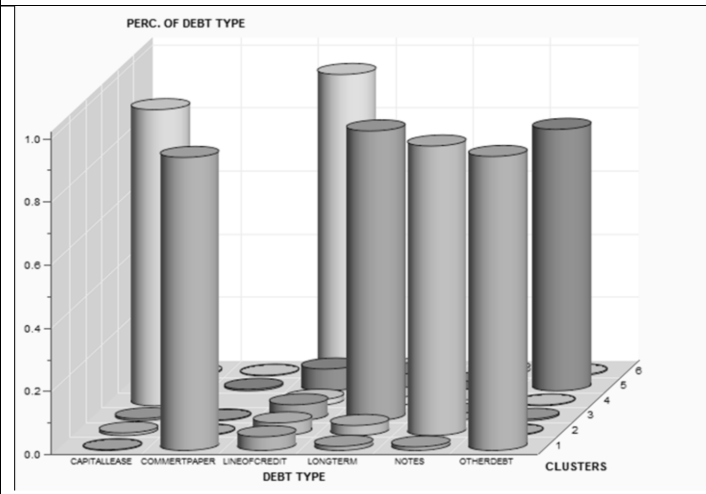


Figure 3.6. The clustering results for the heterogeneity indexes

Graphs in this figure show the results of a clustering study using the heterogeneity index. Panels A and C present results based on firm-1year observations, and Panels B and D using firm-12year observations. To obtain these heterogeneity graphs, the debt types are first categorized into 7 distinct categories using the CapitalIQ Debt database. In the next step for each year (or over ten years), the ratio of each debt type to the total debt as the percentage of that particular debt type in a firm's total debt is calculated. In Panels A and B, Stata's KMEANS command and the Calinski-Harabasz stopping rule are used to categorize these percentages into the most efficient number of clusters. In Panels C and D, 7 clusters are arbitrarily used as a test of robustness. The horizontal axis shows the seven debt types, the vertical axis shows the portion of that debt type in the firm's total debt and the depth axis shows the clusters.

Panel A: Firm-year observations with five clusters	**Panel B: Firm-12year observations with six clusters**
	

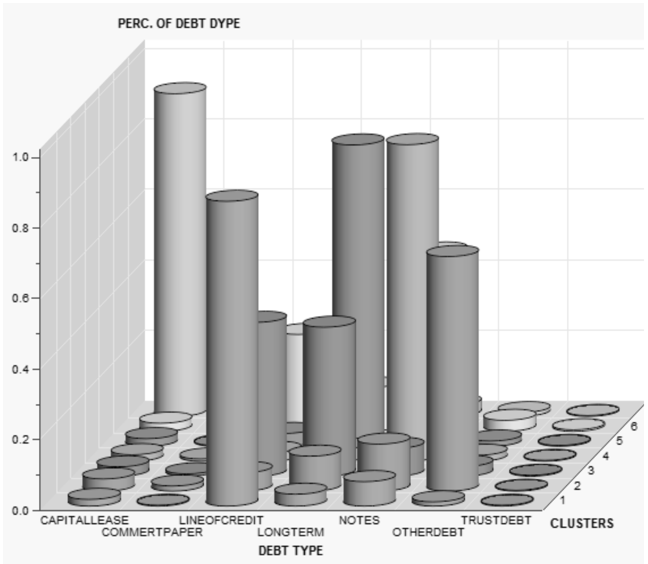
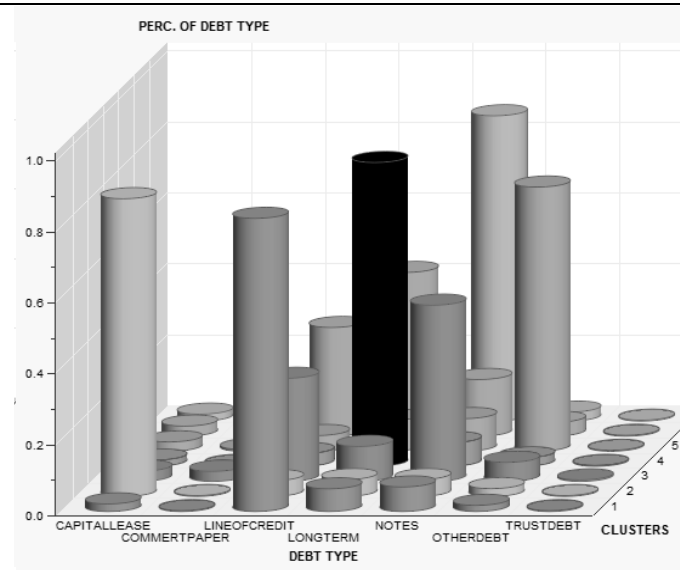
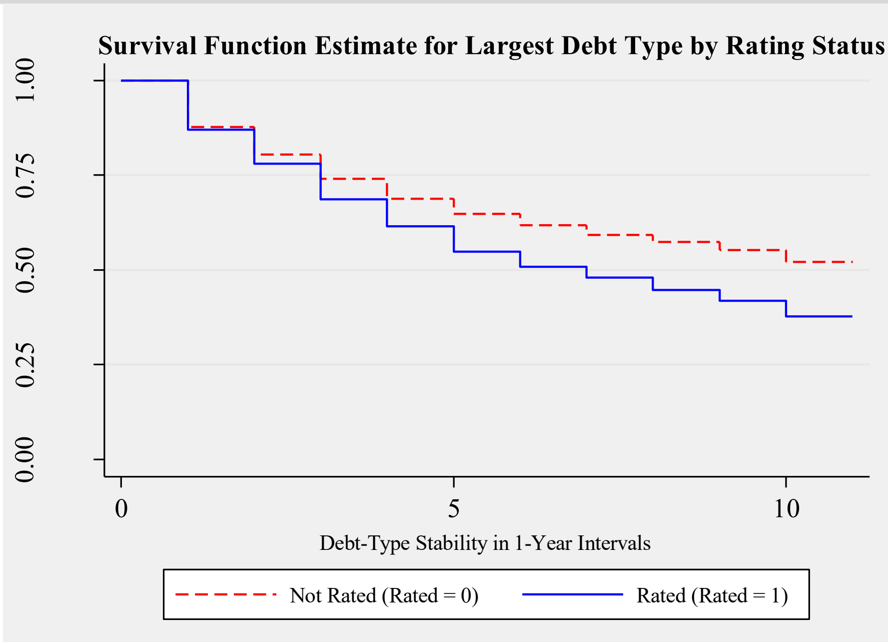
Panel C: Firm-year observations with seven clusters	Panel D: Firm-12year observations with seven clusters
	

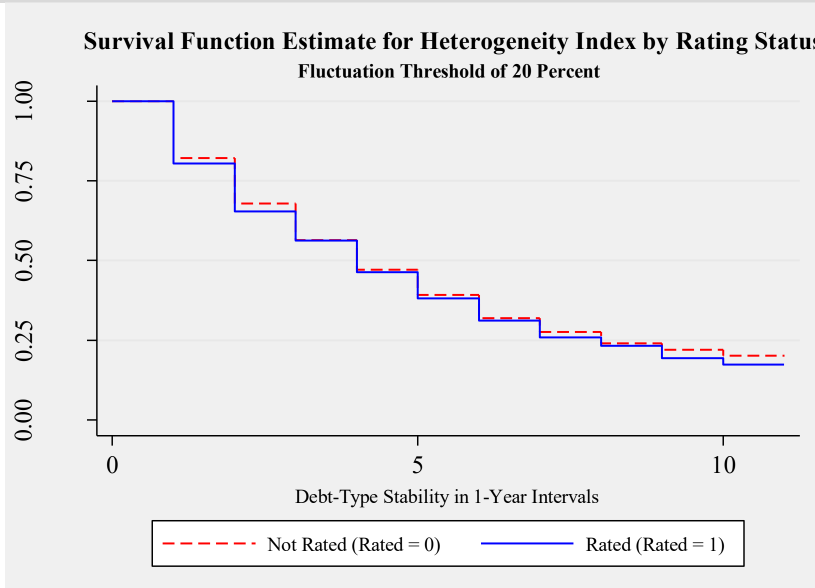
Figure 3.7. The survival analysis results for various debt heterogeneity metrics

This graph reports the Kaplan-Meier survival estimates for the rated and not-rated samples for the various debt heterogeneity metrics. In all panels, the horizontal axis shows the 1-year intervals and the vertical axis reports the estimated survival probabilities. Dashed red lines report survival estimates for the not rated sample, and the solid blue line reports the results for the rated sample. The results for the main debt type are reported in Panel A, those for the heterogeneity index in Panel B and those for debt ranks in Panel C.

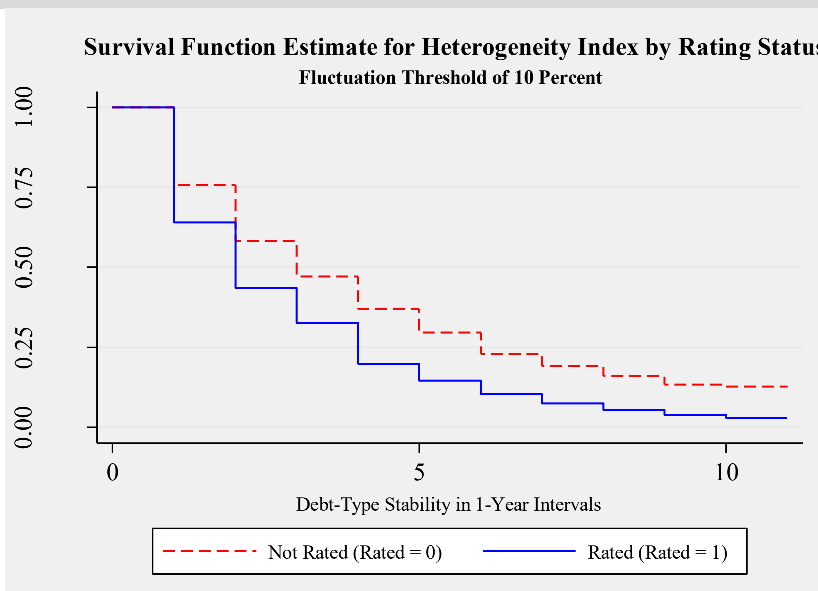
Panel A. Survival function for the main debt type



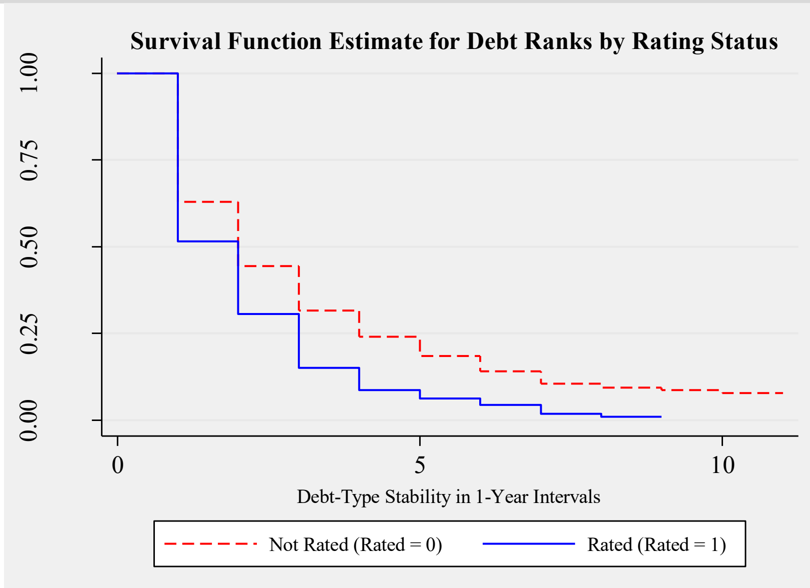
Panel B (Upper): Survival function for heterogeneity index, 10%



Panel B (lower): Survival function for heterogeneity index, 20%



Panel C (Upper): Survival function for all seven debt-type ordered ranks



Panel C (Lower): Survival function for first two debt-type ordered ranks

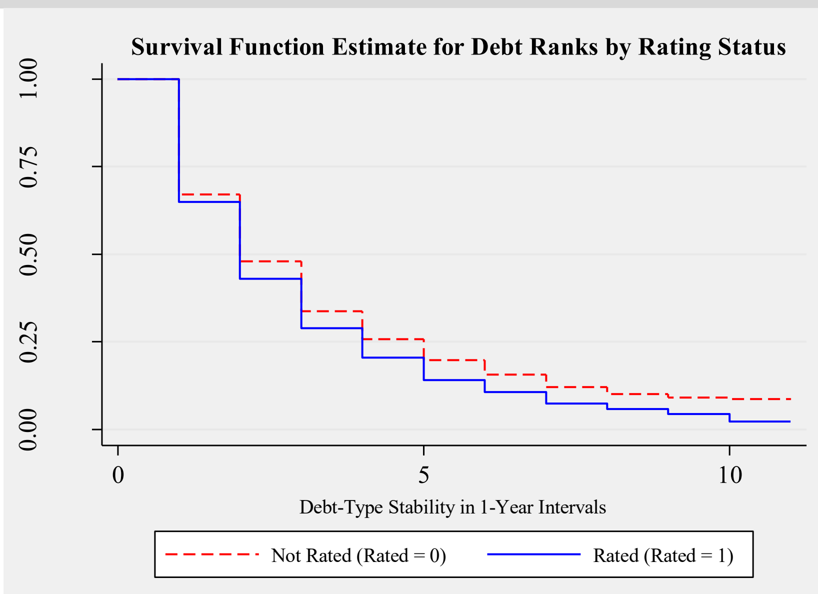


Figure 3.8. Robustness: Clustering using alternative debt categorizations

This figure shows the results of a clustering analysis using the alternative debt categorization similar to Colla et al. (2013). To obtain these heterogeneity graphs, the debt types are first categorized into 7 distinct categories; namely: (1) commercial papers, (2) lines of credit, (3) term loans, (4) senior debt, (5) subordinated debt, (6) capital lease and (7) other debt. Then for each year (or over ten years), the ratio of each debt type to the total debt is calculated as the percentage of that particular debt type in a firm's total debt. Stata's KMEANS command and the Calinski-Harabasz stopping rule are used in grouping these percentages into the most efficient number of clusters (7). The horizontal axis shows the seven debt types, the vertical axis is the portion of that debt type in the firm's total debt and the figure's depth shows the clusters of 1 to 7.

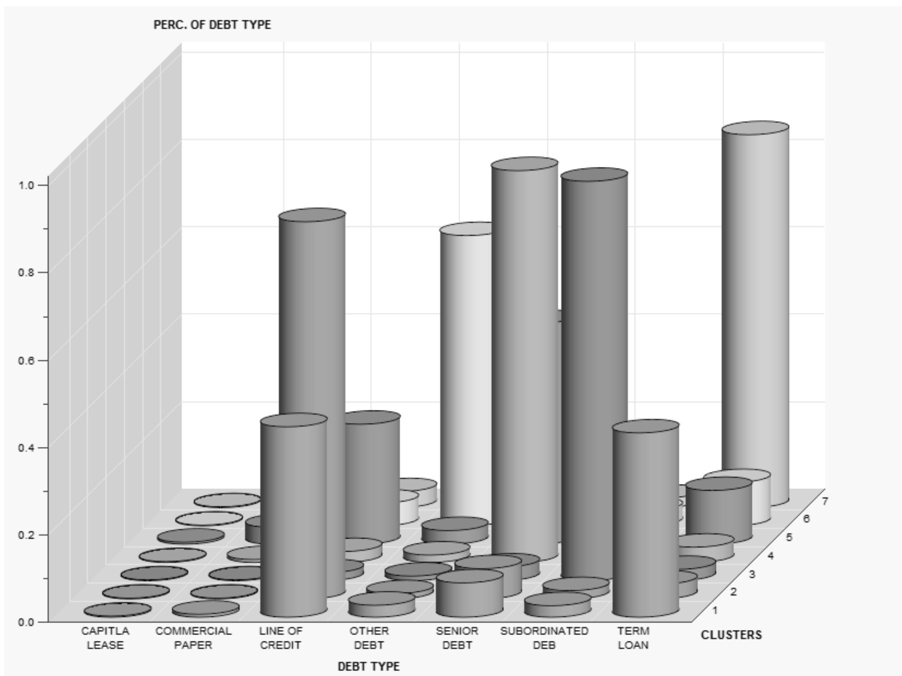


Figure 3.9. Robustness using an alternative number of clusters

This figure shows the results of a clustering analysis based on Stata's KMEANS using the alternative debt categorization similar to Colla et al. (2013) with an arbitrarily chosen 7 clusters instead of using the Calinski-Harabasz stopping rule. To obtain these heterogeneity graphs, the debt types are first categorized into 7 distinct categories; namely: (1) commercial papers, (2) lines of credit, (3) term loans, (4) senior debt, (5) subordinated debt, (6) capital leases and (7) other debt. In each year (or over ten years), the ratio is calculated of each debt type to the total debt as the percentage of that particular debt type in a firm's total debt. The horizontal axis shows the seven debt types, the vertical axis shows the portion of that debt type in the firm's total debt and the figure's depth shows the clusters. The left and right graphs use firm-1year and firm-12year observations, respectively.

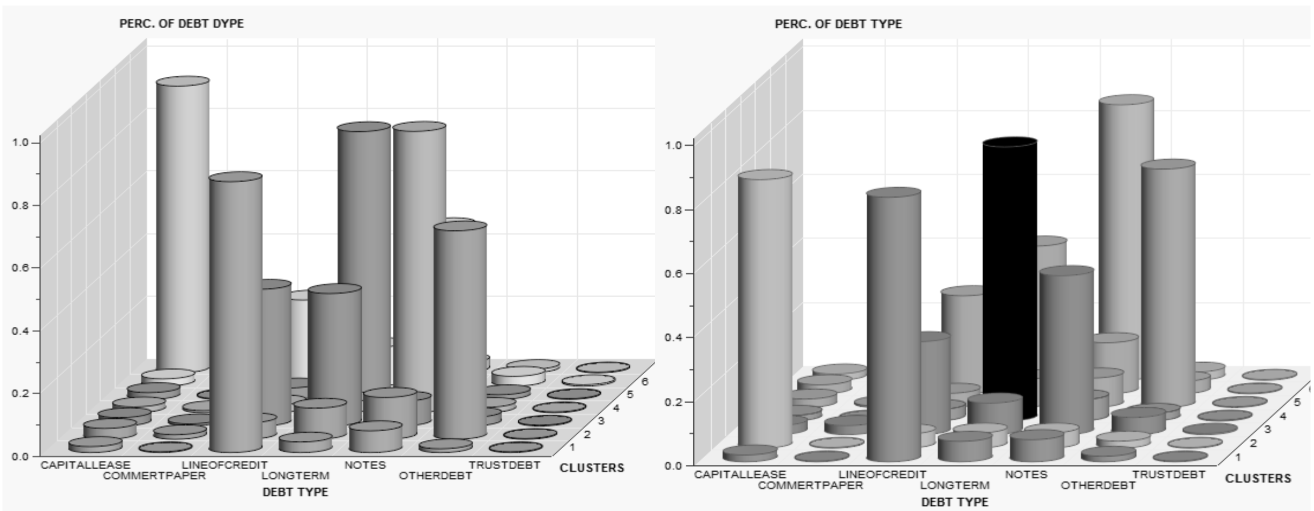


Figure 4.1. Model

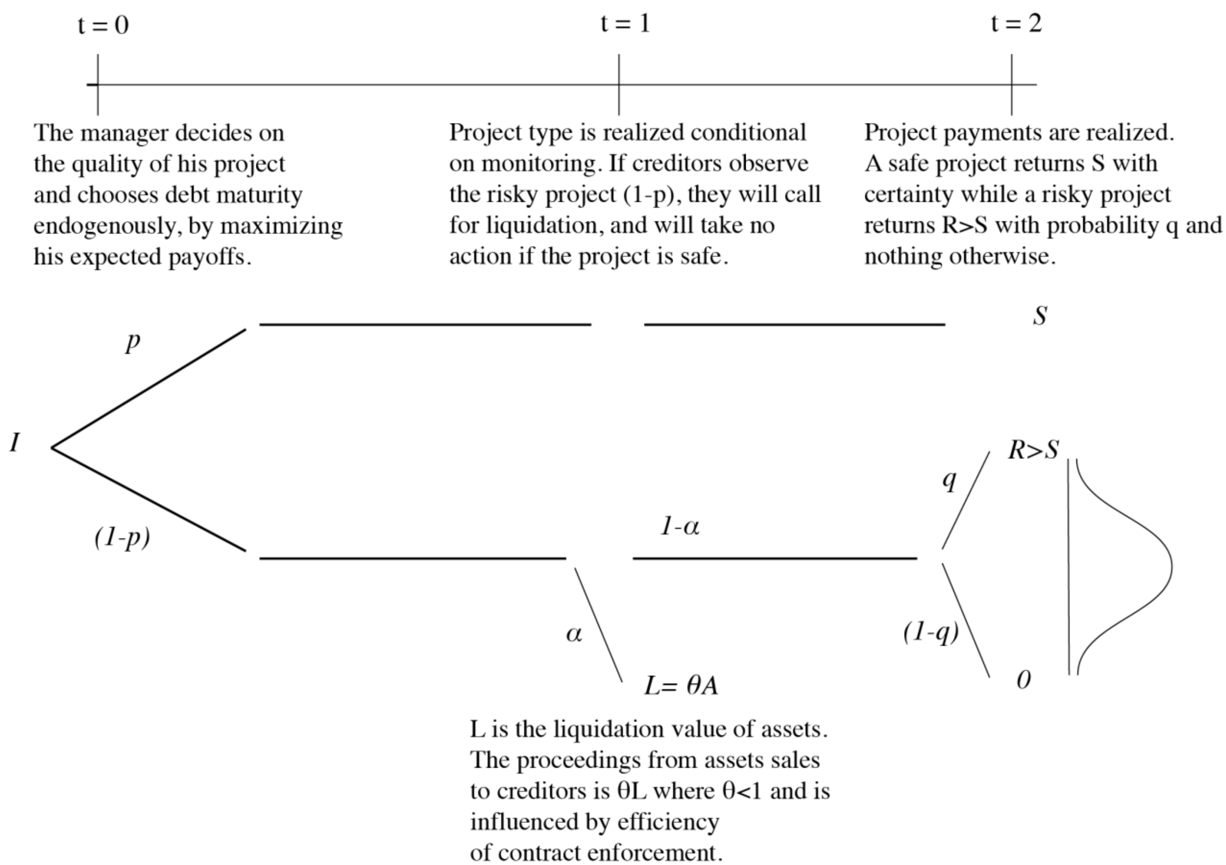


Figure 4.2. Summary statistics

This figure shows the relative position of countries based on their average corporate ratio of long-term to short-term debt. The average maturity in a given country is taken both across time and across all firms with headquarters in that country. The horizontal axis shows country names and the vertical axis shows the ratio of long term to short term debt (in decimal). The maturity data are obtained from the Compustat Global Database.

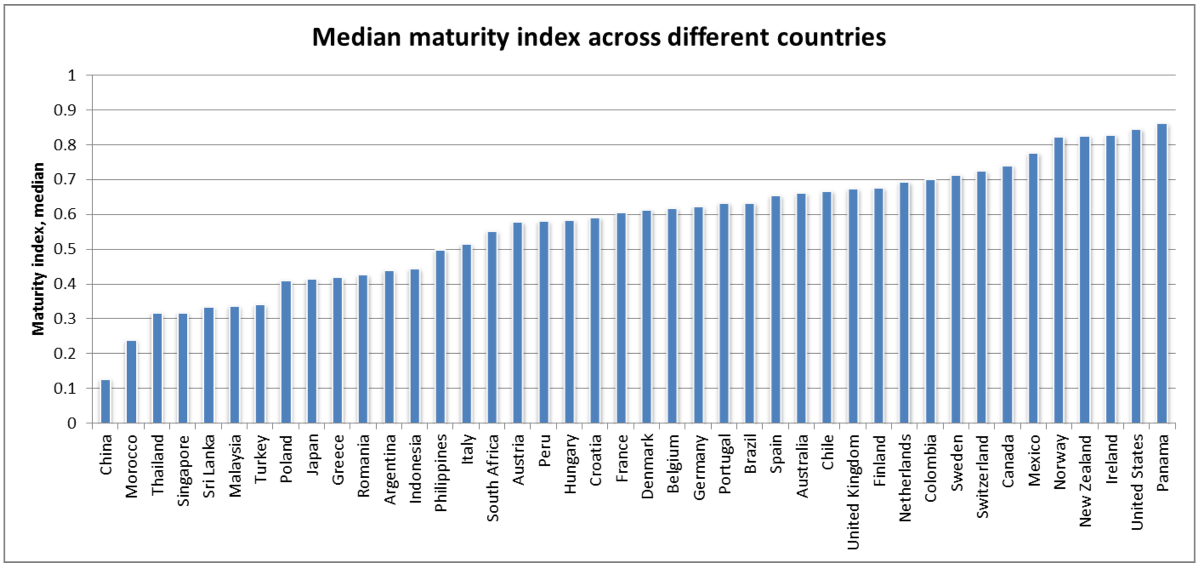


Figure 4.3. Summary statistics for the weighted-average maturity index

This figure plots the weighted-average maturity index. The index for a given country is taken both across time and across all firms with headquarters in that country. The horizontal axis shows country names and the vertical axis shows the weighted average debt maturity index (in years) for the firms in each country.

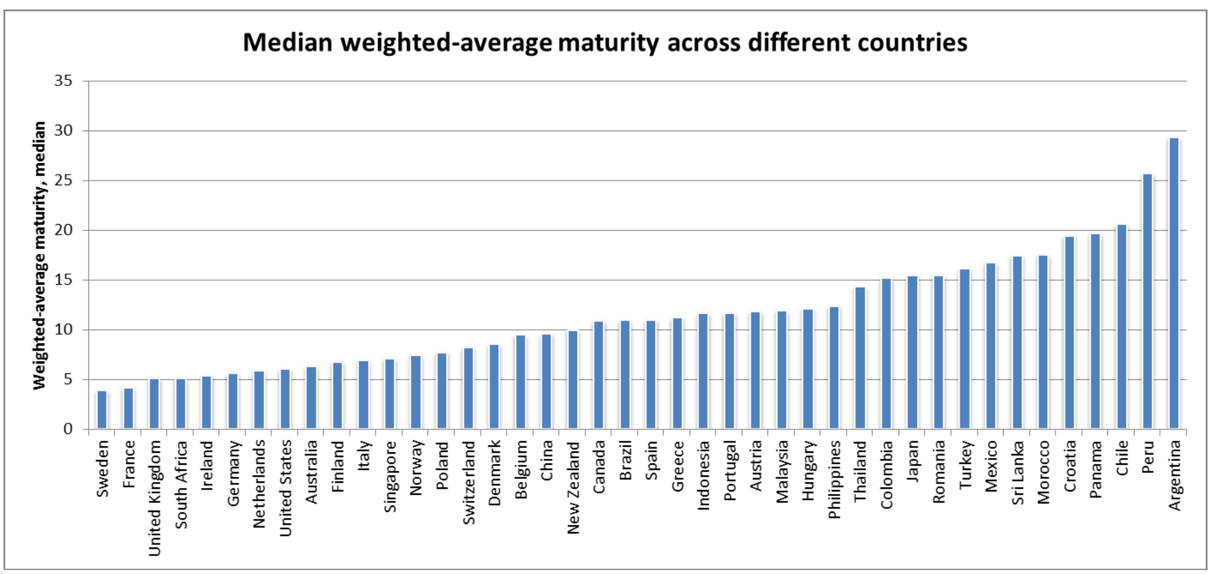


Figure 4.4. Creditor rights index across different countries

This graph shows the level of the creditor rights index across different countries. This index is the sum of four different dummy variables, where each measures a different aspect of creditor rights protection. The index takes integer values from [0, 4]. Higher levels of this index indicate stronger creditor rights and hence better protection for creditors. The horizontal axis shows country names and the vertical axis shows the creditor-rights index for the firms in each country.

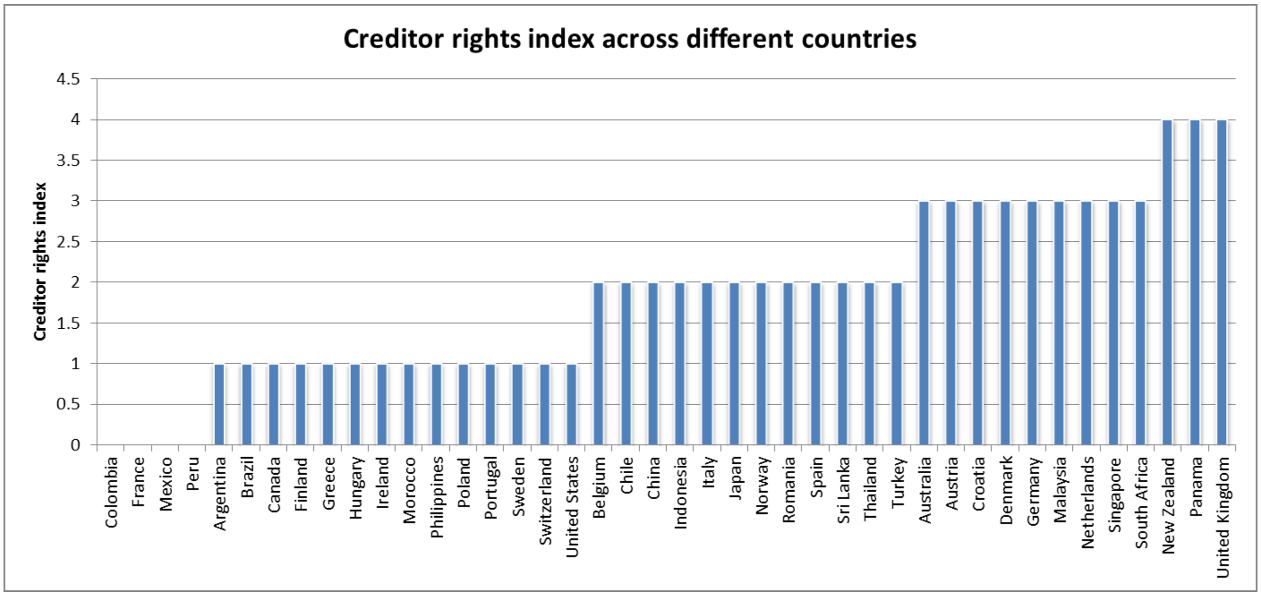
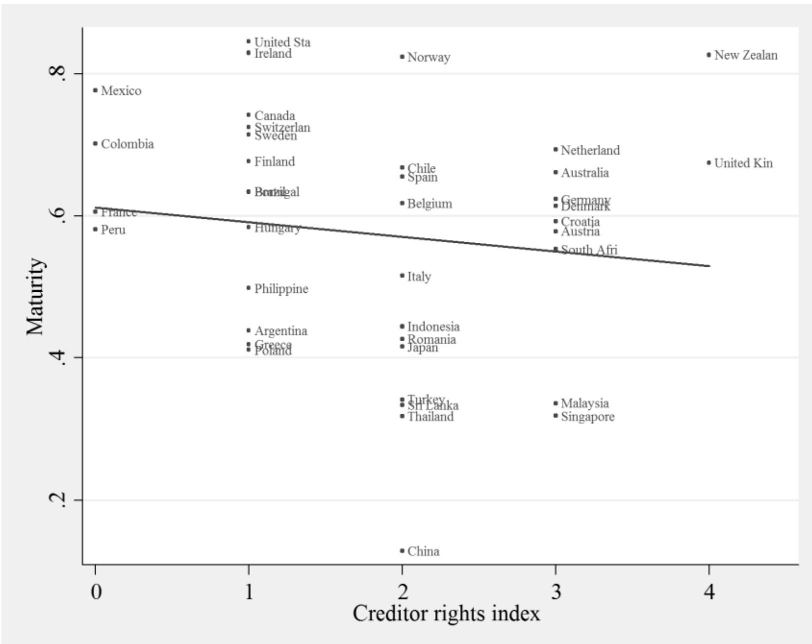


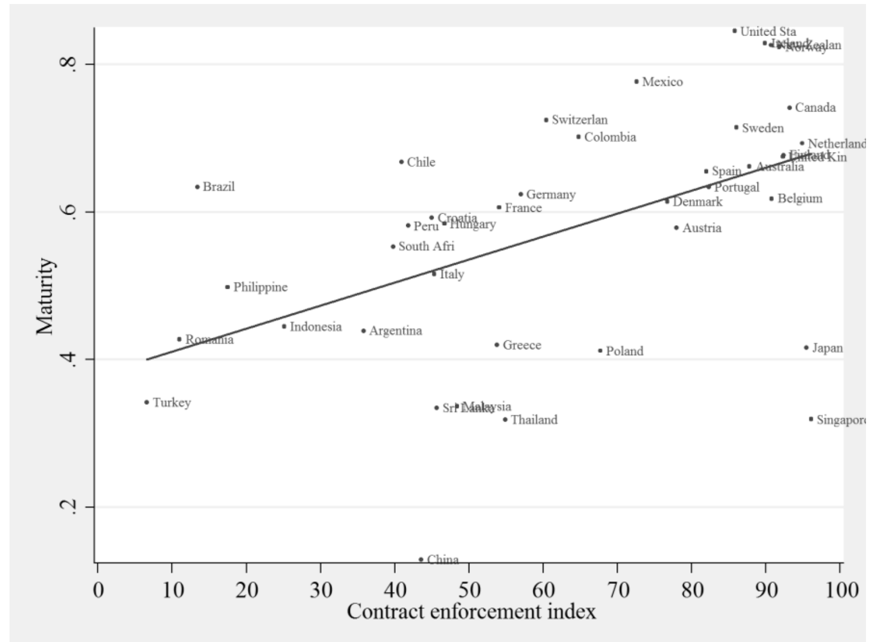
Figure 4.5. Plot of the two maturity indexes against the creditor rights index

Figure 5 provides a plot of the relationship between the creditor rights index and debt maturity as measured by the ratio of long-term debt to total debt (decimal) in Figures 5a and 5b and by the weighted-average maturity index (number of years) in Figures 5-c and 5-d. The maturity index for each country is the average over time and across firms in that country. The interpolation line is plotted using a simple OLS regression.

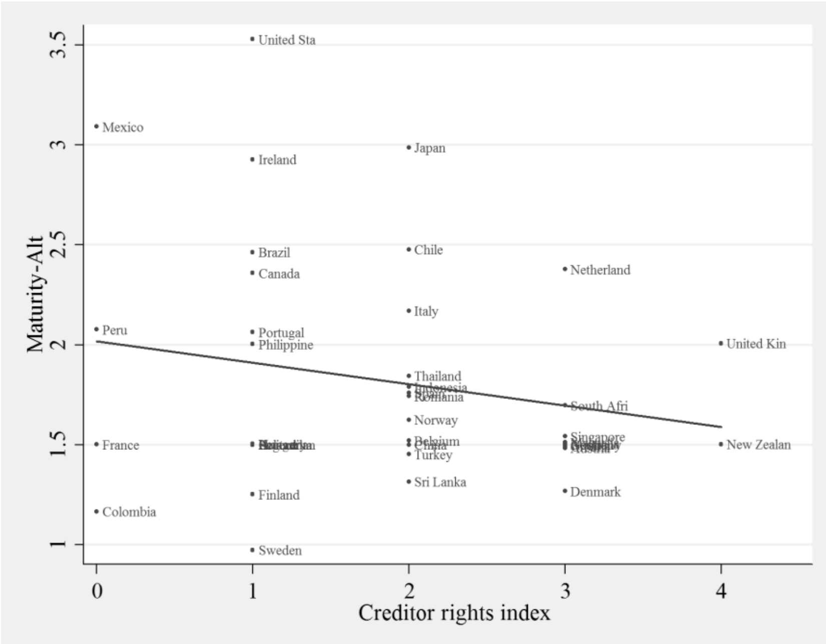
(Figure 5-a)



(Figure 5-b)



(Figure 5-c)



(Figure 5-d)