# When Do Firms Default?
# A Study of the Default Boundary

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**Abstract**

This paper studies whether default is triggered by low market asset values or by liquidity shortages, corresponding to economic versus financial distress. Default is often assumed to occur when market assets fall below a certain boundary. Consistent with this hypothesis, some low-value firms default despite sufficient liquidity. However, liquidity shortages can precipitate default at high asset values when firms are restricted from accessing external financing. Moreover, many distressed firms do not default for years. As a result, even though boundary-based default predictions can match observed average default frequencies, they misclassify a large number of firms in cross-section.

*Keywords:* Credit risk; Default boundary; Liquidity; Default; Covenants

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# Introduction

Understanding what precipitates default is central to the analysis of capital structure, financial reorganization, and credit risk. Assumptions about the conditions that result in default are always present, either explicitly or implicitly, in any discussion involving risky debt. A multitude of such assumptions can be found in different areas of financial research. Structural models of credit risk assume that firms default when they violate a debt covenant, their cash flow falls short of required debt payments, their assets become more valuable in competitors' hands, or their equityholders decide that servicing the debt is no longer in their best interests. Empirical studies of distressed reorganizations associate distress with large negative equity returns or low cash flows relative to interest payments. And theoretical corporate finance models relate default to an insufficient net worth combined with a cash crisis.[1] In essence, default usually is thought of as triggered by some measure of distress crossing a threshold level, or *default boundary*.[2]

Understanding the properties of the boundary is key to formalizing the description of the default event and quantifying default expectations. Yet the profusion of theoretical assumptions regarding the default boundary stands in sharp contrast with the surprising shortage of evidence assessing their empirical validity. Can distress be measured by a single variable, or are there several default triggers? Are such factors independent, or do they interact in some way? And is there a sharp boundary value for these factors that separates defaulting and nondefaulting firms? This paper is the first systematic study aimed specifically at addressing these questions on the basis of distress concepts identified in the theoretical literature.[3]

Despite the notable diversity of assumptions, most theoretical default triggers can be classified broadly according to whether they are related to financial or economic distress. The firm is financially distressed when it has difficulties honoring its financial obligations. Even when the business is fundamentally sound, temporary declines in cash flows may result in the inability of highly-levered firms to make promised debt payments. In contrast, economic distress is not related to the presence of debt, but rather arises when

[1] Any list of related studies in this area is necessarily incomplete. Examples of structural credit risk models with different default triggers include Kim, Ramaswamy, and Sundaresan (1993), Leland (1994), Longstaff and Schwartz (1995), and Hsu, Saá-Requejo, and Santa-Clara (2002). Empirical studies of reorganization that use different criteria for selecting distressed samples are Asquith, Gertner, and Scharfstein (1994) and Gilson, John, and Lang (1990). Theoretical models of the default decision are discussed in Bulow and Shoven (1978) and White (1989). Credit scoring models include Altman (1968, 2000), Zmijevski (1984), and Ohlson (1974).

[2] A different approach is adopted by reduced-form credit risk models (Jarrow and Turnbull (1995), Duffie and Singleton (1999)), which assume that the timing of default is random and inaccessible. Duffie and Lando (2001) point out that incomplete information implies that default is random for investors who do not know how far the firm is from its default boundary.

[3] Related evidence comes primarily from ad hoc empirical bankruptcy-predicting models. For example, in Altman (1968, 2000) $z$-scores of firms that become bankrupt within a year are generally below 1.81, those of safe firms are above 2.67, and in between lies the "zone-of-ignorance" where the outcome is uncertain. Because such models are not grounded in theory, their predictions are not always robust across different studies (Begley, Ming, and Watts (1996), Shumway (2001)). In contrast to such studies, this paper attempts to evaluate existing theoretical assumptions about the default boundary rather than build a better forecasting model.

the firm's prospects deteriorate and the value of its business decreases. Because the degree of the firm's economic prosperity is reflected in the market value of its productive assets, economically distressed firms can be identified by declining asset values, even though they may have no immediate difficulty making ongoing debt payments.

The idea that default is driven by economic distress is behind default triggers expressed in terms of market values or returns (e.g. Gilson, John, and Lang (1990), Leland (1994), Longstaff and Schwartz (1995)). This approach is de facto standard in structural models of credit risk. Since Black and Cox (1976), most such models assume that the firm defaults when the market value of its productive assets falls below a certain boundary, which may be exogenously specified or endogenously determined by stakeholders. In value-based models, should a temporary reduction in cash flow lead to a liquidity crisis, shareholders will meet the required debt payments by raising outside financing, as long as the asset value remains above the boundary. This assumption renders purely financial distress irrelevant. A contrasting view postulates that financial distress and cash shortages do cause firms to default, which justifies the use of liquidity measures as distress indicators (e.g. Asquith, Gertner, and Scharfstein (1994), Kim, Ramaswamy, and Sundaresan (1993), DeAngelo, DeAngelo, and Wruck (2002)). Due to various market frictions, the distressed firm may be unable to raise necessary external financing, even when it is profitable to do so. Consequently, temporary cash shortages may result in the firm's inability to meet its current financial obligations, despite the fundamentally sound nature of its business.

Depending on whether default is believed to be primarily "liquidity-driven" or"value-driven," sharply different predictions arise regarding the states in which it occurs, implying different default probabilities, recovery rates, and security values. Nonetheless, there is little systematic evidence about the role of value and liquidity in precipitating default. It is not clear whether the two factors are distinct, how they interact, and to what extent they are sufficient for explaining observed defaults.

Using a unique sample of risky firms with observed market values of equity, bonds, and bank debt, I investigate whether default is associated with insufficient cash reserves relative to required payments or with low market values of assets relative to debt. My main findings can be summarized as follows. At default, most firms are insolvent both economically *and* financially: The average market value of assets at default is only 60% of the face value of debt, and liquidity ratios are below the industry median for 80% of defaulting firms. Persistent economic distress seems to drive financial distress, as money-losing firms run out of the liquid assets necessary to pay their creditors and suppliers. However, low-value and low-liquidity firms may be distinct. As many as 13% of firms default at low asset values despite the presence of liquid assets in excess of current liabilities, which suggests that "pure" economic distress is important. Furthermore, market asset values exceed the face value of debt for at least 10% of firms at default. Although these firms are clearly solvent economically, they appear to have liquidity problems. Finally, many distressed low-value and low-liquidity firms are able to avoid default for years. In fact, a *majority* of "negative economic net worth" firms, whose market value falls short of the face value of debt, do not default for at least a year. Taken together, these findings suggest that although economic and financial distress are closely related, neither factor alone can fully explain observed defaults.

I hypothesize that the relative importance of financial versus economic distress depends on the availability and costs of external financing. A transitory cash shortage can trigger default only to the extent that the firm is restricted from raising new financing against its remaining assets (or selling some of them). In the absence of such restrictions, firms can overcome liquidity shortages by raising new cash as long as the firm's business remains valuable. Thus, if external financing is costless, then cash shortages are irrelevant, and the firm does not default until a certain level of economic distress. In contrast, if the required cash cannot be raised at any cost, any temporary cash shortage will push the firm into default, despite its sound economic fundamentals. Between these two extreme cases, firms for which external financing is neither costless nor infinitely costly should be able to overcome some but not all liquidity shortages. Consistent with this conjecture, I find that, after controlling for the market value of assets, liquidity shortages are significantly related to default only when external financing is difficult to obtain, for example, because of the presence of restrictive covenants, a lack of collateralizable assets, or the depressed state of the junk loan market. For unconstrained firms, cash shortages are typically inconsequential. Thus, not only are value and liquidity potentially distinct default triggers, but their relative importance depends on financing constraints.

These findings suggest that in the presence of financing frictions, firms will be motivated to carry cash reserves to minimize the probability of a cash shortage, which likely contributes to the high importance managers attach to financial flexibility and financial slack in capital structure and financing policy decisions (Graham and Harvey (2001), Servaes and Tufano (2006)). The evidence regarding the role of value and liquidity in triggering default implies that to describe default accurately it is important to account for the firm's endogenous cash policy and financing costs. This approach has been recently adopted by Acharya et al. (2006), Anderson and Carverhill (2007), and Asvanunt, Broadie, and Sundaresan (2007), who incorporate financial slack into a dynamic structural framework. These models provide a multitude of new insights, but their complexity typically necessitates numerical solutions.

Given that accurate representation of all relevant factors is challenging, how large is the potential error implied by a simple approach that assumes that default is driven by the asset value only? Although value is the best among univariate default predictors, there is no pronounced boundary separating defaulting and nondefaulting firms, both because different firms default at very different asset values, and because the number of firms that do not default when their asset value is low is comparable to the number of firms that do. The threshold value of assets that equalizes the number of defaults above the boundary with the number of nondefaulting firms below it, and thus correctly "predicts" the observed default frequency, is 68% of the face value of debt. Leland (2004) uses a similar boundary level and finds that value-based structural models generate long-term default probabilities that are in line with observed historical default frequencies. Yet notwithstanding this agreement of the data with theory *on average*, in my sample, between one-quarter and one-third of all defaults occur at asset values above the best "average" boundary, and an equal number of firms below it do not default for at least a year. These firms would be misclassified by the boundary rule.

Thus, value-based default predictions result in significant cross-sectional errors, even when they are calibrated to perform well on average. These findings suggests that the lack of cross-sectional accuracy of debt-pricing models and their inability to match the short-term probability of default (Eom, Helwege, and Huang (2004), Leland (2004)) may be attributable in part to the inherent limitations of their approach to specifying the default trigger. In light of this evidence, advancing models that accept a degree of unpredictability of default resulting from information imperfections (Duffie and Lando (2001)) may help improve understanding of cross-sectional determinants of credit risk.

Finally, I study the role of covenant violations in triggering payment defaults. If covenants are set so tightly that violations may occur even in the absence of severe financial or economic distress, and if creditors routinely accelerate repayment upon a covenant violation, ignoring financial covenants may result in an underprediction of the probability of default. I find that covenant violations, renegotiations, and waivers are widespread for the sample firms close to default, and not uncommon for nondefaulting firms as well. Moreover, at least 8% of all bond payment defaults are triggered by a covenant violation that prompts senior creditors to prevent the firm from making a scheduled bond payment, which almost invariably results in bankruptcy. However, other than cases that involve fraud and other irregularities, asset values for covenant-triggered defaults are similar to those of other defaulting firms, which suggests that covenants are rarely enforced unless the firm is economically insolvent. As a result, knowledge of firms' covenant structure appears to add relatively little to our ability to predict default.[4]

[4]This finding pertains to financial covenants, which allow creditors to accelerate repayment when certain performance requirements are not met. In contrast, negative covenants that restrict certain actions, such as asset sales or additional borrowing, may precipitate default indirectly through their effect on investment and the availability of external financing.

The remainder of this paper is organized as follows. Section I discusses the assumptions regarding the default trigger used in the extant literature. Section II describes the data set. Section III compares value and liquidity as potential default triggers, and Section V reports classification properties of boundary-based default predictions. Section VI studies the role of covenants in triggering default. Section VII concludes. Details of the procedure used to estimate the market value of assets are given in the Appendix.

# I. Literature review

Explicit formal assumptions regarding the nature of the default trigger appear most commonly in structural models of credit risk. The de facto standard approach is to assume that default happens when the market value of the firm's assets falls below a certain threshold level, referred to as the default boundary. This approach was introduced by Black and Cox (1976) and extended by Leland (1994) and Leland and Toft (1996). It implies that default is driven by economic rather than financial distress. The level of the boundary may be specified exogenously by existing covenants, typically in relation to the face value of debt. For example, the negative economic net-worth boundary postulates that default happens when the market value of assets falls below the face value of debt for the first time. In other models, the firm's equityholders choose the boundary endogenously as the value of assets at which default becomes their preferred outcome.[5] In models with endogenous default the firm's operating cash flow may at times fall short of required current debt payments, in which case equityholders continue to meet debt obligations and cover the cash shortage by selling newly issued equity, as long as the equity option value is higher than the required debt payment. Once the asset value falls below a certain point, the hopes of recovery become so remote that new funds cannot be raised, no matter how much dilution existing owners are prepared to suffer.[6] Models with exogenous (covenant-triggered) default can support a range of boundary levels, including, as a special case, the level implied by endogenous boundary models, which corresponds to the lowest asset value compatible with a non-negative value of equity.

Although used most often, asset value is not the only default trigger employed in the literature. Some models assume that default happens when the firm's instantaneous cash flow is insufficient to service its

[5]The assumption of an exogenous value-based boundary appears in, among others, Longstaff and Schwartz (1995) and Collin-Dufresne and Goldstein (2001). The endogenous boundary is modeled in Leland (1994), Leland and Toft (1996), and Acharya and Carpenter (2002); Fan and Sundaresan (2000) also allow for strategic default. Some modifications distinguish between default and liquidation (François and Morellec (2004), Broadie, Chernov, and Sundaresan (2007), Galai, Raviv, and Wiener (2007)). Some models, such as Mella-Barral (1999) and Hsu, Saá-Requejo, and Santa-Clara (2002) assume that the default boundary is stochastic and related to the value of the firm's assets in the best alternative use, implying that liquidation can optimally occurs at a positive asset value, even without debt.

[6]Most models also assume that debt covenants prohibit asset sales. If unrestricted asset sales were possible, the firm would be able to service current obligations by selling assets until nothing is left; such behavior would severely damage long-term creditors. See Black and Cox (1976) for a discussion.

current obligations (Kim, Ramaswamy, and Sundaresan (1993), Anderson and Sundaresan (1996), Ross (2005)). In such models, external financing is typically prohibited, and firms do not maintain a cash reserve. As a result, this approach is equivalent to assuming an exogenous "debt service coverage" covenant that specifies that default is triggered whenever cash flows fall short of required debt payments. Moreover, in the absence of cash holdings, in most such models the market value of assets is always proportional to the current cash flow. As a result, the default trigger specified in terms of a threshold cash flow is equivalent to one that uses the boundary market value of assets.[7]

A critical difference between value-based and cash-based models involves their assumptions about the availability of external financing. A pure cash-based default corresponds to the case when new financing is not accessible, no matter how attractive the investment; an endogenous default happens when investors are accessible at zero cost but unwilling to contribute any funds. In reality, new financing is neither costless nor infinitely costly, and as a result, both liquidity and value likely affect the timing of default. Moreover, in the presence of financing frictions there is scope for an optimal cash management policy, because firms may accumulate cash reserves during good times to reduce the necessity for costly outside financing during bad times when cash flows are low. Yet few extant models explicitly consider cash holdings and financing costs. Recent studies by Acharya et al. (2006), Anderson and Carverhill (2007), and Asvanunt, Broadie, and Sundaresan (2007) that incorporate optimal financial slack in the dynamic framework suggest the need for numerical methods to analyze such models.

It is not clear whether the benefits of a general framework that accounts both for economic and for financial distress outweigh its costs due to complexity, compared with the parsimonious representation of default as a first passage time through a value boundary. Extant empirical studies provide no guidance regarding the role of value and liquidity in triggering default. This lack of evidence is especially troubling because models' predictions are highly sensitive to their assumptions about the default trigger. Even within the class of models that use a value-based default boundary, different boundary *levels* result in vastly different predictions, as illustrated in Figure 1. It plots the predicted probability of default in first-passage time models under Leland's (2004) base case parameter values as a function of the assumed default boundary normalized by the face value of debt.[8] For BBB-rated debt, varying the level of the boundary from 0.6 (used in Huang and Huang (2003)) to 1.0 (assumed in Longstaff and Schwartz (1995)) changes the predicted ten-year probability of default from 2.5% to 13.8%. Such sensitivity implies that an empirical evaluation of the

[7]Fan and Sundaresan (2000) allow default to be triggered either endogenously by low asset values or by an exogenous cash flow covenant. However, the proportionality between asset values and cash flows in their model results in corner solutions, so that for a given dividend policy, the firm either always or never defaults because of a liquidity crisis.

[8]The formula for the probability of default can be found in Leland (2004). Note that not all values of the default boundary in Figure 1 may be compatible with a non-negative value of equity.

boundary assumption may be beneficial for advancing structural models of credit risk, which presently lack accuracy in explaining the cross-section of credit spreads (Eom, Helwege, and Huang (2004)) and predicting short-term default probabilities (Leland (2004)).

[FIGURE 1 HERE]

Understanding what triggers default is crucial in many areas of financial research outside risky debt pricing. Similar to the preceding models, the framework used to analyze dynamic capital structure and cash policy decisions relates default to shocks in the value of assets or cash flows (e.g. Fischer, Heinkel, and Zechner (1989), Hennessy and Whited (2007), Anderson and Carverhill (2007), and Asvanunt, Broadie, and Sundaresan (2007)). Theoretical research into firms' bankruptcy and reorganization decisions identifies net worth (the value of assets net of liabilities) as a key factor that affects their ability to raise financing in a liquidity crisis; it also addresses the diverging incentives of different claimholders in distress (Bulow and Shoven (1978), White (1989)). Empirical studies of distressed reorganizations use equity returns (Gilson, John, and Lang (1990)) or debt service ratios (Asquith, Gertner, and Scharfstein (1994)) as measures of distress. In addition, DeAngelo, DeAngelo, and Wruck (2002) point out that declines in cash flows need not trigger immediate default when firms can easily convert their assets into cash and if there are no covenants that allow creditors to enforce early reorganization. And accounting and finance textbooks suggest rules of thumb for evaluating credit risk, such as "the current ratio should be above 2." Overall, various measures of value and liquidity permeate most default triggers used in the literature. Because specific formal assumptions regarding the default boundary are spelled out explicitly in structural credit risk models, I tie my empirical tests directly to these studies.

# II. Data description

The market value of the firm's assets is defined as the value of a perpetual unlimited liability claim on future cash flows generated by the assets, assuming they are operated within the firm. It is arguably the single most important variable in the large structural modeling literature, yet for reasons of data availability, it is rarely studied empirically, especially for distressed firms. The value of firms' productive assets is not directly observable but can be proxied by the sum of the market values of financial claims on those assets, namely, equity and debt. I construct a unique data set to estimate the market values of distressed firms, for which debt is traded significantly below par, at regular time intervals.[9]

[9] A recent paper by Korteweg (2006) estimates monthly market values of assets for a sample of 244 firms. Korteweg does not have prices of bank debt, and his bond prices come from a data base of transactions by insurance companies, which happen at uneven intervals and involve few junk firms close to the default boundary. The irregular nature of transactions data necessitates approximations when measuring debt prices at monthly frequency. My data include monthly prices for 806 defaulting and

### A. Data sources and sample selection

I study the determinants of the timing of default using a sample of speculative-grade bond issuers with observed market values of equity, bonds, and bank debt, a subset of which defaulted on their public bonds during the sample period. Thus, though the primary focus of this paper is on defaulting companies, I also use a control sample to examine the decision *not* to default. The control sample is limited to junk firms (rated BB+ and below, also called speculative grade), because defaults by investment-grade firms are very rare.[10] Default events include bankruptcy filings, bond payment omissions, and successful distressed bond exchange offers.

To estimate the market value of firms' public debt, I use monthly quotes from Merrill Lynch bond trading desks for bonds included in the Merrill Lynch U.S. High Yield Master II Index (MLI) between December 1996 (the month the index was created) and March 2004. The MLI consists of speculative-grade bonds with par amounts of at least $100 million and remaining maturity of one year or more. Bank loan prices come from the LSTA/LPC Mark-to-Market Pricing Database, which includes monthly secondary market loan quotes, each obtained from several dealers. Mergent's Fixed Income Securities Database (FISD) includes descriptive information on bonds, and Loan Pricing Corporation's *DealScan* provides information on bank loans and covenants, as well as aggregate statistics for the distressed loan market. Information on types of outstanding debt, including the use of credit lines, is manually collected from 10-K filings. I use bond, loan, and equity prices in conjunction with the debt structure data to estimate monthly market values of total debt and equity. The estimation procedure is described in detail in the Appendix.

The data set consists of all firms included in the MLI at least once between December 1996 and March 2004. I first exclude all financial firms and all non-U.S. firms, and then manually merge the remaining firms with Compustat, CRSP, FISD, and DealScan, taking into account mergers, acquisitions, and name changes and excluding all firms that cannot be merged reliably. Finally, I check several sources of information on defaults and retain only those firms for which I can unambiguously establish whether they defaulted during the sample period. Accounting data are from quarterly Compustat, and monthly equity prices are from CRSP.[11] The final sample consists of 806 junk firms, 213 of which defaulted at least once between 1997 and 2005.

nondefaulting junk firms and involve few approximations.

[10]Collin-Dufresne, Goldstein, and Helwege (2003) notice that since 1937, only four firms with an investment-grade rating from Moody's have defaulted on their bonds.

[11]On some occasions, a firm is delisted from the stock exchange a few months prior to default (typically because the share price falls below the exchange's threshold), so I obtain market equity prices from quarterly Compustat and extrapolate them to yield monthly prices using a simple linear approximation. The potential errors from this approximation are immaterial, because total equity values for these firms are small compared with the value of debt.

Despite these detailed data and the exclusion of cases with uncertain data quality, the estimates of the market value of a firm's productive assets as a sum of the values of its debt and equity clearly represent an approximation. If default is costly and partially anticipated by investors, observed market values of financial claims such as debt and equity will not sum up to the market value of assets under the assumption that assets remain operated within the firm forever. In other words, market prices of debt and equity may be contaminated by expectations of future default costs. In theory, these costs can be positive or negative, depending on transaction costs and the difference between the value of assets in continuation and their value in the best alternative use. In practice, they appear positive on average (Andrade and Kaplan (1998), Korteweg (2006)), which implies that the sum of debt and equity may underestimate the continuation value of assets.

The potential bias in measured asset values that this effect induces depends on the size of the liquidation costs, as well as the extent to which the market anticipates default. If investors are fully informed and know default is certain and imminent, then the prices of debt and equity should reflect their expected "recovery values" rather than their value under the status quo of continued operations, and upon default prices should not move. However, in practice, default induces large changes in debt and equity prices, implying that default events are not fully anticipated by the market.[12] Duffie and Lando (2001) and Jarrow and Protter (2004) study security pricing when investors are uncertain about either the value of assets or the default boundary and hence cannot predict default perfectly. Even though the values of debt and equity for distressed firms are affected by recovery expectations, they remain informative about the continuation value of assets. As Section III documents, price reactions to default in my sample are similar in magnitude to the total costs of financial distress (Andrade and Kaplan (1998), Korteweg (2006)), which suggests that the information content of observed asset values is high. Still, the numerical estimates should be interpreted with caution. My regression analysis employs instrumental variables to account for the fact that measured market values may be contaminated when the perceived probability of default is high. Moreover, as will become clear below, reversing the possible downward bias in estimated asset values either would not affect the main conclusions of the paper, or might make them stronger.

## *B. Sample of defaults*

"Cashflow" or "payment" defaults on public bonds are failures to supply bondholders with the cash flows stipulated in the bond contract. Rating agencies record payment defaults on all bonds with an assigned

[12] Various articles examine the behavior of stock prices around bankruptcy filings and find significant market activity and returns, suggesting that bankruptcy announcements are far from fully anticipated (e.g., Aharony, Jones, and Swary (1980) and Clark and Weinstein (1983)). See also Subsection III.A.

rating. I adopt the definition of default used by the rating agency Moody's, which includes bankruptcy filings and out-of-court workouts with bondholders through either a distressed bond exchange or payment delays or omissions.[13] Driven primarily by data availability, this focus on bond defaults as defined by rating agencies implies that certain distress reorganization events do not appear in the analysis. First, this study is limited to firms that have outstanding public bonds. Second, firms that restructure their private debt or attempt to renegotiate their bonds *unsuccessfully* are not considered in default as long as they continue uninterrupted bond service, as per the bond contract. Third, covenant violations per se do not change creditors' payoffs and therefore do not constitute an event of default. However, covenant violations allow creditors to require immediate repayment of principal, and as such may precipitate a payment default. For this reason, I study the role of covenants in triggering default in Section VI. Thus, though the adopted definition of default does not embrace all distressed reorganizations, it includes all payment defaults on public bonds, which are the main focus of most credit risk studies.

The master list of defaults is based on the May 2006 issue of Moody's Default Risk Service (DRS) database, which purports to include all defaults since 1970 on bonds whose rating Moody's is authorized to publish. To identify possible omissions in the DRS database, I cross-check it against Standard & Poor's *LossStats* and *CreditPro* databases and default records in FISD. On the few occasions that default events reported in these databases are missing from DRS and could not be confirmed independently, I exclude the firm from the sample. For distressed exchanges, DRS reports the date of successful completion as the date of default. Because the date of the announcement of the bond exchange is more relevant for studying the timing of the default decision, I collect information on announcement dates from news reports in Factiva. I also use Factiva to determine the outcomes of defaults not yet available in DRS.

Not all defaults in DRS are independent events. First, firms often default together with their wholly owned subsidiaries. If both the parent company and its subsidiaries issue Moody's-rated bonds, several entries may be registered in DRS for different legal entities, even if the defaults all result from one default decision by the parent company. This scenario is especially common for financial subsidiaries of industrial firms. I manually analyze the data to identify such cases and use the parent's consolidated financial information to study the default decision for the whole group of bond issuers. Second, for some companies, DRS reports multiple default events within a short period of time. Because not all of these events are independent, I combine

[13]Moody's defines bond default as "any missed or delayed disbursement of interest and/or principal, bankruptcy, receivership, or distressed exchange, where (i) the issuer offered bondholders a new security or package of securities that amount to a diminished financial obligation (such as preferred or common stock, or debt with a lower coupon or par amount), and (ii) the exchange had the apparent purpose of helping the borrower avoid default"(Keenan, Shtogrin, and Sobehart (1999), p. 10). Standard and Poor's adopts a similar definition; the minor differences pertain to grace period defaults and defaults on preferred stock.

defaults for each company if they happen within two years of the first event. These adjustments reduce the number of defaults by non-financial U.S. firms in DRS between 1997 and 2005 from 663 to 589.

Column (1) of Table I shows the number of independent defaults on Moody's-rated bonds since records started in 1970, and column (3) gives the number of defaults in the study sample. Due to a dramatic increase in the number of defaults at the turn of the century, the nine year sample period 1997 to 2005 covers 55.3% of all defaults since 1970. In total, the sample includes 213 defaulted firms, or 36.2% of all bond defaults during the sample period. Twelve firms defaulted twice during the sample period; to ensure comparability, I study only the first default event.

In addition to defaulted firms, the sample includes 593 junk firms from the Merrill Lynch High Yield II Index that did not default during this period. Thus, the overall sample consists of 806 high-yield firms, including 213 firms that defaulted 225 times between 1997 and 2005. The industry composition of the sample appears in Table II. During this time, defaults by telecom firms were particularly common (20.7%), followed by wholesale and retail firms (16.3%) such as KMart and Fleming Cos. Among industrial manufacturers, bankruptcy filings by steel producers such as Bethlehem Steel were frequent. The sample also includes several bankrupt airlines, such as United and Delta.

[TABLES I AND II HERE]

Table III reports the number of sample defaults by the type of the first default event and subsequent bankruptcy, if any, as well as by the eventual outcome. As Panel A shows, 37.1% of firms default by filing for bankruptcy directly, 54.0% miss or delay a payment, and 8.9% complete a distressed bond exchange. In addition, Panel B reports that 87.8% of payment omissions and 31.6% of successful distressed exchanges lead to a bankruptcy filing within two years of the first default event. Of the 186 sample bankruptcies, 88.2% are "traditional" Chapter 11 filings, and the remaining cases are prepackaged Chapter 11s. Only 12.7% of bond defaults do not involve bankruptcy, which corresponds in almost equal parts to successful distressed exchanges and missed or (more often) delayed payments. Finally, Panel C of Table III reports the eventual outcomes of default. Of the 179 bankruptcies resolved as of the time of writing, in 148 (82.7%) the firm successfully emerged from Chapter 11, whereas the rest were either acquired or liquidated.

[TABLE III HERE]

## *C. Descriptive statistics*

Table IV reports the general descriptive statistics for firms at default and the control sample of firm months not followed by default within a year. The "nondefaulting" control sample consists of 593 firms that do not default throughout the sample period, as well as the firm-month observations for defaulting firms preceding the default date by at least a year. For each firm in the control sample, I calculate the sample period mean of each variable and report descriptive statistics for this set of firm means. Panel A of Table IV shows that defaulting and nondefaulting firms with outstanding junk bonds are large and do not differ much in terms of book assets or sales to assets ratios. Almost two-thirds of their debt is in bonds, and bond maturity is higher for nondefaulting firms. Up to 85% of defaulting firms are original-issue junk issuers, meaning that none of their outstanding bonds have ever had an investment grade rating. More "fallen angels" appear in the control sample: Only 69% of nondefaulting firms are original junk issuers. The median nominal share price at default is only \$0.84 compared with \$19.30 for nondefaulting junk firms.

Differences in the equity price mirror major differences in profitability and net worth, reported in Panel B of Table IV. At default, the median profit margin (ratio of pretax income to sales) is –21%, and the mean is –226%. Accounting income is negative for 93.1% of defaulting firms. Moreover, as many as 81.1% have negative operating cash flow. Because these firms cannot finance their operations from cash flow, they must rely on either external financing or existing liquid asset reserves. Junk firms that do not default for at least a year still show negative average profitability (–20.3%), but it is driven by a much smaller number of firms (33.8%) that are making losses during the sample period, and the proportion of negative cash flow firms in the control sample is only 17.1%. Continuing losses erode firms' net worth, so the majority of firms at default (58.9%) have negative book equity, compared with only 12.5% of the control sample. Finally, 39.4% of defaulting firms are in distressed industries, defined as industries with a median equity return in the previous year of less than –30%. This proportion is only 11.4% for the control sample.

[TABLE IV HERE]

Finally, Panel C of Table IV groups variables that have been identified in the theoretical literature as potential determinants of the equity's endogenous default boundary (Leland and Toft (1996)). Both the average debt coupon rate and the overall firm's cash payout ratio (defined as the sum of cash payouts to debt and equity as a proportion of its market value) are higher for firms at default. The average volatility of the monthly asset returns is also somewhat higher for defaulting firms, at 0.327, compared with 0.303 for the control sample. Statistics for the ratio of the replacement cost of tangible assets, such as fixed and current assets, to the book value of total assets suggests that the proportion of valuable tangible assets is higher for firms at default. Further discussion of the variables in Panel C is provided in Section IV. Overall, Table IV thus shows that, though defaulting and nondefaulting firms are similar along many dimensions, the latter have longer debt maturities and are much more profitable by all measures.

## III. Value and liquidity as default triggers

### *A. Univariate analysis*

Table V compares market asset values and various leverage and liquidity measures for defaulting and nondefaulting firms. The default-boundary asset value in credit risk models usually is expressed as a fraction of the face value of debt, such that a boundary of 100% of book debt corresponds to the "positive net worth covenant" in models such as that by Longstaff and Schwartz (1995). As Table V shows, the value of assets at default is on average 59.5% of the face value of debt, and the median is 55.5%. Thus, by the time the average firm defaults, much of its creditors' value is already destroyed. Some firms default while their economic net worth is still positive; others do not default until they are deep in distress. This dispersion is manifested by the large variation in observed asset values at default, ranging from 24% at the fifth percentile to as much as 119% at the ninety-fifth percentile. Asset values for the control sample are significantly higher than those of defaulting firms: The median value of assets for nondefaulting firms is 216% of face debt, and the median for all firm months in the sample, including defaulting and nondefaulting firms, is 198%.

Differences between the values of defaulting and nondefaulting firms remain large when scaled by the book value of assets or the replacement cost of tangible assets. Median market-to-book and especially Tobin's $q$ ratios are considerably lower for defaulting (0.54) than for nondefaulting (1.43) firms. Thus, most firms at default are worth significantly less than the costs of replicating their productive capacity, suggesting a serious degree of economic distress. The average market leverage at default is 87.0%; the median is 91.2 %. In contrast, for the median nondefaulting junk firm equity accounts for more than half of its value, with a market leverage of 47.5%. Statistics on the quasi-market and book leverage ratios, which do not use market prices of debt, are similar for nondefaulting firms, but the differences between the three leverage measures become more pronounced closer to default.

Table V also reports various measures of liquidity. The primary proxy for balance sheet liquidity used in this paper is the quick ratio, which equals cash and near-cash plus accounts receivable, divided by current liabilities. The mean (median) quick ratio at default is 0.55 (0.35), compared with 1.27 (0.92) for the control sample. For 85% of firms at default, the quick ratio is less than 1, compared with 59% for nondefaulting firms in the sample and 47.1% of all firm quarters in Compustat. Although low quick ratios may be the norm rather than a sign of distress in some industries (for example, retail), Table V also shows that 80% of firms at default have a quick ratio below their industry median, whereas nondefaulting junk firms are similar to the industry median. With insufficient liquid asset reserves, the firm must rely on either its operating cash flow or external financing to pay its creditors and suppliers. Because most firms close to default are cash flow negative, as many as 69.5% of defaulting firms have *both* a quick ratio below 1 and negative cash flow. For such firms, the availability of external financing is crucial for avoiding default. By contrast, only 7.6% of nondefaulting firms both have a quick ratio below 1 and negative cash flow. The interest coverage ratio (EBITDA over interest payments) provides additional evidence that defaulting firms do not generate sufficient cash flow to cover their obligations. Whereas the median firm in the control sample can cover its interest payments out of its EBITDA 3.3 times, the median firm at default is making *losses* of 15% its interest payments. Thus, the lack of liquid asset holdings potentially may have much more adverse consequences for such firms, particularly when external financing is not available.

Table V also reports several other measures of liquidity, including the current ratio (current assets divided by current liabilities), cash ratio (cash over current liabilities), and defensive interval. The current ratio is similar to the quick ratio but includes inventories and other current assets in the numerator. Because a firm in decline often cannot convert its inventories into cash quickly, this ratio may be less informative about the firm's liquidity in distress than the quick ratio. The defensive interval, or the ratio of cash and receivables over operating costs, measures the time period (in quarters) during which the firm's costs can be covered by its liquid asset holdings. According to all these measures, firms at default have significantly smaller reserves of liquid assets than nondefaulting firms. At the same time, Table V also reveals that there are many firms with low liquidity ratios among nondefaulting firms, because liquidity shortages need not result in default if firms can retain cash from their cash flow or raise external financing.

[TABLE V HERE]

Figure 2 illustrates the evolution of the market value of debt, equity, and total assets for the median defaulting firm during the five years preceding the default event. Until approximately 3.5 years before default, the ratio of market assets to the face value of debt fluctuates at levels similar to the overall sample median of 1.98, and then the value of assets starts to decline visibly. Initially, the decline is absorbed by equity. About two years before default, debt prices also start to fall. For the median firm, the total value of assets falls below the face value of debt approximately 8 months prior to default, at which point the firm's economic net worth becomes negative. This point corresponds to the level of the default boundary in models with an exogenous net worth covenant (e.g. Longstaff and Schwartz (1995)). In reality, the value of assets for the median defaulting firm continues to decline, until it reaches 56% of the face value of debt by the time of default.[14]

[FIGURE 2 HERE]

Further details on the asset values and returns around default appear in Table VI, which documents a large drop in debt and equity prices in the month when default is announced. For all defaults, the mean raw asset return in the month of default is –10.8%; for bankruptcy filings, it is –15.0%. For comparison, Andrade and Kaplan (1998) document total costs of financial distress between 10% and 20% of firm value, and Korteweg (2006) estimates them as between 0 and 11%. The large negative return in Table VI suggests that a significant proportion of the total costs of financial distress does not appear in the observed asset prices until the month of the default announcement. Thus, the announcement must contain a significant surprise component, which implies that the predefault values of debt and equity are informative about the continuation value of assets, which in turns reflects the degree of economic distress.

Panels B and C of Table VI also document that asset values at default are higher and leverage ratios are lower for non-bankruptcy renegotiations compared with bankruptcy filings. This finding is consistent with evidence in Gilson, John, and Lang (1990) that in a cross-section of defaulted firms' bankruptcies correspond to lower market-to-book ratios than workouts. Gilson, John, and Lang (1990) hypothesize that, conditional on default, high market-to-book firms choose workouts over bankruptcy to preserve the going-concern surplus. This view, and the general approach of studying a reorganization procedure choice *conditional on default*, does not recognize that the choice between workout and bankruptcy is jointly endogenous with that of the *timing* of default, because the firm also can try to avoid or postpone default, for example, by selling assets or raising new financing. Interpreting the market value of assets as a measure of distress, higher asset values for non-bankruptcy defaults suggest that when renegotiation costs are low, firms initiate workouts early in distress. In contrast, firms that cannot profitably renegotiate with their creditors out of court delay filing for bankruptcy until later stages of distress (lower asset values) and may eventually recover and avoid default altogether.

Table VI also shows creditors' recovery rates, measured as debt prices at the end of the calendar month of default. The recovery rate is related to the predefault debt price through the default announcement return. In Panel A of Table VI, the mean creditors' recovery rate for the whole sample is 43.5%, similar to the 42% documented by Acharya, Bharath, and Srinivasan (2007). Bond announcement returns are significantly more negative than loan returns because of their lower priority.

[TABLE VI HERE]

[14]For the median nondefaulting firm, a similar graph around historically low asset values (not shown) suggests that equity typically absorbs the fall in the value of assets, whereas debt prices do not move much.

### *B. Value vs. liquidity as default triggers*

Figure 3 displays asset values (relative to the face value of debt) and balance sheet liquidity (measured by the quick ratio) for firms at default, as well as for the control sample of firms that do not default for at least a year. In the picture, squares correspond to bankruptcy filings, diamonds represent defaults with no bankruptcy in the same calendar month, and circles show nondefaulting firms in the month when their asset value is at their historic minimum. Moving left (down) in the graph corresponds to increasing economic (financial) distress. When the quick ratio is below 1, the firm's current liabilities exceed its liquid assets, indicating insufficient liquidity. Firms whose ratio of market assets to book debt is below 1 have negative economic net worth, which corresponds to default in models with an exogenous net worth covenant.

Several important points emerge from Figure 3. Nearly all firms at default have negative economic net worth, a low quick ratio, or, in most cases, both. This finding is consistent with the idea that economic distress eventually causes financial distress when the firm's continued losses deplete its cash reserves. In general though, liquidity and value are distinct potential default triggers. Of special interest are defaults in the upper left quadrant of Figure 3, representing companies with low asset values but sufficient liquidity for meeting their current liabilities, sometimes several times over. In the sample, the quick ratio at default is above the industry median for 21.3% of firms, above 1 for 14.9%, and above 2 for 3.6%. For comparison, the quick ratio is below 2 for 74% of all Compustat firm months. I use Factiva to gain insight into the motives that drive firms with high balance sheet liquidity to default, looking into details of all such defaults on a case by case basis. News releases and firm statements for these firms emphasize continuing losses, difficulties in obtaining additional financing, and insufficient resources for vital investment expenditures as frequent reasons for default. Some distressed firms file for bankruptcy in recognition of their inability to generate sufficient cash flow to support their obligations in the long term, while others carry out recapitalizations involving a bond exchange, which may seriously dilute existing shareholders' stake but improve the firm's balance sheet.[15]

Observed defaults by high-liquidity, low-value firms are consistent with models that use a value-based default boundary but not with the common perception that firms default when they run out of cash. At the same time, Figure 3 indicates that some defaults happen while the market asset value is still considerable.

[15] As an example, Focal Communications' 10-Q filing dated June 30, 2001, indicates a quick ratio of 2.19. On August 9, 2001, Focal announced a distressed bond exchange, completed in October: "The [recapitalization] plan dilutes the stake of existing shareholders to 20%, but steers Focal away from a potentially debilitating cash crunch. The $80.8 million in cash that sat on Focal's balance sheet before the recapitalization was expected to run out early in 2002. [...] Analysts say that without the massively dilutive recapitalization, shareholders may have ended up with nothing." (*Focal Closes Recapitalization For Shot At Survival* by Christine Nuzum, Dow Jones Newswires, 24 October 2001.)

In the sample, 8.9% of firms at default have positive economic net worth but low liquidity ratios. The true incidence of such defaults likely is even higher, if in distress the expected default costs bias the measured asset value downward. Such defaults by economically solvent firms are unlikely to be correctly predicted by models based on a threshold market value of assets. A case-by-case Factiva analysis indicates that such defaults may be driven by covenant violations (especially those resulting from fraud; see Section VI), litigation, strategic considerations, and, commonly, insufficient liquid reserves coupled with an inability to obtain additional liquidity from external sources. For firms that are unable to pay their suppliers because of a cash shortage, Chapter 11 of the U.S. bankruptcy code relaxes financing constraints by providing access to Debtor-In-Possession (DIP) financing. Overall, Figure 3 suggests that though most defaults happen when both value and liquidity are low, neither factor alone can fully explain observed default decisions.

[FIGURE 3 HERE]

Finally, the large number of circles in Figure 3 indicates the presence of nondefaulting firms with low asset values and/or low liquidity. Even though nondefaulting firms are more valuable and liquid on average, many of them at times become very distressed. Defaulting and nondefaulting firms often appear to be in similarly poor conditions, as measured by the value of assets and the quick ratio, so liquidity and value alone cannot separate them perfectly. Figure 3 suggests that most firms with low liquidity ratios do not default, which implies that the necessary cash usually can be either generated internally or raised from external sources.[16] The regressions reported in the next section show that an important factor separating defaulting and nondefaulting firms in a cash crisis is the availability of external financing.

## IV. Regression analysis

I hypothesize that whether or not shortages of liquid assets cause the firm to default may depend on the availability of external financing, such as bank debt. If the firm can access new financing, it can overcome a temporary cash shortage and will not default unless the economics of the business deteriorates. If, in contrast, external financing is unavailable, temporary cash shortages may push the firm into default. I use instrumental variable regressions to explore this question empirically and also address the role of variables that theory predicts to affect the level of the default boundary.

[16]Consistent with this conjecture, Franks and Sanzhar (2006) conclude that debt overhang is not a common cause of default. They document many firms that overcome a cash shortage by issuing new equity in distress. It is likely that even more firms in distress can secure debt financing instead of issuing new equity.

### *A. Independent variables*

To study the determinants of the probability of default, I use discrete-time hazard regressions, shown by Shumway (2001) to be equivalent to multiperiod logit regressions estimated using all noncensored data points (firm quarters) for both defaulting and nondefaulting firms. This analysis is short term in nature, aiming to investigate the role of cash shortages and variables believed to affect the value-based default boundary, rather than improve on extant empirical models forecasting default.[17] I study the correlation between the probability of default with the market value of assets and liquidity for firms with easy versus difficult access to new financing. Because most independent variables are observed quarterly, these regressions look at the probability of default within the next quarter; the results for monthly frequencies are very similar.

Dynamic value-based models predict that the probability of default depends on the ratio of the market value of assets to the level of the default boundary (e.g. Leland (1994), Leland and Toft (1996)). Accordingly, I use the value of assets and variables expected to affect the default boundary as independent variables that affect the probability of default. However, in the presence of expected costs of default, the noise in empirically measured asset values may be correlated with the perceived probability of default, biasing regression coefficients. To address this problem, I use the firm's cash flow as an instrument for the market value of assets. In most theoretical models, current cash flow is proportional to the continuation value of assets; moreover, unlike market prices of debt and equity, accounting cash flows are not affected by the left-hand side variable, the probability of default. In my empirical tests, quarterly univariate regressions of the asset value on EBITDA, with both variables normalized by the face value of debt, produce an adjusted $t$-statistic of 14.3 and an $R^2$ of 24%. When EBITDA is combined with other explanatory variables, its $t$-statistics in first-stage regressions are around 12, and the adjusted $R^2$ is between 40% and 43%. These results confirm that cash flows provide a potent instrument for the market value of assets.[18]

Leland and Toft (1996) derive an explicit formula for the endogenous default boundary under the assumption of a stationary capital structure. Expressed as a proportion of the face value of debt, the Leland-Toft boundary depends on debt maturity and the coupon rate, the volatility of assets, the cash payout ratio, the deadweight value loss in default (default costs), the risk-free interest rate, and the corporate tax rate. I assume that the tax rate is constant for all firms and proxy for other factors affecting the boundary as follows. *Asset volatility* is the standard deviation of monthly assets returns adjusted for changes in firm size,

[17] Studies of factors that predict default include Altman (1968, 2000), Zmijevski (1984), Ohlson (1974), and Shumway (2001), among others. Such studies typically look at prediction horizons of one year or more and ensure that the explanatory variables are observed at the time when the prediction is formed. Acharya, Davydenko, and Strebulaev (2007) show that the role of liquid asset holdings in such models may be very different for shorter prediction horizons.

[18] I do not report first-stage regression result to conserve space; they are available upon request.

provided there are at least 10 months of data for the firm. *The coupon rate* is the ratio of total interest payments in a given quarter to the average outstanding debt in that quarter. *The payout ratio* is the ratio of the firm's quarterly payouts to debt and equity, calculated as the sum of interest payments, common and preferred dividends, and equity and debt repurchases, to the average market value of assets in that quarter, averaged over all quarters. Finally, *debt maturity* is estimated as the weighted average of maturities of all debt instruments, assuming that all bank debt has a maturity of one year. The results are similar when I use the weighted average bond maturity instead.

Because default costs are not directly measurable for firms that do not default, I use several proxies to control for such costs. The value of the firm's assets in default depends on their specificity and tangibility, as well as general industry conditions. As a proxy for asset tangibility, I use the ratio of the replacement cost of tangible assets (fixed and current assets) to the book value of total assets.[19] Acharya, Bharath, and Srinivasan (2007) find that creditors of firms in distressed industries obtain lower recovery rates in default. Following their paper, I define *industry distress* as a dummy variable that equals one if the equity return of the median firm in the same three-digit SIC industry in the previous year is below –30%, and zero otherwise. Andrade and Kaplan (1998) find that the complexity of the firm's debt structure affects the costs of financial distress. Following Gilson, John, and Lang (1990), I measure the debt structure complexity per dollar of debt using the *normalized number of issues*, which equals the logarithm of the number of outstanding public bonds divided by total book debt. In addition, to control for the possibility that there is a fixed component in the costs of financial distress, I include the *logarithm of total book assets* as a proxy for size. The *risk-free rate* is proxied by the five-year constant maturity Treasury rate. I also parameterize the baseline default hazard by including the logarithm of *time at risk*, or the period since the last time the firm was either (1) downgraded to junk status (if it is a fallen angel) or issued junk bonds for the first time (if it never had an investment grade rating), or (2) emerged from default. The results are not sensitive to this definition of time at risk, and as in Shumway (2001), time at risk is never a significant determinant of the hazard.

Descriptive statistics for the independent variables appear in Panel C of Table IV. It is interesting to compare these estimated values with those that Leland (2004) uses, based on various assumptions and firm averages reported in the literature. The cash payout rate in the sample is 7–9%, compared with 6% in Leland (2004) and Huang and Huang (2003). The mean weighted average debt maturity is approximately 5.29 years for nondefaulting firms and 4.54 years at default. In the Leland-Toft (1996) model, debt is offered

[19]The replacement cost of tangible assets is estimated as the sum of the replacement costs of fixed assets and inventories, calculated using the Lee-Tompkins (1999) modification of the Lewellen-Badrinath (1997) algorithm, plus the book value of current assets other than inventories. The procedure accounts for the effect of inflation on the book values of assets. The results are very similar when I use the sum of book values of fixed and current assets instead.

continuously at constant maturity, so the initial maturity of individual bonds (assumed 10 years in Leland (2004)) is twice the weighted average maturity of debt. The average volatility of assets in the sample falls between 30.3% and 32.7%, higher than the 23% that Leland uses in the base case but very close to the 32% estimate that, in his calibrations, produces the best fit for junk-grade debt. Overall, Panel C of Table IV suggests that many of Leland's (2004) parameter values are close to those observed for an average junk firm.

Of primary interest for my analysis is the role of external financing in moderating the effect of cash shortages on the probability of default. I assume that the firm experiences a liquidity shortage if its quick ratio is below 1; a dummy variable, *cash shortage*, is defined accordingly. The results are very similar if I compare the quick ratio with that of the median firm in the same three-digit SIC industry, or use the ratio instead of the dummy variable. Due to the nonlinearity of logit regressions, including a simple interaction term as a regressor is insufficient for studying whether the marginal effect of cash on the probability of default depends on financing restrictions. Instead, I compare the effects of the cash shortage proxy estimated separately for restricted and unrestricted firm quarter subsamples. I assume that external financing is difficult (relatively easy) and classify the firm as restricted (unrestricted) if the proxies for financing frictions are above (below) the sample median.

Because banks are the most likely source of external cash for distressed firms, I define four proxies for financing costs related to the difficulty of securing additional bank financing. First, banks are less likely to extend new credit if the firm already has high debt levels relative to the value of tangible assets it can pledge as collateral. The first proxy for financing frictions therefore is the ratio of the firm's outstanding *book debt to the replacement cost of tangible assets*, such as fixed and current assets (similar results emerge when I use book values instead of replacement costs). Second, using the FISD database, I count the *number of classes of bond covenants* that restrict the firm's ability to raise cash, including restrictions on senior and subordinated debt, equity issuance, or asset sales, as well as the "negative pledge" covenant that prohibits secured borrowing unless the bonds are also secured on a pari passu basis. Thus, this covenant index varies between 0 and 5. Third, the presence of authorized but undrawn credit lines may indicate better prospects for obtaining additional cash. Thus, the third proxy, *credit lines*, equals 1 minus the amount of undrawn credit lines, normalized by current liabilities. Fourth, the conditions in the distressed loan market may affect the firm's ability to borrow, in that cash shortages may be more likely to result in default when junk loan markets are "cold" and few new junk loans are extended. To control for this possibility, I measure the quarterly par amount of all *new junk loans* in DealScan, detrended and normalized by its maximum value during the sample period. This fourth proxy for financing frictions equals 1 minus this market activity measure.

### *B. Value, liquidity, and the role of financing frictions*

Table VII reports the results of the quarterly instrumental logit regressions of default. In nearly all regressions the ratio of the market value of assets to face debt consistently emerges as the most significant predictor of default. The high predictive power of this variable is especially remarkable, given that it is instrumented using an accounting ratio, *EBITDA over book debt*, which may be noisy and unlikely to summarize all information relevant for valuing the firm's productive assets. The estimated effect is significant both quantitatively and statistically: An increase in the market value of assets equal to the face value of debt reduces the odds of default by approximately 45%. This regression evidence is encouraging for the proponents of the view that default is triggered by a low value of assets.

At the same time, Table VII shows that the short-term probability of default is significantly related to the firm's holdings of liquid assets. Even in the presence of controls for the market value of assets, higher quick ratios in regression (3) reduce the probability of default, whereas cash shortfalls in regression (4) increase it. This evidence contradicts the assumption of value-based models that liquidity shortages are irrelevant as long as the market value of assets remains sufficiently high.

Regressions in columns (5) through (8) estimate the effect of the cash shortage proxy separately for firms with restricted access to new financing (meaning that one of the four proxies for constraints is above the median) and for less constrained firms (costs below the median). Specifically, the constraint proxies are the ratio of debt to tangible assets in column (4), the number of covenants restricting financing in (5), the lack of undrawn credit lines in (7), and the lack of activity in the junk loan market in column (8). Across all these proxies, the correlation of liquidity with the probability of default is greater for the restricted subsample. In contrast, the coefficient for the unrestricted sample is insignificant in three out of four regressions. The last row of Table VII reports the $p$-values for the test of the equality of the cash shortage coefficients for restricted and unrestricted firms. The difference between the two coefficients is highly significant in columns (5) and (7). Only when constraints are measured by the number of covenants (column (6)) is the effect of cash shortages significant for the unrestricted subsample, though it again is smaller than that for restricted firms.

These finding show that even though the market value of assets is the most significant predictor of the probability of default, the firm's cash holdings have incremental predictive power over and above the effect of value. Moreover, liquidity shortages increase the probability of default primarily for firms with restricted access to outside financing, whereas for unrestricted firms cash shortages are typically irrelevant. The role of liquidity in triggering default likely to contribute to the high importance that managers assign to maintaining financial slack and financial flexibility (Graham and Harvey (2001), Servaes and Tufano (2006)). To describe observed defaults accurately, it may be necessary to take into account the firm's endogenous cash holdings in the presence of financing costs, as suggested by Acharya et al. (2006) and Anderson and Carverhill (2007).

[TABLE VII HERE]

### *C. Other determinants of the default boundary*

Controlling for the market value of assets, variables that raise the level of the default boundary should increase the probability of default. The effect of most control variables documented in Table VII conforms with their expected effect on the default boundary, in particular in the Leland and Toft (1996) model. The probability of default is positively related to the debt coupon rate and negatively to debt maturity. In Leland and Toft (1996), an increase in required debt payments, due to either an increase in coupon or a decrease in maturity (which implies refinancing of the principal at a higher rate), raises the endogenously determined default boundary and the probability of default. The effect of coupon and maturity documented in Table VII is consistent with this prediction. It contrasts with models in which the default boundary is specified by an exogenous net worth covenant and therefore depends only on the face value of debt (e.g. Longstaff and Schwartz (1995)). The evidence, however, is not sufficient to conclude that the timing of default is chosen so as to maximize the value of equity, as assumed in endogenous boundary models. The lower maturity of debt at default may be due to the fact that firms that are perceived as risky may choose to issue shorter-maturity debt from the outset. Moreover, contrary to Leland and Toft's (1996) prediction that the default boundary increases in default costs, Table VII shows that asset tangibility (measured by replacement cost over total assets) is positive and marginally significantly related to default. Thus, default may be accelerated when the firm's assets are easier to recover, perhaps because creditors are more inclined to press for reorganization early. Hence, the timing of default may to some extent also reflect creditors' preferences rather than those of shareholders.[20] Assuming that firms with greater debt structure complexity face higher reorganization costs, a significantly negative sign of the *number of issues* suggests that default gets delayed when it is costly. An alternative interpretation is that when renegotiation costs are high, equityholders are discouraged from defaulting strategically to secure debt forgiveness in renegotiations.[21]

Table VII also shows that the volatility of assets is strongly positively related to the probability of default

[20]Carey and Gordy (2007) develop a model in which the default boundary is optimally chosen by creditors.

[21]Davydenko and Strebulaev (2007) find that firms with more complex debt structures have lower bond spreads, consistent with the hypothesis that high renegotiation costs deter strategic default by solvent firms.

when instrumental variables are used to control for the potential endogeneity of the market value of assets. Higher volatility decreases the default boundary in models by Leland (1994) and Leland and Toft (1996), because equityholders are more willing to delay default as a result of the higher value of their real option. At the same time, it also increases the probability of hitting any given boundary level. Because the direct effect dominates, the probability of default is positively related to the volatility of assets, as evidence in Table VII demonstrates. Similarly, an increase in the payout ratio should decrease the default boundary and increase the probability of reaching the boundary, and the latter effect dominates for typical parameter values. The net effect of the payout ratio is therefore moderated, and in Table VII, the payout ratio appears insignificant. After controlling for the value of assets, industry distress significantly increases the probability of default, consistent with the prediction that higher default costs increase the default boundary.[22]

Overall, the evidence in Table VII is consistent with the predictions of structural models regarding the determinants of the default boundary and the probability of default. The ratio of the market value of assets to the face value of debt is the strongest predictor of the probability of default in these regressions, though firms' holdings of liquid assets are also significant. Moreover, the importance of liquidity is related to the costs of external financing: Although cash shortages are generally insignificant when the firm is unconstrained, they are much more important when external financing is costly or unavailable.

## V. Empirical performance of the value boundary

The evidence presented so far suggests that focusing only on the market value of assets and ignoring other potential default triggers such as liquidity shortages is likely to result in prediction errors. Yet studies incorporating endogenous financial slack in the value-based framework suggest that such models are complex and typically can only be analyzed using numerical methods (Acharya et al. (2006), Anderson and Carverhill (2007)). Considering the pragmatic need for a parsimonious description of the default event, how large is the error resulting from the assumption that default is triggered by a threshold market value of assets? This section investigates this question empirically and provides estimates of the level of the default boundary, which can be used in empirical calibrations of value-based models.

[22]Chen (2007) presents a structural model of credit risk with shifts in macroeconomic conditions. During economic downturns, firms default at higher levels of cash flows, which nevertheless correspond to lower market values of assets due to the higher market prices of risk. Although beyond the scope of this article, the role of macroeconomic factors in triggering default appears to warrant a detailed investigation.

### *A. Classifying firms by their asset values*

Figure 4 shows the distributions of the ratio of the market value of assets to the face value of debt for firms at default and for nondefaulting firm months. Models such as Longstaff and Schwartz's (1995) assume it is low values of this ratio that trigger default. Consistent with this conjecture, Figure 4 illustrates that, though the distributions for defaulting and nondefaulting firms overlap, for a large majority of nondefaulting firm months, this ratio exceeds 1.50, its highest value observed at default. Thus, this ratio appears a good candidate variable for a parsimonious, univariate classification rule.

[FIGURE 4 HERE]

A number of studies depart from the assumption that the default boundary is a fixed proportion of the face value of debt. In Leland (1994) and Leland and Toft (1996), among others, the default boundary is an endogenously determined value of assets that maximizes the value of equity, and the probability of default depends on the current asset value relative to the boundary level. To investigate whether firm-specific boundary levels improve prediction accuracy, I estimate the Leland-Toft (1996) boundary for firms in my sample. In addition to the variables described in Subsection IV.A, this calculation uses the initial bond maturity, the firm's tax rate, and its default costs. As debt is constantly retired at the same rate, the relevant maturity in the Lenand-Toft (1996) model is twice the weighted average debt maturity. Following Leland (2004), I use the tax rate of 15%, an estimate of the corporate rate net of the tax advantage of equity at the personal level. To proxy for the cost of default, I use the observed return in the month of default. Because this variable is available only for firms observed to default, I use its sample average of –10.8% for all nondefaulting firms.[23] In Leland and Toft's (1996) model, the firm's capital structure is time independent, and the boundary level is constant. For this reason, and to minimize noise, I use average Leland-Toft boundary estimates for each firm over all sample quarters (excluding post-default). Another firm-specific default boundary is used in the KMV (now Moody's-KMV) model. It equals the sum of the short-term debt plus 50% of the long-term debt at face value (Crosbie and Bohn (2001)). The KMV boundary can be expressed as a fraction of the face value of total debt as $(short + long/2)/(total\ debt) = 0.5 + 0.5 \times short/(total\ debt)$, which is always between 0.5 and 1.

The cross-sectional correlation between the observed value of assets at default and the estimated value of the Leland-Toft boundary is 25.6%, significant at the 1% level. Statistics in Panel A of Table VIII show that

[23]In robustness tests, I estimate firm-specific default costs for nondefaulting firms using a cross-sectional empirical model constructed for defaulted firms. The explanatory power of such regressions in my sample is limited, with $R^2$s generally between 10% and 12%. The resulting estimates are noisier but not substantially different from those reported for a constant assumed default costs.

the Leland-Toft boundary lies considerably higher than the average market asset value observed empirically for defaulting firms. The mean value of the Leland-Toft boundary is 67.9% of the face value of debt, compared with the asset value of 59.5% actually observed at default. This level of the Leland-Toft boundary is slightly below the 73.1% estimated by Leland (2004) on the basis of average firm characteristics reported in the literature, likely because of the high asset volatilities and relatively low default costs of junk firms. Although the sample variation of the Leland-Toft boundary is considerable, from 41.6% to 89.4% between the 5th and 95th percentile, it is substantially smaller than that of the firm value at default. Even allowing for the possibility that observed asset prices at default underestimate the continuation value of assets, the Leland-Toft boundary appears substantially higher than that at which firms default empirically, and leaves unexplained the substantial cross-sectional variation in the timing of default. Intuitively, high levels of the Leland-Toft boundary are to be expected, since the authors assume that instead of debt being retired firms continuously issue new debt to maintain a stationary capital structure. This assumption is likely to raise equityholders' chosen default threshold, compared to the more realistic case in which firms maintain a cash reserve and equityholders are not required to contribute new financing as long as the reserve is positive. Panel A of Table VIII also shows that the KMV boundary is generally lower than the Leland-Toft boundary, with means and medians much closer to those of the observed asset values at default. However, the KMV boundary varies little in the cross-section, its correlation with the observed asset value at default is only 10.1% and statistically insignificant, and its overall predictive power is questionable. Moreover, as discussed in the next subsection, the boundary level that minimizes classification errors (as opposed to explaining asset values of firms observed to default) is much closer to Leland-Toft than the KMV boundary.

[TABLE VIII HERE]

How accurate is the assumption that default is triggered by low asset values? A standard measure of classification quality considers the area under the ROC (receiver operating characteristic) curve, which plots the test's sensitivity (the "true positive" rate, i.e., the proportion of defaults correctly classified as such) against 1–specificity (the "false positive" rate, i.e., the proportion of nondefaulting observations wrongly classified as defaulting). This area which equals the probability that a randomly selected firm at default has a lower classification variable value than a randomly selected nondefaulting observation. Constructing the ROC curve involves calculating the number of firms classified as defaulting and nondefaulting for each assumed threshold value of the classification variable. Figure 5 shows these curves for the asset value over face debt, the Leland-Toft boundary, and the KMV boundary, as well as for two measures of liquidity, interest coverage and the quick ratio. By this standard measure, tests based on the market value of assets separate defaults from nondefaulting firm months with a relatively high degree of confidence, as quantified by the area under the ROC curve. This area has a maximum value of 1 for a perfect test without errors, and a minimum value of 0.5 for a test with no predictive power. Panel B of Table VIII reports this area for the five variables over different predictive horizons and confirms that the ratio of the market value of assets to the face value of debt provides a very powerful classification variable; the area under the ROC curve reaches 97.2% for the one-month horizon and remains above 90% for horizons of up to one year. This evidence supports the approach of value-based models that assume that default is triggered by a low value of assets relative to the face value of debt.

[FIGURE 5 HERE]

Table VIII also shows that, if anything, using the firm-specific default boundary of Leland and Toft (1996) results in lower classification accuracy compared with simpler rule that specifies the boundary value as a fixed proportion of the face value of debt (though the difference between the two is not statistically significant at 5%.) The empirical determinants of the timing of the default decision may be too complex to be captured by the Leland-Toft formula, derived for equity's optimal abandonment decision under the assumption of a stationary capital structure. Firm-specific boundary levels appear too noisy and do not improve over more parsimonious specifications. For the KMV boundary, the classification properties are very similar to those of the asset value to face debt ratio, but rather than suggesting high predictive power, this result is likely due to the lack of variation in the KMV boundary relative to the face value of debt, which limits cross-sectional noise. Overall, Table VIII suggests that the simple boundary specified in terms of the face value of debt performs at least as well as more complex alternatives.

Furthermore, predictions based solely on liquidity measures are significantly less accurate than those based on asset values. The interest coverage ratio is a "flow" measure, essentially assumed to trigger default in cash flow-based models such as Kim, Ramaswamy, and Sundaresan's (1993), and also used as a sample selection variable to identify distressed firms in empirical studies such as Asquith, Gertner, and Scharfstein (1994). Theoretically, assumptions that are standard in the literature, the value of the firm's assets is proportional to its current cash flow, and as a consequence, a default boundary specified in terms of the interest coverage ratio is equivalent to a certain threshold value of assets. The in-sample correlation between the interest coverage ratio and the ratio of market assets to the face value of debt is as high as 44.3%. However, the two are not equivalent, because in reality, the value of assets incorporates information other than the current cash flow. As a result, asset values separate defaulting and nondefaulting firms considerably better than does the interest coverage ratio. Table VIII also reveals that the quick ratio, a "stock" measure of the firm's liquid asset reserves, has little power in univariate predictions, which suggests that the firm's cash reserves should be used only to supplement other variables that reflect distress.[24]

## *B. Boundary levels and classification errors*

The findings of the previous subsection indicate that classification rules based on the market value of assets can separate defaults from a large majority of nondefaulting firms. However, even among distressed firms, only a small proportion of firms default in any given month. As a result, high test specificity does not guarantee that most firms predicted to default actually do so. In other words, a low proportion of "false positives" relative to the total number of nondefaulting observations does not imply a low number of classification errors relative to the number of firms that default. Figure 3 suggests that many firms do not default at low asset values; these are ready candidates for incorrect classification as defaulting by the boundary rule. The large dispersion of asset values at default also limits the power of the test for a wide range of assumed default boundaries, implying a significant probability of wrongly classifying a firm that is about to default as nondefaulting. Figure 6, which plots classification errors as a function of the assumed boundary level, illustrates this point.

[FIGURE 6 HERE]

The "negative net worth" boundary assumption (e.g. Longstaff and Schwartz (1995)), postulating that default happens when assets fall below the face value of debt, misses 8.9% of defaults. For lower assumed values of the boundary this fraction is higher. Moreover, many firms classified as defaulting because of their low asset value do not default for at least some time (one month and one year in Figure 6). Because firms do not always default at their lowest historical asset value, for any default observation there are typically a number of nondefaulting firm months with similar or lower asset values, including historical lows of firms that default later. Figure 6 shows that over the one-month horizon, false positives typically amount to 60% or more of all firms predicted to default, because the majority or firms below *any* asset boundary do not default within the next month. As more firms default over time, false positives are less frequent for longer prediction horizons, but generally they remain a significant problem. For the "negative net worth" boundary and a prediction horizon of one year, the fraction of false positives below the boundary is 55.9%, meaning that most firms with assets below the face value of debt do not default for at least a year. In the longer term (not shown), the probability that a firm with negative economic net worth avoids default for three years is 44.1%; for five years, it is 25.0%. Of course, longer prediction horizons reduce not only the fraction of false positives, but also the informativeness of the prediction regarding the *timing* of default, which makes the

[24] Acharya, Davydenko, and Strebulaev (2007) find that longer-term, riskier firms may have higher cash reserves, because they optimally choose higher liquid asset holdings to minimize the probability of a cash shortage.

interpretation of default as the first passage time through the boundary questionable. Overall, the default boundary equal to the face value of debt is clearly suboptimal and vastly overpredicts the number of observed defaults.[25]

Given this evidence, what boundary level should value-based models use? One approach is to calibrate the boundary to the observed probability of default.[26] In Figure 6, the intersection of false negative and false positive error curves corresponds to the boundary level that correctly "predicts" the probability of default in the sample, in that the total number of firms with asset values below this boundary equals the observed number of defaults. For the one-year horizon, this approach yields a boundary asset value of 68.0% of the face value of debt, which can serve as a benchmark for empirical calibrations of value-based models. However, the cross-sectional errors that this boundary implies are substantial: As many as 27.9% of defaults happen at asset values above it, and an equal number of firms below it do not default for at least a year. The Leland-Toft boundary (not shown) produces classification errors at the "best average" boundary level of 32.1% of defaults. These estimates demonstrate the limits on the cross-sectional accuracy achieved when default is assumed to be triggered by low asset values, even when the boundary is calibrated to predict the average probability of default correctly.

The boundary level of 68.0% of the face value of debt, which equalizes type-I and type-II errors and therefore correctly predicts the probability of default, is remarkably similar to the average level of the Leland-Toft boundary in my sample, which is 67.9%. Leland (2004) uses a similar value of 73.1%, and finds that first passage-time models predict default probabilities that accord well with historical default frequencies for time horizons of five years and longer. He argues that this evidence supports the structural approach to credit risk modeling. Notwithstanding this agreement of theory and evidence *on average*, Figure 6 shows that at the best average boundary level, in cross-section, the boundary rule wrongly classifies between one-quarter and one-third of defaulted firms and an equal number of nondefaulting firms. Moreover, if estimated assets values for defaulting firms are biased downward due to expected default costs, the true incidence of classification errors is likely to be even higher.

In summary, the market value of assets is a powerful classification variable that separates defaults from a large majority of nondefaulting observations; firm-specific boundaries perform no better than a simpler boundary specified as a constant fraction of the face value of debt; the boundary level of 68% of face debt

[25]Huang and Huang (2003) also note that this boundary level is incompatible with observed low recovery rates and default costs and therefore use a much smaller threshold value of 60% of the face value of debt.

[26]By assigning specific costs to type-I and type-II errors, one can choose the "optimal" boundary level that minimizes total expected losses from misclassification. Altman (2000) provides a discussion of this issue. I assume that the costs of the two error types are equal.

correctly predicts the probability of default in the sample; and between one-quarter and one-third of defaults happen above this boundary, while an equal number of firms below it do not default for at least a year. Hence, there is no pronounced default boundary separating defaulting and nondefaulting firms, and though classification errors are small compared with the number of nondefaulting observations, they constitute a significant fraction of firms predicted to default.

## VI. Do covenants trigger default?

Debt covenants allow creditors to exercise some control over the firm's activities by giving them the right to demand debt repayment if covenant violation (technical default) occurs. If covenants are set so tightly that violations occur even in the absence of severe distress, and if creditors routinely accelerate repayment, ignoring covenants may result in underpredictions of the probability of default. Moreover, some credit risk models explicitly rely on financial covenants to justify their assumptions about the default boundary (e.g. Longstaff and Schwartz (1995)), though there appears to be no systematic evidence regarding the role of covenants in triggering payment defaults.[27] Smith (1993) finds that technical defaults usually involve multiple violations of affirmative covenants,[28] and Sweeney (1994) and DeAngelo, DeAngelo, and Skinner (1994) document that a large majority of violations involve private debt contracts rather than public bonds. Bank covenants are set so tightly that they appear to be violated for about one-quarter to one-third of all loans, and most of these violations do not indicate distress (Dichev and Skinner (2002), Chava and Roberts (2007)). Instead, covenants serve as tripwires, allowing banks to renegotiate loan terms and reduce their risk exposure if the firm's financial position deteriorates (Smith (1993)). In this section, I document the incidence of covenant violations for distressed junk firms, and investigate how they are related to bond defaults.

Available data on covenants, covenant violations, and loan contract renegotiations are sparse and imprecise. I use two sources of information to gauge the frequency of covenant violations and their importance in triggering bond payment defaults. First, I look at loan covenant data in the DealScan database, which provides details of loan contracts at the time of loan initiation. If covenants are renegotiated and become looser during the life of the loan, statistics based on the original loan contract may overestimate noncompliance with the covenants in force at later stages of the life of the loan. Hence, the DealScan analysis likely can provide only an upper bound on the incidence of technical defaults. DealScan provides information on

[27] Some papers study at the determinants of the debt's covenant structure, both for bank loans (Bradley and Roberts (2003)) and public bonds (Billett, King, and Mauer (2007)). Another line of research looks at whether the risk of technical default affects firms' accounting practices (e.g. Sweeney (1994) and references therein). Beneish and Press (1995) document equity price reactions to announcements of technical default.

[28] "Affirmative" covenants restrict admissible performance (e.g. a minimum level of net worth) and prescribe actions in certain contingencies, such as a rating downgrade. In contrast, "negative" covenants prohibit certain actions (e.g. asset sales). See also Smith and Warner (1979).

16 financial covenants specifying performance measures that the firm is required to maintain; I exclude 5 that are present for less than 5% of firms. My analysis assumes that covenants are in force and unchanged until the loan maturity date, as well as that they are specified in the same way for all firms, disregarding renegotiations, early loan retirements, and the nuances of each particular contract.[29]

During the sample period, DealScan reports outstanding loans for 80.4% of firms in my sample. The statistics reported herein exclude firms that could not be matched to DealScan data, and in particular those with no outstanding loans. Table IX shows how often the 11 covenants are present and how often they are violated when present. Columns (1) and (3) list the number of defaulting and nondefaulting firms with covenants of each type, expressed as a fraction of all sample firms with DealScan loans. The ranking of covenants for junk firms is similar to that for all loans (Dichev and Skinner (2002)). Six of the 11 covenants, including the top 3 covenants that are in place for more than half of all firms, restrict in some way the required minimum cash flow relative to debt levels or in absolute terms. An average firm has 3 of the 11 covenants.

Comparing firms' financial data with covenant requirements, I find that among all matched defaulting firms, 90% appear in violation of at least one covenant as reported in DealScan, and 46% are in violation of three or more.[30] For all firm quarters not followed by default within a year, at least one covenant appears violated 46% of the time, and three or more less than 9% of the time. These statistics suggest that, though nondefaulting junk firms are in much better financial condition, absent covenant renegotiation during the life of the loan, they would fall into technical default almost half the time. Further details on noncompliance appear in columns (2) and (4) of Table IX, which show the number of firms in violation of a particular covenant as a proportion of those for which the covenant exists. The most frequently used cashflow-based covenants are also those violated most frequently, especially at default. This result is unsurprising, since most firms at default have negative cash flow.

Table IX confirms that by the time the firm defaults on its bonds, violations of financial covenants set forth in the original bank loan contract are the rule rather than the exception. Nondefaulting firms violate most covenant types between one-quarter and one-third of the time, similar to Dichev and Skinner's (2002) and Chava and Roberts's (2007) findings for larger DealScan samples not restricted to junk firms.

[29]To the extent that variables such as cash flow and debt can be defined in different ways, the last assumption likely introduces random noise into my estimates. Dichev and Skinner (2002) and Chava and Roberts (2007) circumvent this problem by studying only the two simplest covenants, those restricting the current ratio and net worth. To provide a more complete description, I look at a wider set of covenants at the potential cost of reduced precision.

[30]When DealScan indicates that covenant values change over time, I use linear extrapolation to infer the value on each date. Three of the eleven covenants use detailed debt data unavailable from Compustat; for these, I estimate the lower bound for noncompliance as follows: Instead of fixed charge and debt service coverage statistics, I use interest coverage, which is less restrictive but does not require knowledge of debt and lease repayments due. The senior debt to cash flow covenant is assumed to be violated when EBITDA is negative.

Clearly, the majority of these presumed violations do not result in bond payment defaults. To investigate this formally, in untabulated tests, I estimate hazard regressions similar to those of Table VII, controlling additionally for covenant violations. These regressions show that dummy variables that indicate individual covenant violations are not significant predictors of default. The only exception is the dummy for the interest coverage covenant, which predicts default better than the interest coverage ratio itself and actually renders the latter regressor insignificant when both are included simultaneously.

[TABLE IX HERE]

The DealScan analysis indicates that violations of covenants stipulated in the original loan contract are almost universal by the time firms default on their bonds and are not infrequent for firms that do not default. However, statistics based on DealScan data ignore possible loan renegotiations and likely overestimate technical defaults if covenants are loosened or waived during the life of the loan. To explore this possibility and establish a lower bound on the frequency of covenant violations at bond default events, I peruse discussions of covenant-related issues in news and company press reports available from Factiva, as well as Moody's case descriptions in the DRS database.[31]

Some discussion of covenants appears for 67.6% of defaulting firms, almost always involving private debt rather than public bonds. For 59.9% of these firms, the reports explicitly indicate that the firm has violated covenants some time before defaulting on its bonds. Covenants are loosened or waived prior to bond default for 84.7% of noncomplying firms in this subsample and for 44.2% of firms that remain in compliance, often when a violation appears imminent. Expressed as a proportion of all firms, whether or not they appear in news reports, covenant violations and renegotiations are reported for 40.4% and 47.9% of defaulting firms, respectively, which establishes lower bounds on their occurrence.

But do covenant violations *trigger* bond payment defaults? In my sample of 213 defaults, at least 8.0% are explicitly said to occur as a result of technical default on a senior debt covenant. In these situations, covenant violation prompts senior creditors to block a scheduled bond payment, and such payment omissions almost always eventually lead to bankruptcy. For 76.5% of covenant-triggered defaults, banks waive or loosen covenants before eventually pulling the plug. In addition to defaults explicitly forced by senior creditors, at least 7.0% of defaults happen around the time of expiration of a previously granted covenant waiver; it is likely that at least some of these defaults are also covenant-related. Forced defaults not preceded by renegotiation most often involve alleged fraud or irregularities, which trigger a nonfinancial covenant and prompt banks to block bond payments. Cases involving irregularities also have relatively high asset values

[31] Specifically, for each sample default, I search Factiva for the terms *covenant (-s), violation (-s), waive (-d, -r, -rs), amend (-ed, -ment, -ments), compliance*, and *technical default* during the year preceding the default date.

and/or quick ratios.[32] With such cases excluded, covenant-triggered defaults appear no different from the rest of the defaulted sample in terms of value and liquidity.

To summarize, covenant violations, renegotiations, and waivers are extremely widespread for firms close to default and not uncommon among nondefaulting junk firms. Only rarely do covenant violations trigger bond payment default. Apart from occasional cases involving fraud and other irregularities, forced defaults occur at asset values similar to those of other defaulting firms, which suggests that creditors are unlikely to enforce covenants unless the firm is economically insolvent. Thus, the knowledge of firms' financial covenant structure appears to add relatively little to our ability to predict default.

## VII. Summary and conclusions

This paper studies factors that trigger default for distressed firms. Although economic distress, manifested by a low market value of assets, is the most important factor contributing to default, liquidity shortages also play an independent role. I observe defaults both by low-value high-liquidity firms and by low-liquidity high-value firms. Moreover, the importance of liquidity varies depending on the availability of external financing. To capture all observed defaults, it may be necessary to account not only for the firm's value of assets *and* its optimal cash management policy but also for factors that influence the costs of accessing external cash. Because these costs depend on both firm-level and economy-wide characteristics, describing all these factors accurately is challenging. Even for relatively simple settings, models incorporating endogenous cash holdings in the dynamic framework are complex and typically necessitate numerical solutions (Acharya et al. (2006), Anderson and Carverhill (2007)).

By focusing on the asset value and ignoring pure financial distress, the analysis can be simplified greatly, but only at the cost of reduced accuracy, arising from the fact that there is no pronounced value boundary separating defaulting and nondefaulting firms. The level of the boundary that balances type-I and type-II errors equals 68% of the face value of debt, which coincides with the average level of the Leland-Toft (1996) boundary in the sample. However, in cross-section, the Leland-Toft boundary underperforms compared with a more parsimonious threshold specified as a fixed proportion of the face value of debt. Moreover, even though the 68% boundary correctly predicts the probability of default on average, in cross-section it misclassifies more than one-quarter of defaulting firms and an equal number of nondefaulting firms. Because only a small fraction of firms defaults in any given month, these classification errors are small relative to the

[32] As an example, aaiPharma delayed filing its 2003 annual report pending SEC investigation, which constituted an event of default under the terms of its senior credit facility, and prompted senior lenders to veto a scheduled bond payment. At the time, the ratio of aaiPharma's market value of assets to the face value of debt was close to 1.42.

total number of observations but significant relative to the number of defaults.

One caveat to this analysis is that when investors anticipate costly default, the observed market prices of debt and equity may underestimate the market value of productive assets in the absence of default. Although this problem is arguably negligible in my data, the quantitative estimates for the default boundary should still be interpreted with caution. However, my instrumental variable regression results are robust to value mismeasurement, and adjusting the asset values for defaulting firms upward either does not affect or even strengthens my principal findings that (1) many defaulting firms are economically solvent, and these have low liquidity ratios; (2) some firms default despite sufficient liquidity; (3) the importance of liquidity depends on the severity of financing constraints; and (4) many firms with low asset values avoid default or delay it for extended periods of time.

Difficulties in specifying the default boundary may be contributing to the low cross-sectional accuracy of debt pricing models documented by Eom, Helwege, and Huang (2004) and their inability to match the short-term probability of default (Leland (2004)). In light of the evidence presented in this paper, it may be beneficial to abandon hope of explaining default as a deterministic cause-and-effect event and assume instead that information imperfections imply that default cannot be predicted perfectly. Duffie and Lando (2001) point out that rather than observing the market value of the firm's assets, investors only receive noisy signals about it. More generally, Jarrow and Protter (2004) argue that the (reduced) information set of investors is relevant for claim pricing, rather than that of managers who may observe both the value of assets and the level of the default boundary. These papers, as well as those by Giesecke (2006) and Çetin et al. (2004), show that structural models with incomplete information are equivalent to reduced-form models in which default time is inaccessible. In contrast with the traditional reduced-form approach (Jarrow and Turnbull (1995), Duffie and Singleton (1999)), their framework provides a structural foundation for modeling the default intensity as a function of fundamentals. Accepting a degree of unpredictability of default and extending existing models along these lines may be a fruitful way to advance understanding of credit risk.

# Appendix: Details of the market value estimation procedure

I estimate the market value of firms' assets as the sum of market values of bonds, bank debt, and equity. The firm's bond structure is inferred from the history of outstanding bond amounts in the FISD database for each bond issued by the firm and its wholly owned subsidiaries. The market value of bonds included in the Merrill Lynch High Yield II Index (MLI) is calculated by multiplying the currently outstanding amount by the invoice price. Issues with remaining maturity of less than one year or face value under $100 million are not included in the MLI. The market value of these bonds is calculated assuming that their yield equals the weighted-average yield of all quoted bonds of the same issuer on each date. If price quotes are unavailable in MLI for any of the firm's bonds, the firm month observation is excluded from the sample.

Estimates of bank loan prices are based on quotes provided by the LSTA/LPC Mark-to-Market Pricing service, available from May 1998. On average, for each loan month, LSTA/LPC provides a mean price quote from 3 dealers. When there are several loans outstanding for a firm, I use their mean price, resulting in 7.5 dealer quotes per bank debt price on average (median is 4). A total of 305 sample firms have loan prices included in the LSTA/LPC database, including 106 of the 213 defaulted firms. For firm months not included in the database, the market price of bank debt is estimated as a nonlinear function of the weighted-average bond price, as follows:

$$\begin{array}{rcl} P_{bank} & = & \underset{(14.2)}{40.18} + \underset{(12.9)}{1.045} \times P_{bond} - \underset{(-8.45)}{0.00461} \times P_{bond}^2, \end{array}$$

where $P_{bank}$ and $P_{bond}$ are average loan and bond prices in cents on the dollar, respectively, and $t$-statistics adjusted for firm clustering are reported in parentheses. The quadratic term controls for nonlinearities due to different seniority of loans and bonds. The regression produces an $R^2$ of 75.5% and is not substantially improved by the inclusion of additional firm-specific or macroeconomic controls.

Preferred equity is rarely important in the sample; its par value is below 1% of the face value of debt for 83.6% of firms. Preferred stock is worth little in default, and thus its par value is likely to vastly overstate its market value in distress. Hamilton, Gupton, and Berthault (2001) find mean recovery rates for preferred stock of 18.1%, compared with 46.9% for senior unsecured bonds (the most common bond type by far). Accordingly, to approximate the market value of preferred stock, I assume that its price relative to par is equal to the constant fraction 18.1/46.9=0.386 of the firm's current bond price.[33]

For the median firm in the sample, bonds and bank loans together constitute 97.8% of total debt. Firms may make use of other debt types, such as capital lease obligations, commercial paper, mortgages, and project finance debt. Because commercial paper (rare in the sample) has short maturity and is backed by credit lines, and most other debt types are secured, I assume that all such debt obligations are similar to bank debt and have the same price-to-par ratio. These types of debt are not frequently used by high-yield firms, so this approximation affects only a small fraction of sample firms.

Potentially more important is the accurate measurement of the split of the firm's total debt between bonds and bank debt. Available data sources do not report outstanding bank debt amounts and, in particular, the utilization of authorized credit lines. The split between bonds and loans is especially relevant when their market prices are significantly different. I use 10-K filings to collect data manually on the composition of debt for 240 sample firms whose difference between the average bond and loan price exceeds 10 cents on the dollar. This subsample includes most defaulted and very distressed firms, which are of primary interest for this study. For other firms, I rely on FISD data to infer the total amount of bonds outstanding for the firm and its wholly owned subsidiaries, and estimate the face value of bank debt as the difference between total debt from Compustat and the FISD-implied par bond amount.[34]

I use Compustat data on total debt in conjunction with the inferred split between bonds and bank debt and their respective prices. I then add the total value of common stock from CRSP and the approximated value of preferred equity to arrive at an estimate of the total value of financial claims on the firm's assets as a proxy for the value of its productive assets.

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[33] As an illustration of the effect of this approximation, the median base case estimate of the total value of assets is 1.980 of the face value of the firm's debt. If I assume that preferred stock is worthless, this estimate changes to 1.961; if I assume its price to par ratio is the same as that of the firm's bonds, the estimate rises to 1.996.

[34] The median difference between the ratio of bonds to total debt implied by FISD and that found from 10-K filings is only 7%. However, the two can be very different for large firms with complex debt structures and many bond-issuing subsidiaries. By using the FISD-based split only for firms with similar prices of bonds and loans, I limit the maximum error due to potential mismeasurement of the bond to loan ratio.

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**Table I. Number of defaults by year**

The table reports the number of unique independent defaults on Moody's rated bonds for U.S.-based nonfinancial issuers by year of default, as well as the number of defaults in this paper's sample. Wholly owned subsidiaries defaulting essentially together with their parent companies are not counted separately. Default events within two years are counted as one default. Default events are bond payment omissions (including those rectified within the grace period), distressed bond exchanges, and bankruptcy filings. For each year, column (1) reports the total number of independent defaults, and column (2) expresses that number as a proportion of the total number of defaults in all years (1970–2005). Column (3) gives the number of defaults in the sample. Column (4) expresses sample defaults each year as a proportion of the total number of defaults that happened in that year.

| | All defaults | | Studied sample | |
|---|---|---|---|---|
| Years | No. of firms (1) | % of all defaults (2) | No. of firms (3) | % of year's defaults (4) |
| 1970-1979 | 36 | 3.4% | - | - |
| 1980-1989 | 161 | 15.1% | - | - |
| 1990 | 72 | 6.8% | - | - |
| 1991 | 68 | 6.4% | - | - |
| 1992 | 37 | 3.5% | - | - |
| 1993 | 26 | 2.4% | - | - |
| 1994 | 22 | 2.1% | - | - |
| 1995 | 35 | 3.3% | - | - |
| 1996 | 19 | 1.8% | - | - |
| 1997 | 22 | 2.1% | 4 | 18.2% |
| 1998 | 45 | 4.2% | 12 | 26.7% |
| 1999 | 69 | 6.5% | 26 | 37.7% |
| 2000 | 92 | 8.6% | 28 | 30.4% |
| 2001 | 143 | 13.4% | 62 | 43.4% |
| 2002 | 87 | 8.2% | 31 | 35.6% |
| 2003 | 59 | 5.5% | 24 | 40.7% |
| 2004 | 37 | 3.5% | 13 | 35.1% |
| 2005 | 35 | 3.3% | 13 | 37.1% |
| 1997-2005 | 589 | 55.3% | 213 | 36.2% |
| 1970-2005 | 1065 | 100% | 213 | 20.0% |

**Table II. Sample industry composition**

The table reports the industry composition of the studied sample. The sample consists of U.S.-based nonfinancial bond issuers included in both the Merrill Lynch U.S. High Yield Master II Index and COMPUSTAT. The control subsample consists of firm that do not default for at least one year after the observation date.

| | Defaulted firms | | Control sample | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Consumer goods | 27 | 13.0% | 82 | 10.2% |
| Business equipment | 12 | 5.8% | 49 | 6.1% |
| Steel | 12 | 5.8% | 26 | 3.2% |
| Other manufacturing | 28 | 13.5% | 126 | 15.7% |
| Telecommunications | 43 | 20.7% | 102 | 12.7% |
| Wholesale and retail trade | 34 | 16.3% | 123 | 15.4% |
| Transportation | 12 | 5.8% | 27 | 3.4% |
| Energy & utilities | 13 | 6.3% | 98 | 12.2% |
| Other industries | 27 | 13.0% | 168 | 21.0% |
| All | 208 | 100.0% | 801 | 100.0% |

**Table III. Default events, bankruptcy, and outcomes**

This table reports the incidence of bankruptcy filings and the eventual outcome of default for sample firms, by the type of the first default event (bankruptcy filing, payment omission, or distressed bond exchange). Panel A gives the total number of defaults by the first default event. Panel B reports the number of bankruptcy filings following the first default event, if any. Panel C reports the eventual outcomes of default. Wholly-owned subsidiaries defaulting essentially together with their parent companies are not counted separately. Default events happening within two years are counted as one default. "Still in bankruptcy" refers to firms that have not emerged from bankruptcy as of July 2007.

| | First default event | | | |
|---|---|---|---|---|
| | Bankruptcy filing | Payment default | Distressed exchange | Total |
| Panel A: First default events | | | | |
| Total number of defaults | 79 | 115 | 19 | 213 |
| | 37.1% | 54.0% | 8.9% | |
| Panel A: Bankruptcy filings subsequent to default | | | | |
| Chapter 11 | 74 | 85 | 5 | 164 |
| | 93.7% | 73.9% | 26.3% | 77.0% |
| Prepackaged Ch.11 | 5 | 16 | 1 | 22 |
| | 6.3% | 13.9% | 5.3% | 10.3% |
| None | - | 14 | 13 | 27 |
| | | 12.2% | 68.4% | 12.7% |
| Panel B: Eventual outcomes of default | | | | |
| Creditors paid in full | - | 6 | - | 6 |
| | | 5.2% | | 2.8% |
| Bond exchange completed | - | 2 | 12 | 14 |
| | | 1.7% | 63.2% | 6.6% |
| Emerged from bankruptcy | 60 | 84 | 4 | 148 |
| | 75.9% | 73.0% | 21.1% | 69.5% |
| Acquired or liquidated | 14 | 14 | 3 | 31 |
| | 17.7% | 12.2% | 15.8% | 14.6% |
| Still in bankruptcy | 5 | 2 | 0 | 7 |
| | 6.3% | 1.7% | 0.0% | 3.3% |
| Unclear | 0 | 7 | 0 | 7 |
| | 0.0% | 6.1% | 0.0% | 3.3% |

**Table IV. Descriptive statistics**

The table reports descriptive statistics for firms at default, and for the control sample of firms that do not default for at least one year after the observation date. Statistics for nondefaulting firms are calculated using firm means for each variable. *Original-issue junk* firms are those whose outstanding bonds were never rated investment grade. *EBIT* is the sum of pretax income and interest expenses. *Profit margin* is the ratio of the pretax income to sales. *% Making losses* is the proportion of firms with negative pretax income. *% Negative cash flow* is the proportion of firms for which the operating cash flow, defined as income before extraordinary items plus depreciation, is negative. *Coupon rate* is interest expense divided by the average outstanding debt in the same quarter. *Payout ratio* is the firm's average ratio of total quarterly payouts to debt and equity, calculated as the sum of interest payments, common and preferred dividends, and equity and debt repurchases, to the average market value of assets in the same quarter. *Debt maturity* is the weighted average of maturities of all debt instruments, assuming that all bank debt has a maturity of one year. *Asset volatility* is the standard deviation of monthly assets returns, provided that there are at least ten return observations for the firm. *Replacement cost* of tangible assets is the sum of the replacement costs of fixed assets and inventories, estimated using the Lee-Tompkins (1999) modification of the Lewellen-Badrinath (1997) algorithm, plus the book value of current assets other than inventories. *Industry distress* is a dummy variable that equals one if the equity return for CRSP firms in the same 3-digit SIC industry over the previous year is below –30%, and zero otherwise. *Risk-free rate* is the five year constant maturity Treasury rate. *Time at risk* is the time period since the last time the firm was either 1) downgraded to junk status (if it is a fallen angel) or issued junk bonds for the first time (if it never had an investment grade rating), or 2) emerged from default.

| | Firms at default | | | | Nondefaulting firms | | | |
|---|---|---|---|---|---|---|---|---|
| | Mean | Median | Std.dev. | N | Mean | Median | Std.dev. | N |
| Panel A: General descriptive statistics | | | | | | | | |
| *Total assets ($ Mil.)* | 2,628 | 812 | 6,253 | 202 | 2,725 | 1,196 | 4,474 | 801 |
| *Sales/Total assets* | 0.257 | 0.200 | 0.243 | 200 | 0.264 | 0.221 | 0.221 | 801 |
| *Bonds/Total debt* | 0.628 | 0.627 | 0.235 | 167 | 0.646 | 0.656 | 0.216 | 754 |
| *Bond maturity (years)* | 6.62 | 6.52 | 3.08 | 176 | 7.70 | 7.08 | 3.44 | 778 |
| *No. of bond issues* | 3.78 | 2 | 5.91 | 176 | 4.50 | 1.89 | 19.48 | 778 |
| *Nominal share price ($)* | 1.33 | 0.84 | 1.61 | 183 | 22.11 | 19.30 | 13.69 | 795 |
| *% original-issue junk* | 85.3% | | | 211 | 69.2% | | | 800 |
| Panel B: Measures of profitability | | | | | | | | |
| *EBIT/Total assets* | -0.091 | -0.021 | 0.219 | 192 | 0.013 | 0.016 | 0.032 | 790 |
| *Profit margin* | -2.263 | -0.211 | 11.405 | 203 | -0.203 | 0.017 | 1.214 | 799 |
| *% making losses* | 93.1% | | | 204 | 33.8% | | | 801 |
| *% negative cash flow* | 81.1% | | | 196 | 17.1% | | | 797 |
| *% negative book equity* | 58.9% | | | 202 | 12.5% | | | 800 |
| Panel C: Regression variables | | | | | | | | |
| *Coupon rate* | 10.4% | 10.2% | 2.51% | 160 | 9.28% | 8.65% | 3.66% | 787 |
| *Payout ratio* | 9.02% | 8.44% | 4.14% | 132 | 7.56% | 6.97% | 4.45% | 678 |
| *Debt maturity* | 4.54 | 4.25 | 2.12 | 132 | 5.29 | 4.92 | 2.46 | 751 |
| *Asset volatility* | 0.327 | 0.269 | 0.198 | 111 | 0.303 | 0.262 | 0.160 | 632 |
| *Replacement cost/Total assets* | 0.766 | 0.790 | 0.169 | 163 | 0.714 | 0.745 | 0.197 | 769 |
| *Industry distress* | 0.394 | | | 142 | 0.114 | | | 745 |
| *Risk-free rate* | 4.57% | 4.62% | 1.11% | 177 | 4.89% | 4.62% | 0.48% | 800 |
| *Time at risk (years)* | 5.69 | 4.56 | 4.17 | 176 | 5.95 | 4.42 | 4.97 | 798 |

**Table V. Asset value, leverage, and liquidity measures**

The table reports statistics on the market value of assets and various measures of leverage and balance sheet liquidity, for firms at default and for the control sample of firms that do not default for at least one year after the observation date. Statistics for nondefaulting firms are calculated using firm means for each variable. *Market assets* is the sum of market values of outstanding debt and equity. *Market to book ratio* is equal to the market value of assets divided by the book value of total assets. *Tobin's q* is the market value of assets divided by the sum of the replacement costs of fixed assets and inventories, estimated using the Lee-Tompkins (1999) modification of the Lewellen-Badrinath (1997) algorithm, and the book value of current assets other than inventories. *Market leverage* is the ratio of the market value of debt to market assets. *Quasi-market leverage* is the book value of total debt divided by the sum of the book value of debt and the market value of equity. *Book leverage* is the ratio of the book value of debt to the book value of total assets. *Quick ratio* is the sum of cash and accounts receivable divided by current liabilities. *% Quick ratio below industry median* is the proportion of firms for which the quick ratio is below its median value for all Compustat firms in the same 3-digit SIC industry. *Current ratio* is the ratio of current assets to current liabilities. *Cash ratio* is the ratio of cash and equivalents to current liabilities. *Interest coverage* is the ratio of EBITDA, calculated as the sum of pretax income, interest expense, and depreciation, to the interest expense. *Defensive interval* is the sum of cash and accounts receivable divided by the sum of cost of goods sold and selling and administrative expenses.

| | Firms at default | | | | | | Nondefaulting firms | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | Median | Std.dev. | 5% | 95% | N | Mean | Median | Std.dev. | 5% | 95% | N |
| *Asset value measures* | | | | | | | | | | | | |
| *Market assets/Face debt* | 0.595 | 0.555 | 0.271 | 0.240 | 1.190 | 146 | 3.067 | 2.215 | 2.863 | 1.045 | 7.991 | 729 |
| *Market to book ratio* | 1.242 | 1.128 | 0.442 | 0.754 | 2.222 | 186 | 1.600 | 1.390 | 0.814 | 0.976 | 2.772 | 791 |
| *Tobin's q* | 0.717 | 0.541 | 0.838 | 0.178 | 1.759 | 138 | 1.989 | 1.425 | 1.647 | 0.676 | 5.300 | 706 |
| *Indebtedness* | | | | | | | | | | | | |
| *Market leverage* | 0.870 | 0.912 | 0.120 | 0.637 | 0.986 | 146 | 0.483 | 0.475 | 0.207 | 0.159 | 0.847 | 729 |
| *Quasi-market leverage* | 0.927 | 0.955 | 0.083 | 0.755 | 0.994 | 146 | 0.489 | 0.482 | 0.211 | 0.159 | 0.867 | 729 |
| *Book leverage* | 0.812 | 0.760 | 0.393 | 0.339 | 1.449 | 200 | 0.483 | 0.452 | 0.221 | 0.168 | 0.899 | 796 |
| *Liquidity* | | | | | | | | | | | | |
| *Quick ratio* | 0.551 | 0.353 | 0.607 | 0.050 | 1.894 | 194 | 1.266 | 0.922 | 1.338 | 0.280 | 3.129 | 772 |
| *% quick rat. below one* | 85.1% | | | | | 194 | 58.8% | | | | | 772 |
| *% quick rat. below ind. median* | 79.7% | | | | | 158 | 52.5% | | | | | 718 |
| *Interest coverage ratio* | -2.80 | -0.15 | 7.41 | -18.19 | 2.10 | 193 | 6.87 | 3.27 | 31.32 | -1.15 | 23.62 | 790 |
| *Current ratio* | 0.953 | 0.737 | 0.816 | 0.108 | 2.525 | 195 | 1.916 | 1.597 | 1.350 | 0.707 | 3.952 | 770 |
| *Cash ratio* | 0.239 | 0.072 | 0.513 | 0.001 | 1.096 | 195 | 0.621 | 0.224 | 1.326 | 0.027 | 2.481 | 773 |
| *Defensive interval* | 1.09 | 0.77 | 1.03 | 0.09 | 3.22 | 178 | 1.62 | 0.98 | 2.19 | 0.15 | 5.66 | 719 |

**Table VI. Asset values and returns at default**

For firms at default, the table reports statistics on the market value of assets, leverage ratios, debt recovery rates, and one-month asset, equity, bond, and bank debt returns. *Market assets* is the sum of market values of outstanding debt and equity. *Market leverage* is the ratio of the market value of debt to market assets. Both *market assets* and *market leverage* are measured at the end of the last calendar month prior to default. *Asset return* is the ratio of the change in the market value of assets in the calendar month of default, which for the purposes of size adjustment is calculated while holding constant the number of common shares, the par values of debt and preferred equity, and the split between bonds and bank debt, to the market value of assets at the end of the calendar month preceding default. Debt and equity returns are estimated from changes in bond, loan, and share prices over the calendar month of default. *Debt recovery rate* is ratio of the market value of total debt to its face value at the end of the calendar month of default.

| | Mean | Median | Std.dev. | 5% | 95% | N |
|---|---|---|---|---|---|---|
| | | Panel A: All defaults | | | | |
| *Market assets/Face debt* | 59.5% | 55.5% | 27.1% | 24.0% | 119.0% | 146 |
| *Market leverage* | 87.0% | 91.2% | 12.0% | 63.7% | 98.6% | 146 |
| *Asset return* | -10.8% | -7.2% | 26.1% | -51.9% | 22.7% | 143 |
| *Equity return* | -16.9% | -22.9% | 54.4% | -85.7% | 78.3% | 175 |
| *Bond return* | -18.1% | -14.7% | 31.1% | -69.2% | 30.8% | 170 |
| *Bank debt return* | -3.8% | -1.6% | 18.2% | -29.7% | 29.0% | 175 |
| *Debt recovery rate* | 43.5% | 41.6% | 21.1% | 11.6% | 80.8% | 164 |
| | | Panel B: Renegotiations | | | | |
| *Market assets/Face debt* | 62.8% | 57.4% | 26.4% | 24.9% | 121.0% | 79 |
| *Market leverage* | 86.3% | 88.9% | 12.2% | 60.7% | 98.9% | 79 |
| *Asset return* | -7.3% | -3.1% | 19.6% | -51.1% | 23.3% | 77 |
| *Equity return* | -9.1% | -13.3% | 46.0% | -67.7% | 75.0% | 93 |
| *Bond return* | -11.9% | -9.2% | 27.9% | -56.9% | 37.8% | 95 |
| *Bank debt return* | -2.5% | -1.0% | 14.8% | -24.1% | 23.3% | 98 |
| *Debt recovery rate* | 47.5% | 43.4% | 20.8% | 17.2% | 82.0% | 91 |
| | | Panel C: Bankruptcy filings | | | | |
| *Market assets/Face debt* | 55.7% | 49.8% | 27.5% | 21.8% | 115.4% | 67 |
| *Market leverage* | 87.7% | 92.0% | 11.9% | 64.7% | 98.5% | 67 |
| *Asset return* | -15.0% | -13.3% | 31.7% | -62.6% | 19.2% | 66 |
| *Equity return* | -25.8% | -32.9% | 61.7% | -86.8% | 120.0% | 82 |
| *Bond return* | -26.0% | -25.2% | 33.3% | -86.3% | 28.2% | 75 |
| *Bank debt return* | -5.4% | -5.1% | 21.9% | -43.5% | 37.8% | 77 |
| *Debt recovery rate* | 38.5% | 37.0% | 20.6% | 8.7% | 80.8% | 73 |

**Table VII. Determinants of the probability of default**

This table reports quarterly instrumental logit regressions of default. The sample consists of all firm quarter observations, excluding post-default quarters. The dependent variable equals one if the firm defaults within the following fiscal quarter, and zero otherwise. *Market assets/Face debt* is the sum of market values of outstanding debt and equity divided by the face value of debt. The ratio of EBITDA to debt is used as an instrument for this variable. *Quick ratio* is the sum of cash and accounts receivable, divided by current liabilities. *Cash shortage* is a dummy variable that equals one if the quick ratio is below one, and zero otherwise. *Restricted* and *unrestricted* are firm subsamples for which a certain proxy for financing constraints is, respectively, below and above its sample median, where the proxies are: in regression (5), the ratio of book debt to the replacement cost of tangible assets; in (6), the number of bond covenant classes that restrict the firm's ability to raise cash; in (7), 1 minus undrawn credit lines divided by current liabilities; in (8), 1 minus the normalized de-trended quarterly par amount of all new junk loans in DealScan. *Coupon rate* is interest expense divided by the average outstanding debt in the same quarter. *Payout ratio* is the firm's average ratio of total debt and equity payouts in each quarter to the average market value of assets in the that quarter. *Debt maturity* is the weighted average of maturities of all debt instruments, assuming that all bank debt has a maturity of one year. *Asset volatility* is the standard deviation of monthly assets returns, provided that there are at least ten return observations for the firm. *Replacement cost* of tangible assets is the sum of the replacement costs of fixed assets and inventories plus the book value of current assets other than inventories. *Industry distress* is a dummy variable that equals one if the equity return for CRSP firms in the same 3-digit SIC industry over the previous year is below –30%, and zero otherwise. *Risk-free rate* is the five year constant maturity Treasury rate. *Time at risk* is the time period since the firm was either downgraded to junk status (for original-junk issuers, issued junk bonds for the first time) or emerged from default. Absolute values of $z$-statistics adjusted for within-firm clustering are reported in parentheses. Coefficients marked ***, **, and * are significant at the 1%, 5%, and 10% significance level, respectively. The last row reports the $p$-value of the Wald test that the two regression coefficients are equal.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| *Market assets/Face debt* | -0.64*** | -0.60*** | -0.58*** | -0.59*** | -0.58*** | -0.50*** | -0.93*** | -0.59*** |
| | (10.22) | (7.99) | (7.16) | (7.69) | (7.19) | (6.37) | (3.62) | (7.57) |
| *Quick ratio* | | | -1.55*** | | | | | |
| | | | (3.30) | | | | | |
| *Cash shortage* | | | | 1.15*** | | | | |
| | | | | (3.34) | | | | |
| *Cash short. if restricted* | | | | | 1.40*** | 1.21*** | 1.48*** | 1.26*** |
| | | | | | (3.64) | (3.62) | (3.79) | (3.59) |
| *Cash short. if unrestricted* | | | | | 0.39 | 1.02*** | 0.26 | 0.46 |
| | | | | | (0.87) | (2.70) | (0.52) | (0.82) |
| *Coupon rate* | | 10.27*** | 11.18*** | 10.22*** | 11.87*** | 10.91*** | 9.71* | 9.68*** |
| | | (3.05) | (2.72) | (2.90) | (3.08) | (3.29) | (1.77) | (2.76) |
| *Payout ratio* | | 3.28 | 1.97 | 2.60 | 2.00 | 0.53 | -7.18 | 2.36 |
| | | (1.16) | (0.65) | (0.89) | (0.63) | (0.20) | (1.60) | (0.80) |
| *Debt maturity* | | -0.16** | -0.11 | -0.14** | -0.16** | -0.15** | -0.19** | -0.14** |
| | | (2.34) | (1.56) | (2.02) | (2.22) | (2.35) | (2.31) | (2.02) |
| *Asset volatility* | | 3.08*** | 4.61*** | 3.85*** | 3.80*** | 3.53*** | 3.06*** | 3.88*** |
| | | (4.36) | (5.92) | (5.13) | (5.12) | (4.18) | (2.84) | (5.17) |
| *Log(Total assets)* | | -0.15 | -0.25 | -0.20 | 0.10 | -0.16 | 0.00 | -0.21 |
| | | (0.67) | (1.13) | (0.92) | (0.45) | (0.83) | (0.01) | (0.95) |
| *Replacement cost/TA* | | 1.40** | 1.03 | 1.18* | 1.83** | 0.75 | 0.95 | 1.21* |
| | | (2.23) | (1.51) | (1.81) | (2.47) | (1.44) | (1.26) | (1.85) |
| *Norm. no. of bonds* | | -0.20* | -0.22* | -0.21* | -0.03 | -0.25** | 0.02 | -0.21* |
| | | (1.67) | (1.82) | (1.78) | (0.23) | (1.98) | (0.11) | (1.77) |
| *Industry distress* | | 0.69** | 0.70** | 0.73*** | 0.74*** | 0.76*** | 0.16 | 0.64** |
| | | (2.41) | (2.47) | (2.60) | (2.59) | (2.85) | (0.47) | (2.18) |
| *Risk-free rate* | | -0.14 | -0.17 | -0.16 | -0.17 | -0.08 | -0.13 | -0.05 |
| | | (1.32) | (1.58) | (1.51) | (1.55) | (0.87) | (0.89) | (0.42) |
| *Log(Time at risk)* | -0.04 | 0.13 | 0.03 | 0.06 | 0.06 | 0.12 | -0.07 | 0.07 |
| | (0.44) | (0.70) | (0.17) | (0.37) | (0.35) | (0.75) | (0.29) | (0.40) |
| *Const.* | -2.88*** | -4.17** | -2.26 | -4.51** | -7.47*** | -4.73*** | -3.52 | -4.89*** |
| | (14.11) | (2.35) | (1.14) | (2.57) | (3.57) | (2.94) | (1.60) | (2.74) |
| *Firm-quarter obs.* | 8734 | 7057 | 6925 | 6925 | 6925 | 6925 | 2180 | 6925 |
| *p-value $H_0$: Cash short. if restricted = Cash short. if unrestricted* | | | | | 0.016 | 0.516 | 0.006 | 0.133 |

**Table VIII. Classification properties of value-based default boundaries**

Panel A reports statistics on the market value of assets for defaulting firms at the end of the calendar month preceding default, as well as the value of the Leland-Toft (1996) boundary and the KMV boundary for all firms, all expressed as a proportion of the face value of debt. Panel B reports the area under the ROC (receiver operating characteristic) curve (sensitivity vs. 1-specificity) for tests that classify all firm month observations as defaulting and nondefaulting on the basis of each of the five classification variables, for different prediction horizons. *Asset value/Face debt*, *Asset value/Leland-Toft boundary*, and *Asset value/KMV boundary* are ratios of the sum of market values of outstanding debt and equity to the face value of debt, and to the firm's average Leland-Toft and KMV boundary levels, respectively. *Interest coverage* is the ratio of EBITDA, calculated as the sum of pretax income, interest expense, and depreciation, to the interest expense. *Quick ratio* is the sum of cash and accounts receivable divided by current liabilities.

Panel A: Default boundary levels

| | Mean | Median | Std.Dev. | 5% | 95% | N |
|---|---|---|---|---|---|---|
| *Asset value/Face debt* | 0.595 | 0.555 | 0.271 | 0.240 | 1.190 | 146 |
| *Leland-Foft boundary/Face debt* | 0.679 | 0.694 | 0.174 | 0.416 | 0.894 | 678 |
| *KMV boundary/Face debt* | 0.551 | 0.530 | 0.060 | 0.501 | 0.668 | 800 |

Panel B: Area under the ROC curve

| | 1 month | 3 months | 6 months | 1 year | 3 years |
|---|---|---|---|---|---|
| *Asset value/Face debt* | 0.972 | 0.962 | 0.943 | 0.896 | 0.782 |
| *Asset value/Leland-Toft boundary* | 0.958 | 0.942 | 0.920 | 0.861 | 0.738 |
| *Asset value/KMV boundary* | 0.971 | 0.961 | 0.942 | 0.896 | 0.785 |
| *Interest coverage* | 0.858 | 0.861 | 0.849 | 0.822 | 0.764 |
| *Quick ratio* | 0.738 | 0.692 | 0.643 | 0.589 | 0.523 |

**Table IX. Financial covenants in DealScan**

This table reports statistics on loan covenants from the DealScan database for sample firms at default and for the control sample of firms that do not default for at least one year after the observation date. Statistics for nondefaulting firms are calculated using firm means for each variable for all sample quarters. Columns (1) and (3) show the number of firms that have covenants of each type as a fraction of all sample firms for which DealScan indicates that loans are outstanding. Columns (2) and (4) show the number of firms in violation of a particular covenant as a proportion of firms for which the covenant is present. *Debt to cash flow* is long-term (funded) debt divided by four-quarter cumulative EBITDA. *Interest coverage* is quarterly EBITDA divided by interest expense. *Fixed charge coverage* is quarterly EBITDA divided by the sum of interest expense and the current portion of long-term debt and capitalized leases. *Net worth* is total assets minus total liabilities. *Leverage ratio* is total debt divided by total assets. *Senior debt to cash flow* is senior debt divided by four-quarter cumulative EBITDA. *Tangible net worth* is the sum on current, fixed, and other assets minus total liabilities. *Debt service coverage* is quarterly EBITDA divided by the sum of interest expense and principal repayments. *Current ratio* is current assets divided by current liabilities. *EBITDA* is the sum of pretax income, interest expense, and depreciation, cumulated over the last four quarters. *Debt to tangible net worth* is long-term debt divided by the sum on current, fixed, and other assets minus total liabilities. These statistics are estimated for the subsample of firm months for which DealScan indicates the presence of outstanding loans, which consists of 141 defaulting and 626 nondefaulting firms.

| Covenant | Firms at default | | Nondefaulting firms | |
|---|---|---|---|---|
| | Present | Violated | Present | Violated |
| | (1) | (2) | (3) | (4) |
| *Debt to cash flow* | 68.1% | 85.2% | 67.3% | 44.7% |
| *Interest coverage* | 70.2% | 96.6% | 62.4% | 35.0% |
| *Fixed charge coverage* | 53.2% | 83.5%+ | 50.9% | 20.6%+ |
| *Net worth* | 29.1% | 75.0% | 29.5% | 15.2% |
| *Leverage ratio* | 21.3% | 51.7% | 22.7% | 10.2% |
| *Senior debt to cash flow* | 33.3% | 60%+ | 22.1% | 8.3%+ |
| *Tangible net worth* | 14.9% | 71.4% | 19.6% | 11.9% |
| *Debt service coverage* | 13.5% | 87.5%+ | 12.5% | 26%+ |
| *Current ratio* | 9.9% | 66.7% | 10.8% | 23.2% |
| *EBITDA* | 24.1% | 82.8% | 9.4% | 26.9% |
| *Debt to tangible net worth* | 2.8% | 100% | 8.9% | 33.1% |

**Figure 1. Predicted default probability in boundary models**

For each level of the default boundary expressed as a proportion of the face value of debt, $V_B/P$, this graph shows the probability of reaching the boundary over a horizon of 10 years, as given in Leland (2004). The parameter values correspond to the base case in Leland (2004), and are as follows: The risk free rate is $r = 5\%$, the asset risk premium is $\lambda = 6\%$, and the cash payout ratio is $\delta = 6\%$. For BBB-rated bonds, the volatility of assets is $\sigma = 0.23$, and the firm leverage is $P/V_0 = 43.3\%$. For B-rated bonds, the volatility of assets is $\sigma = 0.32$, and the firm leverage is $P/V_0 = 65.7\%$.

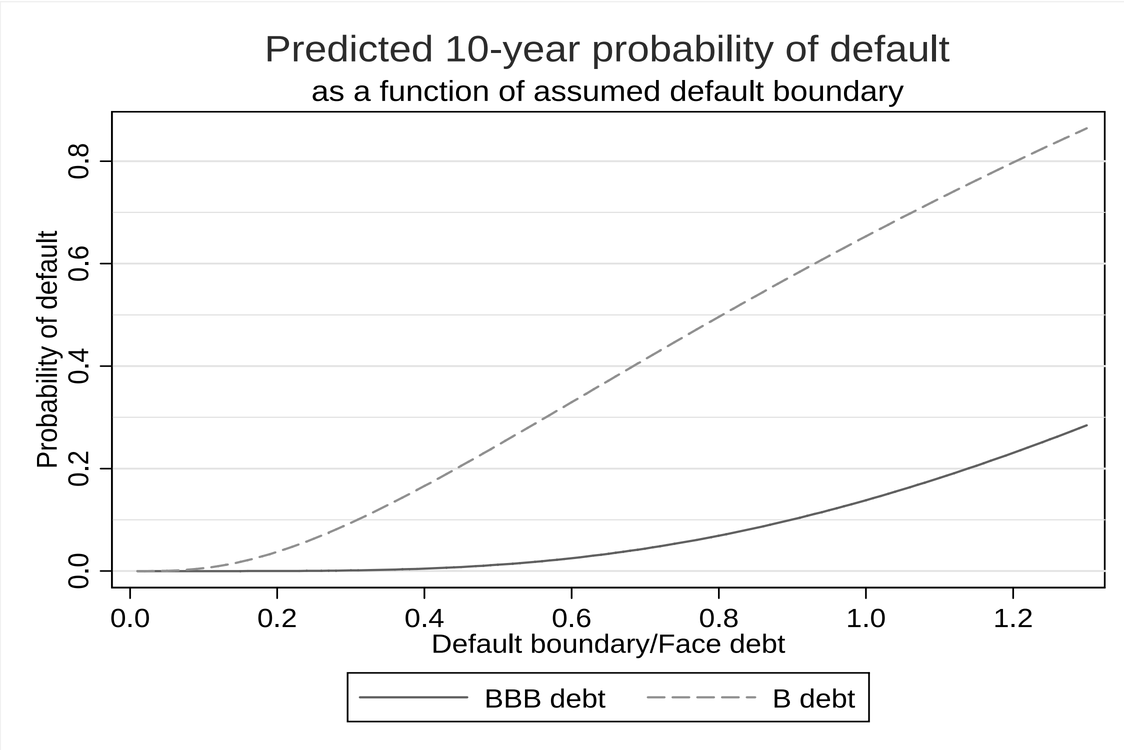

**Figure 2. Evolution of the asset value for defaulting firms**

This graph illustrates the evolution of the market value of debt, equity, and total assets for the median firm observed to default on its bonds, over the five-year period preceding the default event. Date 0 corresponds to the end of the last calendar month preceding default. All market values are normalized by the face value of debt. Default events are bond payment omissions, distressed bond exchanges, and bankruptcy filings.

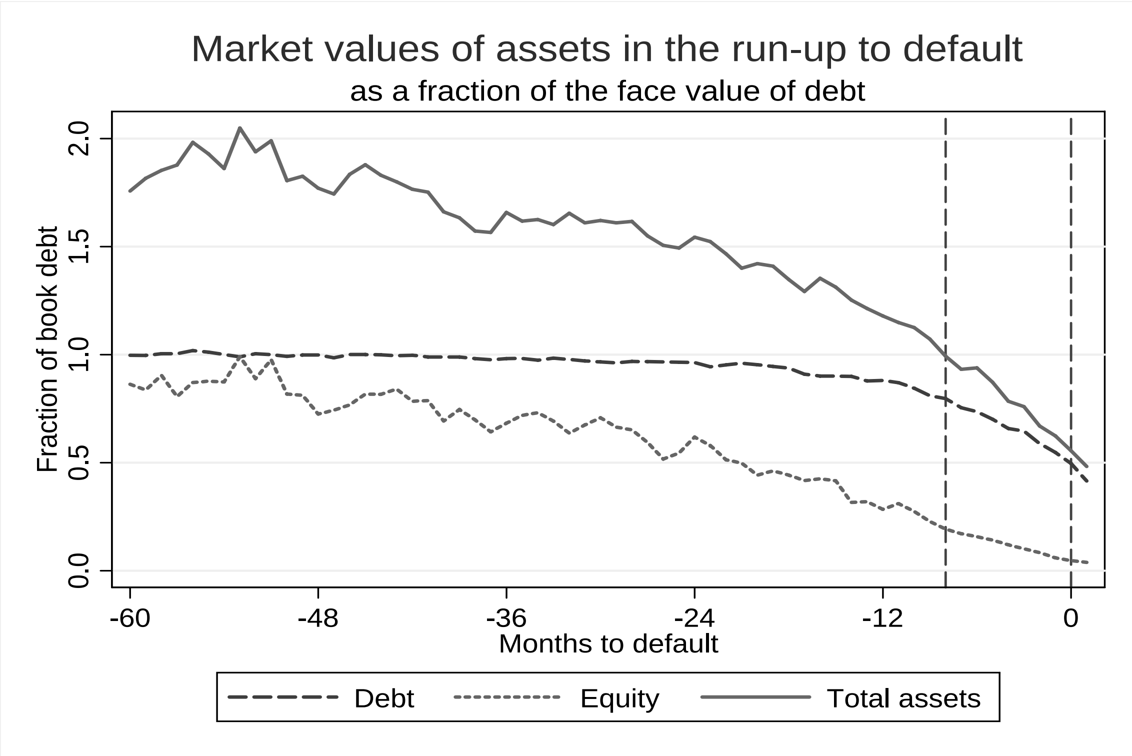

**Figure 3. Value and liquidity of defaulting and nondefaulting firms**

This graph shows observed combinations of asset values and quick ratios for firms at default and for firms that did not default for at least a year after the observation date. Each nondefaulting firm is represented by one point, corresponding to the month-end when the ratio of its market asset value to the face value of debt is at its sample period minimum.

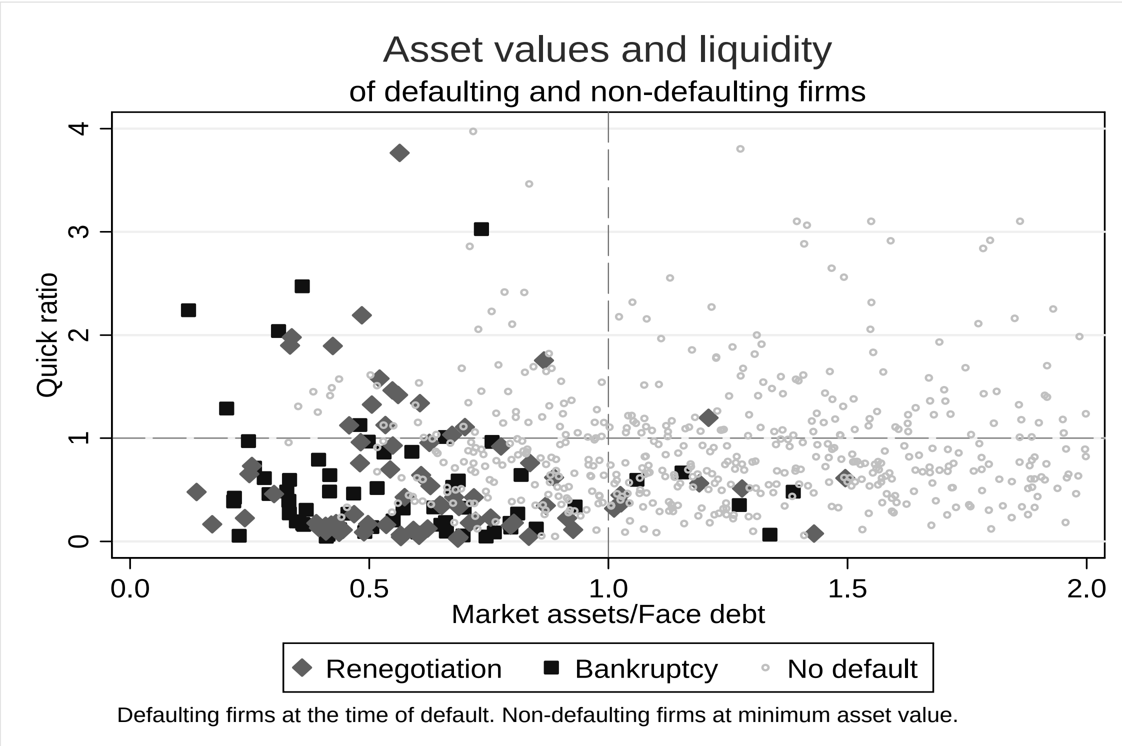

**Figure 4. Market value histograms**

This graph shows the distribution of the market value of assets for firms at default, as well as for all firm months not followed by default within a year after the observation date.

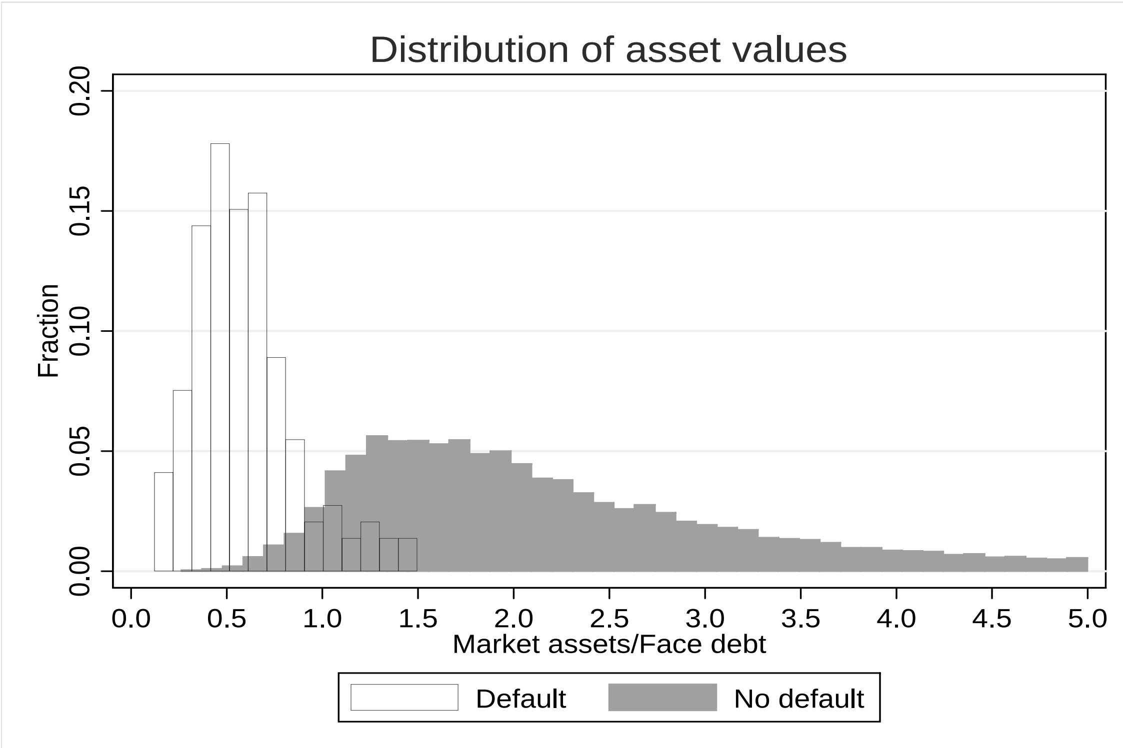

**Figure 5. Univariate classification accuracy**

This graph presents ROC (receiver operating characteristic) curves for diagnostic tests that classify all firm month observations as defaulting and not defaulting within the next month. For each of the five classification variables, the curve is constructed by calculating the test sensitivity and 1–specificity at each threshold value of that variable, where test sensitivity is the proportion of firms at default with the value of the variable below the threshold, and 1–specificity is the proportion of nondefaulting firm months with the value of the variable above the threshold. The reference line corresponds to a test with no predictive power.

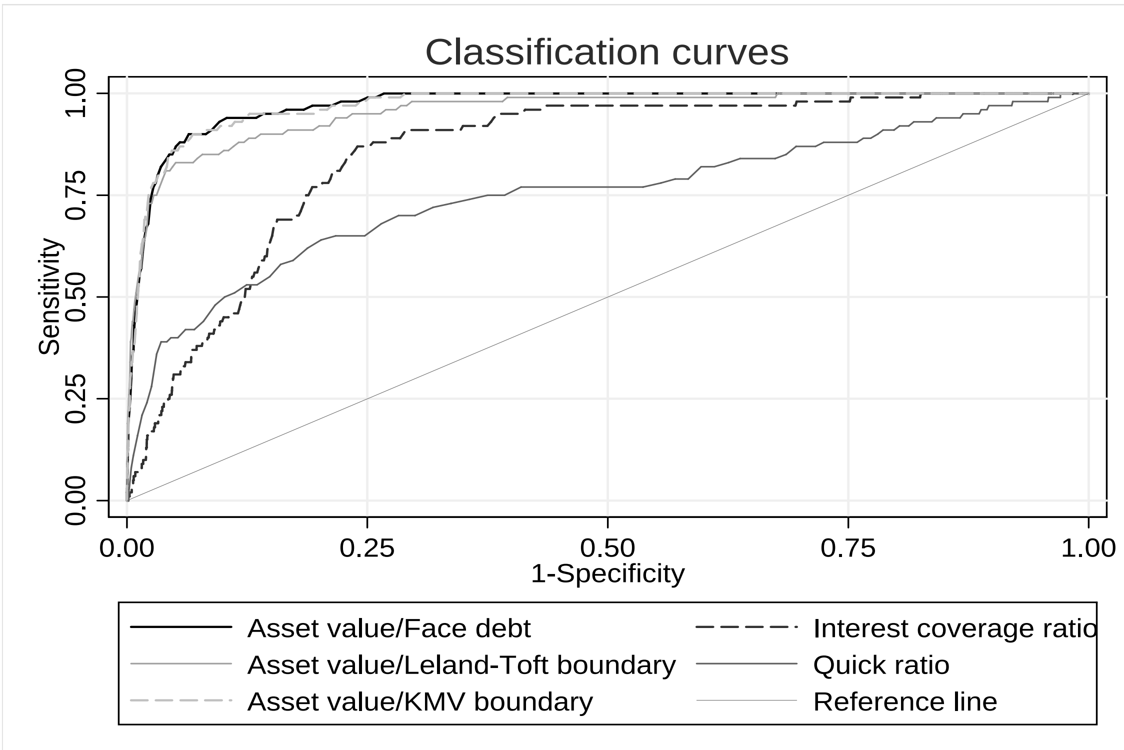

**Figure 6. Classification errors of the value boundary**

For each assumed boundary value of assets, this graph plots the fraction of observed defaults that happen at asset values above the boundary, as well as the fraction of firms with asset values below the boundary that do not default for at least a month and for at least a year.