Insolvency, Illiquidity, and the Risk of Default

Sergei A. Davydenko*

Preliminary

February 2013

Abstract

This paper studies whether default is triggered by insolvency (low market asset values relative to debt) or by illiquidity (low cash reserves relative to current liabilities), corresponding to economic versus financial distress. Although most firms at default are distressed both economically and financially, the two factors are distinct: A quarter of defaults are either by insolvent firms with abundant cash, or by solvent firms in a cash crisis. Consistent with the core assumptions of structural models of risky debt, the market value of assets is the most powerful factor explaining the timing of default by far, outperforming most other commonly used variables put together. By contrast, the marginal contribution of illiquidity is much smaller and depends on financing constraints that restrict the firm’s access to external financing.

*Joseph L. Rotman School of Management, University of Toronto. Email: davydenko@rotman.utoronto.ca; Phone: (416) 978-5528. Financial support from the Social Sciences and Humanities Research Council (SSHRC) is gratefully acknowledged.

Keywords: Credit risk; Structural models; Default; Insolvency; Illiquidity; Cash shortage; Default boundary

JEL Classification Numbers: G21, G30, G33
Introduction

This paper studies the role of insolvency (economic distress) and illiquidity (financial distress) in triggering corporate default. I look at whether the two factors are distinct, how they interact, and to what extent they explain empirically observed defaults.

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. Different theories about what causes firms to default result in dramatically different predictions regarding default probabilities, security prices, and corporate financing decisions.

Most models of risky debt assume that a firm defaults when the market value of its assets, which summarizes the firm’s economic distress or prosperity, falls below a certain threshold, known as the default boundary (e.g., Black and Cox (1976), Leland (1994), Longstaff and Schwartz (1995)). One view is that default occurs as soon as the market value of assets falls below the face value of debt, so that the firm becomes economically insolvent. Other “value-based” models predict that firms may find it optimal to continue operating with negative economic net worth, as long as the option value of equity is high enough to keep the firm alive. In most such models, if the firm’s cash flow is insufficient for debt service while the asset value is still high enough, equityholders can contribute additional funds at no cost. As a result, temporary cash shortages are irrelevant.

A contrasting view is that default is triggered by financial distress, i.e., the firm’s inability to meet its current financial obligations (e.g., Kim et al. (1993), Anderson and Sundaresan (1996), Ross (2005)). Even when the business is fundamentally sound, temporary declines in cash flow may leave the firm with a lack of cash necessary for uninterrupted debt service. Thus, in the presence of short-term financial obligations insufficient balance sheet liquidity may result in default despite the absence of economic distress.
Which of these two views is more suitable for credit risk modeling is unclear, because evidence on the role of insolvency versus illiquidity in triggering default is sparse. Empirical studies of distressed reorganizations have struggled to find an accurate proxy for “pure” economic distress unrelated to the firm’s financial obligations, which makes disentangling its effect from that of financial distress challenging.\footnote{Asquith et al. (1994) focus on cash flows relative to interest payments, and conclude that poor firm-specific performance contributes much more to distress than high leverage, whereas Andrade and Kaplan (1997) use the same approach to identify firms that are likely to be distressed financially but not economically. Gilson et al. (1990) associate distress with poor share price performance, and Pulvino (1998) identifies financially distressed firms as those with high leverage and low liquidity ratios. None of these studies measure the market value of assets, which is central in structural credit risk models.}

Prior evidence on the role of different factors in default comes primarily from empirical bankruptcy-predicting models, such as Altman (1968). Such studies do not measure the market value of assets, which is unobserved yet central to structural credit risk modeling. Shumway (2001) shows that a low value of equity is a strong predictor of bankruptcy. Yet this result does not necessarily imply that default is driven by a low value of assets: Since that existing shareholders are likely to be wiped out in bankruptcy, equity prices should fall endogenously whenever the probability of default increases, regardless of whether default is triggered by insolvency, illiquidity, or any other factor. This effect could explain why the value of equity is a good predictor of default (Shumway (2001)), but would not allow one to conclude that falling asset values provide the economic reason for default, as assumed by value-based models.

In contrast to existing studies, the main goal of this paper is not to build a better empirical forecasting model, but rather to investigate which of the two structural assumptions about what triggers default – low value or low liquidity – is better supported by empirical evidence. Davydenko (2012) studies the properties of the value-based default boundary, and shows that even though value-based models, which constitute a large majority of structural models, can explain the average probability of default, their assumption that the value of assets fully characterizes credit risk results in mis-classification of a large proportion of defaulting firms in the cross-section, which translates directly into errors in predicted credit spreads (Eom et al. (2004)). This paper studies the conditions that result in default further, looking into the extent to which our understanding of credit risk can be improved by allowing for defaults driven by
cash shortages, which are irrelevant in most extant models. I show theoretically and empirically that low balance sheet liquidity can only be important when the firm is also to some extent distressed economically, as well as financially constrained.

Following Davydenko (2012), I use a sample of defaulted firms with observed market prices of bonds, bank loans, and equity, and estimate their market value of assets by adjusting the total market firm value for the effect that costs of financial distress have on asset prices when investors partially anticipate default. I investigate whether default events such as missed bond payments, distressed exchange offers, and bankruptcy filings are associated with low market values of assets relative to debt (insolvency) or with insufficient cash reserves relative to current payments (illiquidity).

Figure 1 displays asset values (normalized by the face value of debt) and balance sheet liquidity (measured by the quick ratio, equal to cash and receivables divided by current liabilities) for firms at default, as well as for distressed firms that do not default. Firms with assets-to-debt ratios below 1 are economically insolvent, whereas those with a quick ratio below 1 have current liabilities in excess of liquid assets. Figure 1 shows that most firms at default are both insolvent and illiquid, as continued losses eventually deplete the firm’s cash reserves. Yet in general value and liquidity are distinct potential default triggers. In the sample, 13% of defaulting firms have enough liquid assets to cover their current liabilities (sometimes several times over) but low asset values. The existence of such firms suggests that “pure” economic distress is important even when the firm has ample liquidity at its disposal. However, I also find that the market value of assets exceeds the face value of debt for at least 10% of firms at default. Although these firms are solvent economically, they appear to have liquidity problems. Finally, there are many low-value and low-liquidity firms that are seriously distressed but that are able to avoid default or postpone it for years. A majority of economically insolvent firms, whose market value falls short of the face value of debt, do not default for at least a year, and the number of non-defaulting firms with low liquidity ratios is even higher. Thus, as can be seen from Figure 1, neither liquidity nor value can explain all observed defaults.
Fig 1. Value and liquidity of defaulting and non-defaulting firms

This graph shows observed combinations of asset values and quick ratios for firms at default and firms that do not default for at least a year. 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.

Consistent with the standard structural approach, I find the market value of assets to be the single most important variable affecting the timing of default. In regression analysis, the ratio of the market asset value to the face value of debt outperforms most popular accounting– and equity–based variables used in empirical studies put together. However, I also find that, controlling for solvency, cash shortages are the second most important factor explaining the timing of default. This finding contrasts with the view adopted by standard models that cash shortages are irrelevant because firms can access external financing at no cost. The evidence confirms that the roles of insolvency and illiquidity in distress are distinct, so that accounting for both factors as possible default triggers may potentially improve the
accuracy of structural models. However, I also find the economic significance of liquidity shortages to be limited, and its quantitative contribution to explaining the timing of default to be much smaller than that of the value of assets.

I hypothesize that, for a given asset value, a cash shortage is more likely to trigger default when the firm is more constrained in accessing external financing. In the absence of market frictions firms can raise new financing as long as the business remains sufficiently valuable. In this case, as in traditional value-based models, cash shortages are irrelevant and default is triggered by a low value of assets. By contrast, if the required cash cannot be raised at any cost, any temporary cash shortage would mean the firm’s inability to meet its current obligations, pushing it into default regardless of the economic fundamentals. In 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. Using firm-specific and economy-wide proxies for financing constraints, I find cash shortages to be substantially more important for constrained than for unconstrained firms.

The possibility of default due to illiquidity has important implications for corporate financing policies. In the presence of financing frictions and default costs, firms may find it optimal not only to use less debt ex ante, but also to maintain a cash reserve to reduce the probability of a liquidity-driven default (Acharya et al. (2012)). This precautionary motive for hoarding cash may partially explain the importance that managers attach to financial flexibility and financial slack (Graham and Harvey (2001)), and is likely to be particularly prominent at times when market disruptions restrict firms’ access to external financing.

Finally, as an alternative to insolvency and illiquidity, I study the role of covenant violations in triggering bond defaults. I find that covenant violations, renegotiations, and waivers are widespread for firms close to default, and not uncommon for nondefaulting firms as well. At least 8% of all bond payment defaults are triggered by a covenant violation that prompts senior creditors (i.e., banks) to block a scheduled bond payment, which almost invariably results in bankruptcy. Moreover, in another 7% of defaults the firm files for bankruptcy voluntarily, but does so in anticipation of a previously granted bank
covenant waiver. However, after excluding cases involving 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 adds relatively little to our understanding of the timing of default.

Taken together, what do these findings imply for credit risk studies? Davydenko (2012) shows that the inability of structural models to explain the cross-section of credit spreads (Eom et al. (2004)) is due at least in part to their assumption that the market value of assets fully characterizes the firm’s financial health and the probability of default. This raised the possibility that the lack of accuracy may be overcome by accounting for factors other than pure economic distress, such as liquidity. Recent models, such as Acharya et al. (2006) and Anderson and Carverhill (2012), incorporate financial slack in the dynamic structural framework and allow for defaults driven by cash shortages. Such studies provide a wealth of insights into corporate financing decisions, but their complexity necessitates numerical analysis, and their ability to explain default risk quantitatively is unclear. My results suggest that accounting for liquidity in this way, while complicating the models considerably, may not improve their accuracy dramatically. Indeed, not only is the quantitative effect of liquidity modest, but also it depends on firm-specific and economy-wide financing constraints, which are difficult to measure in practice. Focusing on solvency while recognizing the importance of investors’ uncertainty about the factors that affect the timing of default (Duffie and Lando (2001)) and exploring the nature of information imperfections that make it unpredictable for investors may be a promising way to advance our understanding of credit risk.

1. A model of the default decision

1.1. Model outline

This section outlines a simple model of default that integrates solvency, liquidity, and strategic considerations, and shows how they interact in triggering default.
Consider a levered firm whose productive assets in conjunction with the management’s human capital at time $t$ have a market value of $V$. The firm is also characterized by its accumulated cash reserve $x \geq 0$, which must remain non-negative for the firm to be able to continue operations. The firm is financed by equity and debt with a face value $B$, which includes the current claim of $S \leq B$ due at time $t$. Denote by $h$ the dollar “cash shortage” by which current debt exceeds the firm’s cash reserves:

$$ h = \max\{S - x, 0\} = S \max\{1 - Q, 0\}, $$

where $Q = \frac{x}{S}$ is the ratio of liquid assets to current liabilities.

The firm can raise new financing from external sources by selling new securities. Market frictions make such external financing costly, and at least some of the costs are borne by the firm’s shareholders. These can be deadweight costs; alternatively, they may arise because new securities can only be sold at a discount from their fair value, resulting in a wealth transfer from existing to new investors. Assume that raising $m$ dollars without changing the firm’s operations reduces the value of equity for existing shareholders by $\delta m$ dollars, where the parameter $\delta \geq 0$ measures financing costs for shareholders.

Failure to make the current debt payment constitutes default, which can be resolved either in bankruptcy or an out-of-court renegotiation. Unless the debt contract is renegotiated, nonpayment results in bankruptcy, in which case the value of the firm’s assets becomes $(1 - \alpha)V$, where $\alpha$ is the fraction of assets lost to bankruptcy costs. For simplicity, assume that in bankruptcy the value of existing equity is zero: $E_B = 0$. The debt contract can also be renegotiated at a proportional cost of $\gamma$ if both creditors and shareholders agree on the terms. Upon renegotiation, existing debt and equity are exchanged for new securities whose value is determined in a Nash bargaining game, whereby the net surplus from renegotiation (which equals $(\alpha - \gamma)V$) is split between shareholders and creditors according to their relative bargaining power in proportions $\theta$ and $1 - \theta$, where $0 \leq \theta \leq 1$.

---

2Early studies of Chapter 11 bankruptcies documented positive payoffs to shareholders in a substantial fraction of bankruptcies (e.g., Franks and Torous (1989)). However, recent evidence suggests that the practice of Chapter 11 bankruptcy has changed dramatically over the past decades, and equity deviations from absolute priority are now exception rather than the norm (e.g., Baird and Rasmussen (2003), Bharath et al. (2010)).
Managers, who act in the best interest of shareholders, decide how much external financing to raise, and which “operating policy” to adopt (continuation, \( C \), renegotiation, \( R \), or bankruptcy, \( B \)). If there is a shortage of cash \( (h > 0) \) and shareholders want to avoid default, they need to raise \( h \) from external sources.\(^3\) If managers propose renegotiation, creditors must accept its terms or trigger bankruptcy; otherwise, they have no decision to make.

Denote by \( E = E(V) \) the value that the firm’s equity would have in continuation if the firm had no short-term debt but were otherwise identical. For instance, in the Merton (1974) model, after repaying the short-term debt, equity is a European call option on the firm’s assets with the maturity equal to the maturity of long-term debt and the strike price equal to its face value, \( B - S \). In general, equity’s limited liability implies that \( E(V) \) is a convex function of \( V \). If \( S > 0 \), then after paying off the short-term debt in full the value of assets is reduced to \( V - S \), and the value of equity in continuation is given by \( E(V - S) \) (if positive), less the cost of external financing raised, if any. Thus, the value of equity under continuation, bankruptcy, and renegotiation is

\[
E_C = E(V - S) - \delta h, \tag{2}
\]

\[
E_B = 0, \tag{3}
\]

\[
E_R = \theta (\alpha - \gamma)V. \tag{4}
\]

Managers choose the operating policy that results in the highest value of equity.

1.2. Predictions

The reduced-form renegotiation game in the model ensures that neither shareholders nor creditors prefer bankruptcy over renegotiation if and only if the renegotiation surplus is non-negative, meaning that \( \alpha \geq \gamma \). Hence, whenever shareholders choose to propose renegotiation, creditors agree automatically and never trigger bankruptcy. There are two possible default regimes in the model, depending on whether the cost of renegotiation is greater or smaller than the cost of bankruptcy.

\(^3\)Notice that with proportional financing costs, it is never optimal to raise more.
Fig 2. Model predictions: High renegotiation costs

This graph shows shareholders’ preferred operating policy for different combinations of solvency and liquidity when renegotiation is prohibitively costly ($\gamma > \alpha$). Along the horizontal axis is the market value of assets, $V$, normalized by the face value of total debt. Along the vertical axis is the firm’s cash reserve normalized by current liabilities, $x/S$. The shaded area corresponds to bankruptcy and the non-shaded area, to continuation without default.

Fig 3. Model predictions: Low renegotiation costs

This graph shows shareholders’ preferred operating policy for different combinations of solvency and liquidity when renegotiation is feasible ($\gamma \leq \alpha$). The shaded areas correspond to renegotiation and the non-shaded area, to continuation without default.
1.2.1. Renegotiation is too costly

If the cost of renegotiation is greater than that of bankruptcy (\(\gamma > \alpha\)), managers continue if \(E_C > 0\), where \(E_C\) is given by Equation (2), and file for bankruptcy otherwise. This choice is illustrated by Figure 2. The graph plots the firm’s chosen operating policy (continuation vs. bankruptcy) for different combinations of solvency (measured by the ratio of the market value of assets to the face value of debt, \(V/B\)) and liquidity (measured by the liquidity ratio, \(Q = \frac{x}{S}\)).

Several intuitive predictions emerge from Figure 2. First, as long as external financing is possible (\(\delta < \infty\)), default happens when the firm is in sufficient economic distress, in the sense that the value of assets is below a certain threshold (default boundary). Put differently, for any given cash reserve, the firm does not default if its asset value is high enough. Second, if the firms is in a liquidity crisis (\(Q < 1\)), the value-based default boundary is decreasing in the firm’s balance sheet liquidity (equivalently, increasing in the size of the cash shortage that the firm must finance to avoid default).\(^4\) Third, given the size of the cash shortage, the default boundary increases in the cost of external financing, \(\delta\). At the limit, if external financing is costless (\(\delta = 0\)), the firm defaults at the lowest asset value compatible with a non-negative equity value in the absence of liquidity concerns, \(V = S\), and liquidity is irrelevant. Conversely, if external financing is not available at any cost (\(\delta = \infty\)), any cash shortage forces the firm into default, regardless of the firm’s solvency and economic prospects.

1.2.2. Renegotiation is feasible

If renegotiation is a cheaper option than bankruptcy (\(\gamma \leq \alpha\)), then bankruptcy is never chosen. Shareholders make the required debt payment and continue without defaulting if \(E_C \geq E_R\); otherwise, they propose renegotiation, and the debtholders agree. Equity’s chosen operating policy is shown in Figure 3. Renegotiation is proposed whenever \(V\) is below the renegotiation boundary \(V_R\), given implicitly by the equation \(E_C = E_R\). From Equations (2) and (4), the boundary satisfies

\[
E(V_R - S) - \delta h = \theta(\alpha - \gamma)V_R.
\]

Even when the firm has sufficient liquidity to repay its short-term debt in full (i.e., \(h = 0\)), the debt is renegotiated at low enough asset values.\(^5\) The renegotiation boundary is increasing in the cost

\(^4\)To see this, notice that, for a given asset value, \(V\), bankruptcy is triggered when the cash shortage \(h\) is so big that the cost of raising external financing necessary to cover the shortage, \(\delta h\), exceeds the option value of equity, \(E(V - S)\). Hence, the default boundary \(V_B\) satisfies the equation \(E(V_B - S) = \delta h\), and as such it is an increasing function of \(h\). For a given \(\delta\), the default boundary does not exceed \(V_B\), defined by the equation \(E(V_B - S) = \delta S\).

\(^5\)The linear dependence of \(E_R\) on \(V\), which follows from the assumption that in renegotiation the parties play a Nash
of bankruptcy and in shareholders’ bargaining power, and decreasing in the cost of renegotiation. In a liquidity crisis \((h > 0)\) the boundary is higher, increasing in the amount and the cost of external financing that the firm must raise to continue. Comparing Figures 2 and 3, one can see that in addition to renegotiations initiated to avoid bankruptcy, there are states in which shareholders propose renegotiation even though they would make the required debt payment and avoid default if renegotiation were impossible. This is the area of strategic renegotiations, which shareholders initiate to extract concessions from creditors by threatening costly bankruptcy. The strategic-default area is increasing in shareholders’ bargaining power, \(\theta\), and the net benefit of renegotiation, \(\alpha - \gamma\).

1.2.3. Summary of predictions

Thus, the model predicts that the firm defaults when the market value of its assets falls below a certain default boundary, which in general need not coincide with the face value of debt. The boundary may depend on liquidity and on the cost of external financing. In general, there is a minimum asset level below which default is triggered regardless of the firm’s liquidity position, in particular when renegotiation is feasible. If external financing is costless, the firm does not default until the value of assets falls below this level. Conversely, if external financing is unavailable, then any cash shortage triggers default regardless of the value of assets. These two polar cases correspond to the existing assumptions of purely value-based defaults, where cash shortages are irrelevant (e.g., Leland (1994)), and purely liquidity-based defaults, where external financing is unaccessible (e.g. Kim et al. (1993)). In between these two extremes, for a given solvency level external financing can be used to overcome some, but not all, liquidity shortages. In general, the default-triggering value of assets is increasing in the size of the liquidity shortage and the cost of external financing, so that firms default at higher levels of solvency when there is a severe cash shortage and the firm is financially constrained. Finally, when renegotiation is a viable alternative to bankruptcy, firms default earlier in distress (i.e., at higher solvency levels); otherwise, they wait until more advanced stages of distress before filing for bankruptcy.

Overall, the model shows that, as long as (costly) external financing is available, there exists a threshold asset value above which default does not occur regardless of liquidity. Put differently, financial distress can only trigger default when the firm is also sufficiently distressed economically. Moreover, the bargaining game, ensures that the equation \(E(V_R - S) = E_R\) has a solution, which in turn implies that there is a minimum asset value below which the firm always defaults regardless of liquidity. But this result also holds for any non-negative weakly monotonically increasing function \(E_R(V)\). Indeed, even if shareholders always get zero in any renegotiations (for example, because they have no bargaining power), the parties would still choose to renegotiate for \(V \leq S\).
more financially constrained the firm, the smaller the cash shortage that results in default – provided that the value of assets is also small enough.

2. Data description

2.1. Estimating the market value of assets

Most structural models assume that a firm’s credit risk is fully summarized by the market value of its productive assets. Unfortunately, the market value of assets is almost never observable, and few extant studies measure it for firms in distress. Following Davydenko (2012), I estimate the market value of assets using a sample of risky firms with observed market prices of bonds, bank loans, and equity. I collect detailed information on the debt structure of these firms, and use it in conjunction with the pricing data to compute the value of the firm, \( M_t \), as the total value of its debt and equity: \( M_t = E_t + D_t \).

Unfortunately, when default is costly, the value of the distressed firm is not an unbiased proxy for the value of its unlevered assets, \( V_t \), because expected default costs may affect debt and equity prices long before default is declared.\(^6\) Roughly speaking, in a static one-period model the value of the firm before default can be written

\[ M = D + E = V - q \times c \]  

where \( q \) is investors' estimate of the risk-neutral probability of default and \( c \) is the dollar cost of default, i.e., the total drop in the value of assets attributed to default. Equation (5) illustrates the problem of disentangling economic and financial distress: If the observed value of the firm, \( M \), declines, it may indicate economic problems (a decline in the asset value, \( V \)), or an increase in the probability of default, \( q \), when the firm’s ability to meet its financial obligations becomes more doubtful despite sound economic fundamentals.

To undo the effect of expected default costs on debt and equity prices, I employ the procedure suggested by Davydenko, Strebulaev, and Zhao (2012). The approach is based on the idea, first introduced in the structural credit risk literature by Duffie and Lando (2001), that investors do not have the full information necessary to conclude with certainty whether or not the firm is about to default in the next instant. As a result, the observed market value of the firm just prior to default depends on the “recovery”

\(^6\)In addition to default costs, another factor that makes the value of the firm differ from the value of its assets is the tax shield. However, as 93% of firms at default are making losses, their marginal tax rates are low, and thus tax shields are unlikely to have a large effect on firm values.
value of assets in default, \( V - c \), (which can be observed ex post), on the value that the assets would have if default were never possible, \( V \), (i.e., the unlevered asset value), and on the probability that investors attach to default conditional on the information available to them, \( q \), (which can be parameterized and estimated from the data). Inverting the relationship, one can find the value of assets implied by the firm value observed just prior to default and immediately after.

Specifically, notice that in this static setting the observed value of the firm just prior to default satisfies Equation (5), where investors’ conditional probability of default \( q \) can be estimated using historical default data or information about expected default embedded in debt prices. Upon the announcement of default, the firm value falls to the “recovery” value of assets, \( L \), that incorporates the cost of default in full: 
\[
L = V - c.
\]
Substituting \( c = V - L \), Equation (5) can be solved for the unobserved value of assets, \( V \), implied by firm values immediately prior to and immediately following default (\( M \) and \( L \), respectively).

The actual estimation procedure that I use, outlined in the Appendix, is based on the dynamic model of Davydenko et al. (2012), which accounts for the fact that even if the firm does not default immediately, it will still be risky until its debt matures. Because the expected cost of default is a modest fraction of total assets, the specifics of the estimation procedure have a relatively small effect on the resulting estimates of the market value of assets.\(^7\)

2.2. Data sources and sample selection

My empirical analysis is based on a sample of defaulted firms with observed prices of equity and debt, which I use to estimate the market value of assets and thus the level of economic solvency. I evaluate the role of solvency and balance sheet liquidity in triggering default and study the role of the costs of external financing.

Events of default in the sample include bankruptcy filings, missed or delayed bond payments, and distressed bond exchange offers. The specific definition of default that I use is the one employed by the rating agency Moody’s (Emery and Ou (2010)); the definition used by Standard & Poor’s is similar, with minor differences pertaining to grace period defaults and defaults on preferred stock. Thus, in addition to bankruptcy filings, default events include out-of-court renegotiations with bondholders through either a distressed bond exchange or payment delays or omissions. As in most extant studies of defaults, this definition does not encompass bank loan renegotiations or covenant violations (technical defaults), but

\(^7\)Davydenko (2012) discusses the effect of expected default costs in detail, and shows that any model-induced error in the estimated market value of assets is unlikely to exceed a few percent.
accounts for all situations in which bondholders’ cashflows are reduced relative to those stipulated in the original contract.

The master list of defaults is based on the Default & Recovery Database (DRD) from Moody’s, which purports to include all defaults on public bonds since 1970.\textsuperscript{8} To evaluate the ability of value and liquidity to discriminate between defaulting and non-defaulting firms, I also use a control sample of risky (high-yield) firms that did not default throughout the sample period. The market value of firms’ bonds is calculated using monthly price quotes for bonds included in the Merrill Lynch U.S. Investment Grade Index and High Yield Master II Index between December 1996 (the month the index was created) and September 2010. 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, starting from May 1998. Mergent’s Fixed Income Securities Database (FISD) provides descriptive information on bonds, and Thomson Reuters LPC’s DealScan is used for information on bank loans and covenants. Information on types of outstanding debt, including the use of credit lines, is manually collected from 10-K and 10-Q filings. Using bond, loan, and equity prices in conjunction with the debt structure data, I first compute the market value of assets for each sample firm at the end of each calendar month as described in Section 2.3, and then adjust firm values for expected default costs to compute the market value of assets.

The sample of defaults is selected as follows. Using the list of defaults in the DRD, I extract all bond defaults by U.S.-based firms between January 1997 and December 2010. I retain only defaults by industrial, transportation, and utility companies. I combine defaults by firms related through parent-subsidiary relationships, and, if a firm defaults several times, I retain only the first default event. I manually merge the data to Compustat/CRSP, FISD, and the Merrill Lynch bond pricing data. For those firms that are delisted from the exchange prior to default, I obtain equity prices from CapitalIQ. The resulting sample includes 306 firms that defaulted during the sample period; estimates of the market value of assets at default are available for 205 of them.\textsuperscript{9} I cross-check the information on default dates from DRD against news reports in Factiva, and amend the bankruptcy data with the information from Lynn LoPucki’s bankruptcy database. For distressed exchanges, DRD reports the date of successful

\textsuperscript{8}To identify possible omissions in the DRD 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 DRD and could not be confirmed independently, I exclude the firm from the sample.

\textsuperscript{9}The main reason why defaulting firms get excluded from the sample is the lack of market bond prices. Another important factor is that many defaulting firms are privately held (many have undergone a levered buy-out), and as such do not have traded equity or accounting data necessary to compute their market value.
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. Also, as DRD is not always consistent in its treatment of grace-period defaults, I use Factiva to manually identify the dates of missed payments. Firm-month observations following default are removed from the sample.

As a control sample, I use monthly observations for nondefaulting firms included in the Merrill Lynch indices, merging them with the other data bases and estimating their market values of assets in a similar manner. To make the control sample comparable to defaulting firms, I restrict it to firms rated below investment grade (i.e., BB+ or below, also referred to as “high yield” or “junk”). The final control sample includes 808 non-defaulting firms, as well as firm-month observations for defaulting firms that precede default by more than a year.

2.3. Computing the market value of the firm

For each sample firm, I estimate monthly market values of the firm as the sum of the 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 indices (MLI) is calculated by multiplying the currently outstanding amount by the bond price. Bonds with remaining maturity of less than one year or face value under a certain threshold 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 in any given month no bond prices are available for the firm, 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, the data base 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 (the median is 4). LSTA/LPC quotes are available for 69% of the sample firms, but only for 40% of firm-months that correspond to default. For firm-months not included in this database, the market price of bank debt is estimated as a quadratic function of the weighted-average bond price, as follows:

\[ \text{market price of bank debt} = a + b \times \text{weighted-average bond price} + c \times (\text{weighted-average bond price})^2 \]

\(^{10}\)Firms almost never default while rated investment grade (Collin-Dufresne, Goldstein, and Helwege (2010)). The control sample includes both “fallen angels” that were downgraded to junk, as well as original-issue junk bonds.
\[
P_{\text{bank}} = 40.18 + 1.045 \times P_{\text{bond}} - 0.00461 \times P_{\text{bond}}^2,
\]

where \( P_{\text{bank}} \) and \( P_{\text{bond}} \) 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 that arise due to the different priorities of loans and bonds in bankruptcy. 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 5\% of the face value of debt for 79\% of firms at default. Preferred stock is worth little in default, and thus its par value is likely to vastly overstate its market value in distress. Varma (2003) finds mean recovery rates for preferred stock of 15.3\%, compared with 36.1\% for senior unsecured bonds (the most common bond type by far). Hence, to approximate the market value of preferred stock, I assume that its price relative to par is equal to the constant fraction 15.3/36.1=0.424 of the firm’s current bond price. Sensitivity analysis shows that this approximation has a negligible effect on my estimates.

For the median firm at default, bonds and bank loans together constitute about 98\% of total debt. Firms may make use of other types of borrowing, such as 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 have the same price-to-par ratio as the firm’s bank debt. These types of debt are not frequently used by risky firms that dominate my sample, so this approximation affects only a small fraction of the firms.

Where available, I use equity prices from CRSP. However, firms are occasionally delisted from the stock exchange and disappear from CRSP some time before default. For these cases, I use OTC equity prices from CapitalIQ. Finally, I also rely on CapitalIQ for the details of the firms’ debt structure, including the split of debt between bonds and bank loans. The market value of the firm is then computed as the weighted average of the values of common and preferred stock, and all outstanding debt instruments.

Once the market value of the firm is computed, I adjust if for the effect of expected default costs, as outlined in Section 2.1 and described in more detail in the Appendix, to estimate the market value of the firm’s unlevered assets.
2.4. Descriptive statistics

Table 1 reports the number of defaults by year and by the first default event. The sample is dominated by firms that defaulted during the dot-com crash of the early 2000s. By contrast, although default rates were even higher in 2009, most firms that defaulted during the financial crisis were privately held, and as such are not in my sample. Further details are reported in Table 2. About one-third of firms (100 out of 306) default by filing for bankruptcy directly, close to one half (155 out of 306) miss or delay a payment, and the remaining defaults are distressed bond exchanges. Panel B shows that 87.1% of payment omissions and 37.5% of successful distressed exchanges lead to a bankruptcy filing within two years of the first default event. In untabulated tests, I find that the proportion of defaults that result in bankruptcy varies from year to year, but the incidence of bankruptcy in the sample is close to the DRD average. Panel C of Table 2 shows that 56% of defaults result in the firm emerging from bankruptcy, and, in addition, 26% of defaulters are either acquired or liquidated in the restructuring that follows. By contrast, defaults that result in the debt being eventually repaid or renegotiated outside of bankruptcy add up to less than 18% of all bond defaults.

Table 3 reports descriptive statistics for firms at default and for nondefaulting junk firms. The “nondefaulting” control sample consists of 808 firms that did not default throughout the sample period, as well as the firm-month observations for defaulted firms that precede the default date by at least a year. For each firm in the control sample, I calculate the sample period average of each variable and report descriptive statistics for this set of firm averages.

Table 3 shows that defaulting firms are large and do not differ much from nondefaulting junk firms in terms of book assets or sales-to-assets ratios, but have lower market-to-book ratios and higher leverage. Bond maturity is slightly lower and the proportion of short-debt higher for defaulting firms.\footnote{Balance sheet data on short-term debt for distressed firms should be interpreted with caution. Should the firm be in violation of a debt covenant, all its debts must be classified for accounting purposes as due immediately, regardless of actual maturity. This requirement results in a sharp increase in reported short-term debt for firms close to default compared with the previous quarter. To preserve the information on the maturity structure, for firms at default, I use the second most recent balance sheet for information on debt due in one year, rather than the most recent.} This finding is consistent with firms defaulting due to difficulties in refinancing short-term debt. An alternative possibility is that riskier firms endogenously issue debt with shorter initial maturity. The median nominal share price at default is only $1.18, compared with $18.73 for nondefaulting junk firms. Thus, it is unsurprising that the firm’s market capitalization can be used as a predictor of bankruptcy (Shumway}
The weighted average price of debt is 46 cents on the dollar for firms at default, but close to par for nondefaulting firms. This suggests that approximating the market value of debt by its face value, as is often done in academic studies, may be acceptable for healthy junk firms, but not for distressed ones. This is also evident from the comparison of various market- and book-based measures of leverage. The median market leverage, defined as the market value of debt over the market value of the firm, equals 90.4% for defaulting firms, but only 48.1% for the control sample. Thus, for nondefaulting junk firms, equity accounts for slightly more than half of the total value, but at default, it is only 9.6% of the median firm. The other two measures of leverage in the table use book rather than market values of debt. The quasi-market leverage ratio, which uses market equity values in the denominator, is close to the market leverage for firms away from default, but at default, it understates the equity’s share in the capital structure by about half. Book leverage is also close to the other two measures for nondefaulting firms, but is far off at default. These statistics underscore the importance of using market rather than book values of debt for very distressed firms.

2.5. Scheduled debt payments and the timing of default

The model of Section 1 analyzes the role of liquidity shortages in a static setting. Because in reality debt payments are made at discrete time intervals, the ‘short-term debt’ that the model focuses on is effectively zero between scheduled debt payments. Hence, insufficient cash reserves only become relevant close to scheduled payment dates, whereas in between firms may default due to economic distress, but not due to illiquidity.

Most structural models starting from Leland (1994) assume for tractability that debt payments are made continuously. One consequence of this assumption is that the default boundary that maximizes the value of equity is always positive, and the firm may default at any point in time. In reality, debt payments are made several times a year. In models with discrete debt payments, such as Geske (1977) and Merton (1974) the firm defaults only at times when a debt payment is due; put differently, the default boundary is zero between scheduled payments. By contrast, if a firm violates a debt covenant, it may be forced into bankruptcy by creditors. Models that assume that the timing of default is exogenous (not chosen by shareholders to maximize the value of equity) rely on covenants to justify the existence of a value-based

---

12By contrast, current liabilities reported on a firm’s balance sheet and used to compute its liquidity ratios are not instantaneous but spread over the next year. Notice that, in addition to funded debt that matures within a year, current liabilities also include other short-term obligations.
Fig 4. The timing of default relative to scheduled debt payments

This graph shows the distribution of defaults by the number of days left until the next scheduled bond payment.

default boundary (e.g., Longstaff and Schwartz (1995)). Exogenous defaults may occur at any time, and there is no reason to expect them to coincide with scheduled debt payments.

To evaluate these assumptions, I look at whether sample firms default at debt maturity, at dates when interest is due, or in between scheduled debt payments. Interest on most corporate bonds is paid semiannually, and even when there are several bonds outstanding for the same issuer, they often pay interest in the same calendar month. As a result, for the median firm in my sample, all bond payments occur in only two calendar months each year (most frequently, June and December). If the timing of default were random and unrelated to debt payments, only 2 out of 12 defaults would be expected to occur in the month preceding a scheduled interest payment. Yet in my sample 62% of all defaults occur within the 30 days preceding a scheduled bond payment, including 29% that happen on a scheduled payment date. Although this analysis does not account for payments on bank debt, it clearly indicates that most firms do not default until a debt payment is due. Most of these defaults are on bond interest payments, with only 1.6% of sample firms defaulting close to a bond maturity date.

These findings suggest that firms rarely declare default when there is no immediate requirement
to make a debt payment. Thus, the precise timing of default may appear to be driven by liquidity considerations, since in value-based models default can happen at any time, especially if the default boundary is exogenous. However, the observed behavior is also entirely consistent with value-based models that incorporate discrete debt payments, such as Geske (1977). While for sufficiently distressed firms these findings can be used to pinpoint the timing of default precisely, a far more important and challenging problem is to identify the factors that make the firm ‘sufficiently distressed.’ The next section documents the role of two such factors, insolvency and illiquidity.

3. Are firms at default insolvent or illiquid?

A potentially important factor missing from traditional structural models is the availability of cash and other liquid assets, which allow firms to continue uninterrupted debt service when their cash flow declines temporarily. Cash shortages are irrelevant in value-based models, because such models assume that firms can always raise external financing against future cash flow as long as the value of assets is high enough. However, in reality market frictions may restrict firms’ access to external financing in distress, for instance, owing to information asymmetry or agency problems (Myers (1977), Myers and Majluf (1984)). If external financing is unavailable, temporary cash shortages may push the firm into default even if the business is still valuable. The model of Section 1 shows that the firm’s ability to access external financing depends on its net worth, implying that both asset values and liquidity can affect the timing of default. I proceed to evaluate the role of illiquidity and its interaction with value in triggering default.

3.1. Univariate statistics

Table 4 reports measures of solvency, profitability, and liquidity for defaulting and non-defaulting firms. The mean (median) ratio of the market value of assets to the face value of debt at default is only 64.1% (60.7%). Thus, in contrast with the assumption that firms default as soon as they become economically insolvent, on average over two-thirds of creditors’ value is already destroyed by the time the firm defaults. The market value of assets at default coincides with the default boundary in value-based models such as Leland (1994).\footnote{This statement assumes that the value of assets does not experience jumps, as is the case in most, but not all, value-based models.} A detailed study of the empirical properties of the default boundary can be found in Davydenko (2012). Table 4 shows that 89% of defaulting firms have negative economic net worth, so that only 11% of them are economically solvent. By contrast, only 5% of the control sample of firms that do
not default for at least a year are economically insolvent, and the mean market value of assets for these firms is over three times the face value of debt. Because the control sample consists of risky firms, in the general population of firms such as all Compustat firms the value of assets is even higher. Panel A of Table 4 also shows that if solvency is measured using book rather than market values of assets, only 60% of firms at default are insolvent (equivalently, have negative book equity), and the median ratio of assets to liabilities is 94%. Thus, some economically insolvent firms at default appear solvent when book asset values are used.

Panel B of Table 4 reveals major differences in cash flows and profitability between defaulting and nondefaulting firms. At default, the median profit margin is –19.5%, and the mean is –272%. Accounting income is negative for 90.7% of defaulting firms, and as many as 77.6% of them have negative operating cash flow. By contrast, even though nondefaulting junk firms in my sample also have negative profitability on average (–13.7%), it is driven by a much smaller number of loss-making firms (36.6%), and the proportion of negative cash flow firms in the control sample is only 17.8%. The interest coverage ratio (EBITDA over interest payments) provides additional evidence that defaulting firms do not generate sufficient cash flow to cover their obligations. While the median firm in the control sample can cover its interest payments out of its EBITDA 2.8 times, the median firm at default is making losses equal to 6% its interest payments.

Panel C of Table 4 reports various measures of balance sheet liquidity. The primary proxy for liquidity used in this paper is the quick ratio, or the ratio of cash and near-cash plus accounts receivable to current liabilities. The mean (median) quick ratio at default is 0.53 (0.35), compared with 1.19 (0.91) for the control sample. For 87% of firms at default, the quick ratio is less than 1, compared with only 60% for nondefaulting firms in the sample and 47.1% for all firm quarters in Compustat. While low liquidity ratios may be the norm rather than a sign of distress in some industries, 81% of firms at default have a quick ratio below their industry median, whereas nondefaulting firms are fairly similar to the industry norm. Other measures of liquidity, such as the current ratio (current assets divided by current liabilities) and cash ratios (cash over current liabilities) are also much lower at default.14

With insufficient liquid asset reserves, distressed firms must rely on either their operating cash flow or on external financing to pay their creditors and suppliers. However, as many as 67.9% of firms at default

14The 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.
have both a quick ratio below the industry median and negative cash flow, compared with only 7.2% for nondefaulting junk firms. Loss-making firms with insufficient liquid assets need access to external financing to be able to avoid default.

3.2. Solvency/liquidity combinations at default

Figure 1 on p. 4 shows market asset values (relative to the face value of debt) and liquid asset reserves (relative to current liabilities) for firms at default as well as for firms that do not default for at least a year. Figure 5 splits the sample of defaults into renegotiations (circles) and bankruptcy filings (diamonds). Firms with assets-to-debt ratios below 1 are economically insolvent, whereas those with a quick ratio below 1 have current liabilities in excess of liquid assets. Moving left (down) on both graphs corresponds to increasing insolvency (illiquidity).

Several important insights emerge from the graphs. All but three sample firms at default have either negative economic net worth or a quick ratio below 1. Moreover, as many as 76% of them are both insolvent and illiquid. This finding is consistent with the intuition that economic distress (falling cash flows) eventually causes financial distress (the inability to honor financial obligations) when the firm’s continued losses deplete its cash reserves. In general, though, insolvency and illiquidity appear to be distinct potential default triggers: Some firms default while solvent but illiquid, and vice versa. Specifically, 13% of defaulting firms are in the upper left quadrant on these graphs. They have low asset values but cash reserves that are sufficient to meet their current liabilities, sometimes several times over. In the sample of firms at default, the quick ratio is above the industry median for 20% of firms, above 1 for 14.9%, and above 2 for 3.6%. For comparison, the quick ratio is above 2 for 26% of all firm-quarters in Compustat. Conversely, 10% of defaults are in the lower right corner, corresponding to a cash shortage with positive economic net worth. Thus, neither insolvency nor illiquidity alone can explain all observed defaults.

These empirical findings are broadly consistent with the predictions of the model of Section 1, summarized in Figures 2 and 3 on p. 9. Insolvent firms that default despite sufficient liquidity (i.e., those in the upper-left quadrant) have relatively low asset values. As many as 73% of them default by renegotiating their debt contract, compared with only 51% for illiquid firms. In the model, this preference for renegotiations arises because sufficient liquidity means that these firms are not in immediate danger of bankruptcy, while their low asset values give them ammunition in strategic renegotiations with creditors.
This graph shows observed combinations of asset values and quick ratios at default, separating bankruptcy filings from out-of-court renegotiations.

wanting to avoid large losses in bankruptcy. Similarly, the proportion of renegotiations by solvent but illiquid firms (64%) is also higher than the sample average. In the model, shareholders may renegotiate strategically at relatively high levels of solvency even though, were renegotiation impossible, they would rather raise costly external financing necessary to overcome the cash shortage than to file for bankruptcy. Also consistent with the model, bankruptcy filings correspond to lower solvency levels than renegotiations (62.0% of the face value of debt for bankruptcies vs. 65.7% for renegotiations). This conforms with the prediction that firms default strategically early in distress when renegotiation is feasible, but wait longer before filing for bankruptcy when it is not.

An important stylized fact transpiring from Figure 1 is that many insolvent and/or illiquid firms are able to avoid default or at least delay it for a year or more. This evidence extends the finding of Davydenko (2012) that the use of the value of assets to separate defaulting and nondefaulting firms results in a large number of falls positives, i.e., nondefaulting firms wrongly classified as defaulting by the default boundary rule. 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 neither liquidity nor value can separate them perfectly.

3.3. High-liquidity and high-value defaults

I use Factiva to gain insight into the motives that drive firms with substantial liquid assets into default, looking into the details of all such defaults on a case-by-case basis. News releases and press 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 over the long term; others carry out recapitalizations involving a bond exchange, which may seriously dilute existing shareholders’ stake but improve the firm’s balance sheet.\(^\text{15}\) Observed defaults by high-liquidity, low-value firms are consistent with models that use a value-based default boundary, but not with the popular perception that firms default when they run out of cash.

At the same time, Figure 1 also indicates that some defaults happen while the market asset value is still substantial. In the sample, 8.8% of firms at default have positive economic net worth but low liquidity ratios.\(^\text{16}\) A case-by-case Factiva analysis indicates that such defaults may be driven by litigation, covenant violations, and, commonly, insufficient liquid reserves coupled with the 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.

Next, I proceed to evaluate the quantitative contribution of value vs. liquidity in explaining the timing of default, and explore the role of financing constraints in amplifying the effect of cash shortages.

\(^{15}\) 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, Dow Jones Newswires, 24 October 2001).

\(^{16}\) Although in models with endogenous default, such as Leland and Toft (1996), shareholders’ optimal boundary can sometimes exceed the face value of debt, this does not explain defaults by solvent firms in my sample. The Leland-Toft boundary is above 1 for 5.7% of defaulted firms, but the empirical boundaries for these firms are all below one, with the mean and median close to those of the overall defaulted sample. Conversely, for the 8.8% of firms observed to default while solvent, estimated Leland-Toft boundaries are all below one and similar to those of other defaulted firms.
4. Explaining the timing of default

To study the role of various factors in triggering default, I estimate hazard models of default using all defaulting and nondefaulting firm-month observations. Hazard analysis has become the instrument of choice in empirical studies predicting default and bankruptcy (e.g., Shumway (2001); Bharath and Shumway (2008); and Campbell, Hilscher, and Szilagyi (2008)). In contrast to predictive studies, the main goal of my analysis is not to build a better forecasting model, but rather to evaluate the role of two specific factors, value and liquidity, at the time when default is triggered. Following Bharath and Shumway (2008), I avoid the need to specify the baseline hazard by using the Cox (1972) proportional-hazard model.

4.1. Value, liquidity, and traditional predictors of default

Table 5 compares the ability of liquidity and the market value of assets to explain the timing of default with that of other accounting-based and market-based variables commonly used in empirical default-predicting studies. To facilitate comparisons of different models, all regressions in this table use the same subsample of 30,744 firm-months for which all variables are available. Following Shumway (2001) and Bharath and Shumway (2008), all independent variables are winsorized at their 1% and 99% levels.\footnote{The winsorization boosts the predictive power of accounting and equity-based variables significantly, but has almost no effect on the asset value.}

Column (1) shows that the ratio of the market value of assets to the face value of debt is a very powerful variable affecting the timing of default, with a \( z \)-statistic of \(-15.5\) and pseudo-\( R^2 \) of 49%. Remarkably, its explanatory power exceeds that of all other factors in Table 5 put together, including predictors based on the market value of equity. These findings provide support for those one-factor models that use the value of assets as a state variable that determines the risk of default.

However, contrary to such models, Table 5 shows that liquidity ratios are also robustly significant, although their explanatory power is substantially lower than that of the asset value. Column (2) uses the size of the cash shortage normalized by the current liabilities, computed as \( h/S = \max\{1 - Q, 0\} \), where \( Q \) is the quick ratio (see Equation (1)). Table 5 shows that \( z \)-statistics for liquidity ratios exceed those of other variables except for the value of assets. However, the \( R^2 \) in Column (2) is only 10%, compared with 49% in Column (1). Moreover, once the market value of assets is included in the specification, the marginal effect of liquidity is quite modest: In Column (3), its inclusion raises the \( R^2 \) from 49% to only
50%. In unreported tests, I find similar results when the market value of assets is used in combinations with other proxies for balance sheet liquidity, such as the quick ratio, working capital over total assets, or the current ratio. Thus, the market value of assets is far more powerful factor explaining the timing of default than liquidity, providing strong support to value-based models over those that assume that default is driven by cash shortages.

Other regressions in Table 5 compare the ability of the market value of assets to explain the timing of default with that of other variables commonly used in empirical default-predicting studies. Regression (4) includes three accounting ratios suggested by Zmijewski (1984), namely, the current ratio \((CA/CL)\), net income over total assets \((NI/TA)\), and total liabilities over total assets \((TL/TA)\). As in Shumway (2001), these variables are strongly statistically significant, although the \(R^2\) in this regression is only about one third of that provided by the asset value alone. Moreover, when they are combined with the value of assets in regression (5), the coefficients for \(TL/TA\) and \(NI/TA\) become insignificant, and the former even changes its sign. At the same time, the current ratio \(CA/CL\), which measures balance sheet liquidity, remains strongly significant.

Regression (6) includes the five ratios used in Altman’s (1968) \(z\)-score model, namely, working capital over total assets \((WC/TA)\), retained earnings over total assets \((RE/TA)\), EBIT over total assets \((EBIT/TA)\), market equity over total liabilities \((ME/TL)\), and sales over total assets \((S/TA)\). Three of the ratios are statistically significant, but once again all of them together explain less of the variation of the timing of default than does the asset-value alone in regression (1). Moreover, column (7) shows that once the value of assets is added to the specification, only two variables remains significant, one of which \((WC/TA)\) is Altman’s proxy for balance sheet liquidity.

Columns (8) and (9) of Table 5 use an estimate of the probability of default based on the equity-implied distance to default. Similar to the Expected Default Frequency \((EDF)\) provided by Moody’s/KMV (MKMV), it is loosely based on the Merton (1974) model calibrated to observed market values of equity. The use of such measures of the probability of default was pioneered by KMV LLC and later introduced into academic research by Vassalou and Xing (2004). The estimation procedure developed by KMV involves solving a series of nonlinear equations in order to estimate the unobserved market asset value and volatility implied by observed equity prices and leverage ratios (Crosbie and Bohn (2002)). Bharath and Shumway (2008) find that the distance to default estimated using a nonproprietary version of the KMV algorithm is, if anything, a slightly weaker predictor of default than a “naïve” measure that uses
the same inputs and functional form, but is much easier to estimate. Consequently, I compute the probability of default $\pi$ based on the “naïve” version of distance to default suggested by Bharath and Shumway (2008).

Regression (8) shows that $\pi$ is strongly associated with the timing of default. In combination with the proxy for cash shortage, this variable explains 43% of the variation in the timing of default, which is high compared to most other specifications, but still lower than the 49% produced by the market value of assets alone in regression (1). Importantly, even though $\pi$ incorporates information embedded in the market value of equity, it loses much of its power in the presence of the market value of total assets in column (9), as both the coefficient and its $z$-statistic drop by a factor of three. By contrast, the coefficient for the value of assets changes much less in the presence of these and other controls in the table.

Overall, in these tests the market value of assets is the most powerful variable by far, explaining a higher proportion of the variation in the timing of default than all other default predictors put together, most of which become insignificant in its presence. While balance sheet liquidity remains strongly statistically significant, its incremental ability to explain the timing of default quantitatively is limited. The results broadly support standard structural models that use the market value of assets as a variable summarizing the firm’s economic well-being, as other univariate factors perform much worse. However, even together, solvency and liquidity can explain only about half of the observed variation in the timing of default, so that even those structural models that incorporate both factors are unlikely to be able to explain the cross-section of defaults and credit spreads. In the next subsection I show that differences in the availability of external financing for different firms are likely to exacerbate the lack of cross-sectional accuracy, as they affect the relative role of the two default-triggering factors.

4.2. Financing constraints and the relative importance of value versus liquidity

I hypothesize that whether or not shortages of liquid assets cause the firm to default depends on the availability of external financing. In the absence of financing constraints any cash shortage can be overcome by raising new financing, rendering liquidity irrelevant. If, in contrast, external financing is completely unavailable, then any temporary cash shortage can push the firm into default regardless of its solvency. In between these two extreme cases, the relative importance of value versus liquidity as default triggers should depend on how difficult it is to raise external financing in distress.

The existence and the real effects of financing constraints are a subject of extensive debate in corporate
finance (e.g., Fazzari, Hubbard, and Petersen (1988); Kaplan and Zingales (1997)). As one proxy for financing constraints, I use the measure suggested by Hadlock and Pierce (2010), which is a function of firm age and size. Unfortunately, most other standard proxies for constraints suggested in the literature, such as whether or not the firm is rated by a major credit rating agency and whether it pays dividends, are inapplicable for my sample of bond issuers on the brink of default. Instead, because banks are the most likely source of external cash for very distressed firms, I construct three firm-specific and two economy-wide proxies related primarily to how difficult it is to raise new debt in distress. The first proxy is 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, and asset sales, as well as the “negative pledge” covenant that prohibits secured borrowing unless the bonds are also secured on a pari passu basis. This covenant index varies between 0 and 5. The second proxy is the ratio of secured debt (loans and bonds) to fixed assets. The idea behind this variable is that banks are less likely to extend new credit if the firm has few unincumbered assets that can be pledged as collateral. The third proxy equals one minus the amount of undrawn credit lines, normalized by current liabilities. The presence of authorized but unused credit lines may indicate better prospects for obtaining additional cash, even though they may be curtailed in distressed.

In addition to firm-specific proxies for constraints, I use two variables that characterize the overall state of the market for risky debt. Cash shortages are more likely to result in default when junk debt markets are “cold” and few new risky loans are bonds are issued, as was the case after the failure of Lehman Brothers in 2008 (Ivashina and Scharfstein (2010)). Using the FISD data base, I compute the quarterly par amount of all new junk bonds issued by U.S. firms, subtract the linear trend, and normalize the resulting variable by its maximum value during the sample period. The fourth proxy for financing frictions equals one minus this measure of the risky debt market activity. Finally, the fifth proxy is the spread between Baa and Aaa corporate bonds reported by Moody’s, expected to be negatively associated with the market activity and the availability of financing for distressed firms. These five proxies for financing constraints are used in regressions (1) through (5) of Table 6, respectively.

To test this hypothesis that a cash shortage of a given size is more likely to trigger default when the firm is financially constrained, as suggested by the model of Section 1, I interact the five proxies for constraints with the size of the cash shortage, computed as max \{1 − Q, 0\}, where Q is the quick ratio. For each of the five proxies for constraints, observations with the value of the proxy above its sample
median are classified as constrained, and those below the median as unconstrained.\textsuperscript{18} Table 6 presents the results. The last row reports the \( p \)-value of the test that the coefficients for the two interaction terms are equal. The effect of liquidity shortages is significantly greater when the firm is constrained, and, with the exception of column (5), the difference is highly statistically significant.

The results of this section have a number of important implications. First, the superior power of the market value of assets in explaining the timing of default suggests that the asset value is a good candidate for the state variable in traditional single-factor structural models. Second, such models cannot explain all observed defaults, in particular because cash shortages play an independent role in triggering default. Third, the relative importance of value versus liquidity depends on the availability of external financing, which can vary across firms and over time, and is difficult to measure in practical applications.

5. 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.\textsuperscript{19} Smith (1993) finds that technical defaults usually involve multiple violations of affirmative covenants,\textsuperscript{20} 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 (2008)). 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

\textsuperscript{18}\textsuperscript{18}Due to the nonlinearity of hazard 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.

\textsuperscript{19}\textsuperscript{19}Some papers study at the determinants of the debt’s covenant structure and their strictness, both for bank loans (Bradley and Roberts (2003), Murfin (2012)) 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.

\textsuperscript{20}\textsuperscript{20}“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).
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 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.\footnote{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 (2008) 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.}

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 7 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.\footnote{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,} 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 7, 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 7 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 (2008) findings for larger DealScan samples not restricted to junk firms. 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 5, 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.

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 DRD database.\footnote{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.}

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 defaulted firms, 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 and/or quick ratios. 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.

6. Summary and conclusions

This paper evaluates the relative importance of insolvency (low asset value relative to debt) and illiquidity (low liquid assets relative to current liabilities) in triggering default. Consistent with the core assumption of value-based models, the market value of assets is the most powerful variable explaining the timing of default, outperforming most available alternatives put together. Yet Davydenko (2012) shows that using

\[ \text{As an example, aaiPharma delayed filing its 2003 annual report pending SEC investigation, which constituted an event of default under the terms of its senior credit facility, and prompted senior lenders to veto a scheduled bond payment. At the time, the ratio of aaiPharma’s market value of assets to the face value of debt was close to 1.42.} \]
it as a sufficient statistic for default results in a substantial cross-sectional error in predictions, which adversely affects the accuracy of debt pricing models (Eom, Helwege, and Huang (2004)) and their limited success in explaining short-term default probabilities (Leland (2004)). To what extent might this lack of accuracy be due to the failure of traditional value-based models to account for balance sheet liquidity?

I find that, controlling for the value of assets, cash shortages are the second most important factor explaining the timing of default. But although liquidity is robustly significant statistically, its marginal contribution to the models’ ability to explain the cross-section of defaults quantitatively is far below that of the market value of assets. Moreover, the importance of liquidity varies with the availability of external financing, which may depend both on firm-specific as well as on economy-wide factors. Furthermore, even taken together, value and liquidity fail to explain a substantial part of the variation in the observed timing of default.

One interpretation of these findings is that in order to improve the accuracy of structural models, it is necessary to account not only for the firm’s value of assets and its optimal cash management policy, but also for factors that affect the costs of access to external financing. But because these costs depend on both firm-level and economy-wide characteristics, capturing all relevant factors while maintaining analytical tractability 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 (2012)). Although such models generate a wealth of insights into corporate financing policies, whether their ability to explain observed credit spreads and default probabilities quantitatively is superior to existing value-based models is unclear, given the limited incremental power of liquidity relative to value. Incorporating other factors known to predict defaults is also unlikely to improve the models’ accuracy substantially, as they are typically even less powerful than liquidity. Instead, it may be beneficial for structural models to recognize that default cannot be predicted perfectly based on the information available to investors, as evidenced by large observed price reactions to default (Duffie and Lando (2001)). Focusing on investors’ uncertainty may be the most promising way of advancing our understanding of the nature and pricing of credit risk.
Appendix: Estimating the market value of assets

When default is costly, the value of the firm prior to default is affected by expected default costs, and hence differs from the value of the firm’s productive assets. This section outlines the procedure used to estimate the unobserved value of assets from the observed value of the firm. It is adapted from Davydenko, Strebulaev, and Zhao (2012), who provide a detailed discussion of the procedure, its assumptions, and estimated costs of default.

A. Assumptions and pricing equations

As is common in reduced-form credit risk models, default is modeled as a doubly-stochastic (Cox) process. I make the following specific assumptions:

1. The market value of the firm’s productive assets $V_t$ (i.e., the unlevered value of the firm) follows a geometric Brownian motion. Under the risk-neutral measure,

$$dV_t = rV_t dt + \sigma V_t dW_t^Q,$$

2. Conditional on the history of $V_t$, default is the first jump of a heterogeneous Poisson process with the following intensity under the real probability measure:

$$\lambda_t^P = e^{\beta_0 + \beta_1 \log \frac{V_t}{B}}, \quad (A1)$$

where $\beta_0$ and $\beta_1$ are parameters common to all firms, which are to be estimated as part of the procedure.

3. The risk-neutral default intensity is a multiple of the real-measure intensity:

$$\lambda_t^Q = \xi \lambda_t^P, \quad (A2)$$

where $\xi \geq 1$ is the risk premium, assumed constant across firms. For each year, the risk premium is estimated from the value of debt of an average firm and its characteristics, as described in Davydenko et al. (2012).

4. The “recovery” value of the firm $L_t$ (i.e., the value of its assets upon a hypothetical default at time $t$) is a constant (although possibly firm-specific) fraction of its continuation value:

$$L_t = (1 - \alpha)V_t. \quad (A3)$$

5. The face value of debt $B$ and the risk-free rate of interest $r$ are constant.

Davydenko et al. (2012) show that under the above assumptions, the value of the firm at any time prior to default (or maturity, whichever comes first) satisfies

$$M_t = L_t + (1 - L_t/V_t)e^{-r(T-t)}E_t^Q \left[ V_T e^{-\int_t^T \lambda_s^Q \, ds} \right]. \quad (A4)$$

When $M_t$ and $L_t$ are both known, this equation can be solved for the unobserved $V_t$. If the proportional cost of default $\alpha$ is known instead of the recovery value $L_t$, this equation can be re-written as:

$$M_t = (1 - \alpha)V_t + \alpha e^{-r(T-t)}E_t^Q \left[ V_T e^{-\int_t^T \lambda_s^Q \, ds} \right]. \quad (A5)$$

Finally, the value of the firm’s debt is given by

$$D_t = e^{-r(T-t)}E_t^Q \left[ e^{-\xi \int_t^T \lambda_s^Q \, ds} \right] + \xi \int_t^T E_t^Q \left[ Re^{r\int_t^s [r + \xi \lambda_s^Q(V_u)] \, du} \lambda_s^Q(V_u) \right] ds, \quad (A6)$$

where $R$ is the recovery rate, assumed to be constant.

B. The estimation procedure

To find the value of assets from Eq. (A4), parameter values $\beta_0$ and $\beta_1$ of the function $\lambda^Q$ specified in Eq. (A1) are required. But to estimate these parameters, one needs to know the asset values of the sample firms. To overcome the joint estimation problem, Davydenko et al. (2012) suggest the following sequential procedure:
**Step 1.** As an initial approximation for \( V_t \), choose \( V_t^{(1)} = M_t \).

**Step 2.** Applying standard tools of parametric survival analysis to all firm-month observations for defaulting and nondefaulting firms, estimate the parameters of the hazard function given by Eq. (A1), with \( V_t \) replaced by \( V_t^{(1)} \). This yields initial coefficient estimates \( \beta_0^{(1)} \) and \( \beta_1^{(1)} \).

**Step 3.** To obtain the risk-neutral default hazard \( \lambda_t^Q \), multiply the real-probability hazard by a risk-premium coefficient \( \xi \): \( \lambda_t^Q = \xi \lambda_t^P \). The risk premium is found from debt prices before and after default by solving Equation (A6) for \( \xi \) using debt prices, recovery rates, and firm characteristics for an average firm in the sample.

**Step 4.** For defaulted firms, approximate the value of the firm at default \( M_\tau \) (where \( t = \tau \) is the default time) by its value at the end of the last calendar month prior to default. Also, approximate the recovery value \( L_\tau \) by the value of the firm at the end of the calendar month of default, adjusted for the market return in the month of default. Then, solve Eq. (A4) for \( V_\tau \) using simulations. This yields a new approximation for the value of assets at default, \( V_\tau^{(2)} \), and the proportional cost of default \( \alpha^{(2)} = 1 - L_\tau/V_\tau^{(2)} \). For firms not observed to default, assume that the cost of default equals the sample average of \( \alpha^{(2)} \).

**Step 5.** Given the current approximation for \( \alpha \), solve Eq. (A5) for \( V_t \) using all nondefaulting firm-months. The solution for nondefaulting firm-months, combined with the solution for firms at default obtained in the previous step, forms a new approximation for asset values in all firm-months. This approximation is denoted \( V_t^{(2)} \).

**Step 6.** Go back to step 2 and re-estimate hazard function coefficients using the current approximation \( V_t^{(2)} \). Repeat steps 2 through 5 until changes in the hazard function parameters \( \beta_0^{(1)} \) and \( \beta_1^{(1)} \) and in estimated asset values at default \( V_t^{(j)} \) become negligible.
References


Crosbie, P.J., and J.R. Bohn, 2002, Modeling default risk, KMV LLC.


Varma, P., 2003, Recovery rates on defaulted corporate bonds and preferred stocks, Moody’s Corp.


This table reports the number of defaults in the sample by year and by the type of the first default event (bankruptcy filing, payment omission or delay, or distressed bond exchange).

<table>
<thead>
<tr>
<th></th>
<th>Bankruptcy filings</th>
<th>Payment defaults</th>
<th>Distressed exchanges</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>1997</td>
<td>3</td>
<td>4</td>
<td>1</td>
<td>8</td>
</tr>
<tr>
<td>1998</td>
<td>3</td>
<td>7</td>
<td>3</td>
<td>13</td>
</tr>
<tr>
<td>1999</td>
<td>9</td>
<td>15</td>
<td>6</td>
<td>30</td>
</tr>
<tr>
<td>2000</td>
<td>13</td>
<td>21</td>
<td>2</td>
<td>36</td>
</tr>
<tr>
<td>2001</td>
<td>24</td>
<td>34</td>
<td>8</td>
<td>66</td>
</tr>
<tr>
<td>2002</td>
<td>7</td>
<td>28</td>
<td>5</td>
<td>40</td>
</tr>
<tr>
<td>2003</td>
<td>12</td>
<td>16</td>
<td>2</td>
<td>30</td>
</tr>
<tr>
<td>2004</td>
<td>6</td>
<td>6</td>
<td>3</td>
<td>15</td>
</tr>
<tr>
<td>2005</td>
<td>8</td>
<td>5</td>
<td>2</td>
<td>15</td>
</tr>
<tr>
<td>2006</td>
<td>1</td>
<td>3</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>2007</td>
<td>2</td>
<td>3</td>
<td>0</td>
<td>5</td>
</tr>
<tr>
<td>2008</td>
<td>5</td>
<td>4</td>
<td>7</td>
<td>16</td>
</tr>
<tr>
<td>2009</td>
<td>7</td>
<td>6</td>
<td>10</td>
<td>23</td>
</tr>
<tr>
<td>2010</td>
<td>0</td>
<td>3</td>
<td>1</td>
<td>4</td>
</tr>
<tr>
<td>All</td>
<td>100</td>
<td>155</td>
<td>51</td>
<td>306</td>
</tr>
</tbody>
</table>
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 whether there was a bankruptcy filing within two years after the first default event. Panel C reports the eventual outcomes of default.

<table>
<thead>
<tr>
<th>First default event</th>
<th>Bankruptcy filing</th>
<th>Payment default</th>
<th>Distressed exchange</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A: First default events</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total number of defaults</td>
<td>100</td>
<td>155</td>
<td>51</td>
<td>306</td>
</tr>
<tr>
<td></td>
<td>32.7%</td>
<td>50.7%</td>
<td>16.7%</td>
<td>100%</td>
</tr>
<tr>
<td>Panel B: Bankruptcy filings subsequent to default</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Chapter 11</td>
<td>82</td>
<td>84</td>
<td>7</td>
<td>173</td>
</tr>
<tr>
<td></td>
<td>82.0%</td>
<td>54.2%</td>
<td>13.7%</td>
<td>56.5%</td>
</tr>
<tr>
<td>Prepackaged Ch.11</td>
<td>18</td>
<td>51</td>
<td>7</td>
<td>76</td>
</tr>
<tr>
<td></td>
<td>18.0%</td>
<td>32.9%</td>
<td>13.7%</td>
<td>24.8%</td>
</tr>
<tr>
<td>None</td>
<td>-</td>
<td>20</td>
<td>37</td>
<td>57</td>
</tr>
<tr>
<td></td>
<td>12.9%</td>
<td>72.5%</td>
<td>18.6%</td>
<td></td>
</tr>
<tr>
<td>Panel C: Eventual outcomes of default</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Creditors paid in full</td>
<td>-</td>
<td>9</td>
<td>-</td>
<td>9</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>5</td>
<td>32</td>
<td>37</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>3.2%</td>
<td>62.7%</td>
<td>12.1%</td>
</tr>
<tr>
<td>Bond exchange completed</td>
<td>-</td>
<td>63</td>
<td>101</td>
<td>172</td>
</tr>
<tr>
<td></td>
<td>63.0%</td>
<td>65.2%</td>
<td>15.7%</td>
<td>56.2%</td>
</tr>
<tr>
<td>Emerged from bankruptcy</td>
<td>37</td>
<td>34</td>
<td>9</td>
<td>80</td>
</tr>
<tr>
<td></td>
<td>37.0%</td>
<td>21.9%</td>
<td>17.6%</td>
<td>26.1%</td>
</tr>
<tr>
<td>Acquired or liquidated</td>
<td>-</td>
<td>6</td>
<td>2</td>
<td>8</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>3.9%</td>
<td>2.6%</td>
<td></td>
</tr>
</tbody>
</table>
This table reports descriptive statistics for firms at default, and for firms that do not default for at least one year after the observation date. *Market to book ratio* is the ratio of the market value of equity plus the book value of total liabilities, divided by the book value of total assets. *Debt maturity* is the weighted average of maturities of all debt instruments, assuming that all bank debt has a maturity of one year. *Short-term/Total debt* is the ratio of the debt in current liabilities to total debt, adjusted for the re-classification of long-term liabilities in the event of technical default. *Firm value* is the total market value of all of the firm’s financial claims. Statistics for nondefaulting firms are calculated using firm means for each variable.

<table>
<thead>
<tr>
<th></th>
<th>Firms at default</th>
<th>Non-defaulting firms</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Median</td>
</tr>
<tr>
<td><strong>Book assets ($ Mil.)</strong></td>
<td>3,981</td>
<td>824</td>
</tr>
<tr>
<td><strong>Sales/Book assets</strong></td>
<td>0.249</td>
<td>0.210</td>
</tr>
<tr>
<td><strong>Market to book ratio</strong></td>
<td>1.26</td>
<td>1.13</td>
</tr>
<tr>
<td><strong>Debt maturity</strong></td>
<td>5.34</td>
<td>5.01</td>
</tr>
<tr>
<td><strong>Short-term/Total debt</strong></td>
<td>0.200</td>
<td>0.029</td>
</tr>
<tr>
<td><strong>Nominal share price ($)</strong></td>
<td>2.52</td>
<td>1.18</td>
</tr>
<tr>
<td><strong>Debt price (¢)</strong></td>
<td>48.01</td>
<td>45.99</td>
</tr>
<tr>
<td><strong>Market debt/Firm value</strong></td>
<td>0.862</td>
<td>0.904</td>
</tr>
<tr>
<td><strong>Book debt/(Book debt + Market equity)</strong></td>
<td>0.901</td>
<td>0.949</td>
</tr>
<tr>
<td><strong>Book debt/Book assets</strong></td>
<td>0.846</td>
<td>0.791</td>
</tr>
</tbody>
</table>
Table 4
Solvency, cash flows, and liquid assets

Market assets is the firm value adjusted for expected default costs, as described in the Appendix. % Negative economic net worth and % negative book equity are the fractions of firms for which, respectively, the market value of assets is below the face value of debt, and the book value of assets is below total liabilities. Profit margin is the ratio of the pretax income to sales. % Making losses is the proportion of firms with negative pretax income. EBIT is the sum of pretax income and interest expenses. % Negative cash flow is the proportion of firms for which the operating cash flow, defined as income before extraordinary items plus depreciation, is negative. Interest coverage ratio is EBIT plus amortization and depreciation, divided by the interest expense. Quick ratio is the sum of cash and accounts receivable divided by current liabilities. % Quick ratio < industry median is the proportion of firms for which the quick ratio is below its median value for all Compustat firms in the same industry, using Fama-French’s 50 industries. Current ratio is the ratio of current assets to current liabilities. Cash ratio is the ratio of cash and equivalents to current liabilities. Defensive interval is the sum of cash and accounts receivable divided by the sum of the cost of goods sold and selling and administrative expenses. Statistics for nondefaulting firms are calculated using firm means for each variable.

<table>
<thead>
<tr>
<th></th>
<th>Firms at default</th>
<th>Non-defaulting firms</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Median</td>
</tr>
<tr>
<td>--------------------------------</td>
<td>-------</td>
<td>--------</td>
</tr>
<tr>
<td><strong>Panel A: Asset values and solvency ratios</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Market assets/Face debt</td>
<td>0.641</td>
<td>0.607</td>
</tr>
<tr>
<td>% negative economic net worth</td>
<td>89.3%</td>
<td>205</td>
</tr>
<tr>
<td>Book assets/Total liabilities</td>
<td>0.977</td>
<td>0.941</td>
</tr>
<tr>
<td>% negative book equity</td>
<td>60.8%</td>
<td>301</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Panel B: Profitability</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Profit margin</td>
<td>-2.272</td>
<td>-0.195</td>
</tr>
<tr>
<td>% making losses</td>
<td>90.7%</td>
<td>300</td>
</tr>
<tr>
<td>EBIT/Total assets</td>
<td>-0.092</td>
<td>-0.019</td>
</tr>
<tr>
<td>% negative cash flow</td>
<td>77.6%</td>
<td>286</td>
</tr>
<tr>
<td>Interest coverage ratio</td>
<td>-2.600</td>
<td>-0.061</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Panel C: Balance sheet liquidity</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quick ratio (QR)</td>
<td>0.531</td>
<td>0.349</td>
</tr>
<tr>
<td>% QR &lt; 1</td>
<td>86.6%</td>
<td>284</td>
</tr>
<tr>
<td>% QR &lt; industry median</td>
<td>81.0%</td>
<td>284</td>
</tr>
<tr>
<td>Current ratio</td>
<td>0.922</td>
<td>0.739</td>
</tr>
<tr>
<td>Cash ratio</td>
<td>0.221</td>
<td>0.071</td>
</tr>
<tr>
<td>Defensive interval</td>
<td>1.052</td>
<td>0.781</td>
</tr>
</tbody>
</table>
Table 5
Value, liquidity, and traditional default predictors

This table reports proportional Cox hazard regressions of default. \( V/B \) is the market value of assets divided by the face value of debt. \( H/CL \) is the dollar cash shortage normalized by current liabilities, computed as \( \max \{1 - Q, 0\} \), where \( Q \) is the sum of cash and accounts receivable divided by current liabilities. \( CA \) is current assets, \( CL \) is current liabilities, \( WC \) is working capital, \( TA \) is the book value of total assets, \( NI \) is net income, \( TL \) is the book value of total liabilities, \( RE \) is retained earnings, \( EBIT \) is the sum of pretax income and interest expenses, \( ME \) is the market value of equity, \( S \) is sales, and \( \pi \) is the probability of default based on the “naïve” estimate of the distance to default proposed by Bharath and Shumway (2008). The sample consists of 30,744 firm-months observations for defaulting and nondefaulting firms for which none of the variables are missing. Values of z-statistics are reported in parentheses. Coefficients marked ***, **, and * are significant at the 1%, 5%, and 10% significance levels, respectively.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>( V/B )</td>
<td>-5.16***</td>
<td>-4.91***</td>
<td>-4.74***</td>
<td>-4.19***</td>
</tr>
<tr>
<td></td>
<td>(-15.5)</td>
<td>(-14.0)</td>
<td>(-13.4)</td>
<td>(-9.47)</td>
</tr>
<tr>
<td>( H/CL )</td>
<td>3.44***</td>
<td>1.30***</td>
<td>1.48***</td>
<td>1.08***</td>
</tr>
<tr>
<td></td>
<td>(10.3)</td>
<td>(3.81)</td>
<td>(4.43)</td>
<td>(3.15)</td>
</tr>
<tr>
<td>( CA/CL )</td>
<td>-1.70***</td>
<td>-0.86***</td>
<td>-2.32***</td>
<td>-1.74***</td>
</tr>
<tr>
<td></td>
<td>(-7.86)</td>
<td>(-4.39)</td>
<td>(-6.32)</td>
<td>(-4.74)</td>
</tr>
<tr>
<td>( WC/TA )</td>
<td>-2.32***</td>
<td>-1.74***</td>
<td>-2.32***</td>
<td>-1.74***</td>
</tr>
<tr>
<td></td>
<td>(-6.32)</td>
<td>(-4.74)</td>
<td>(-6.32)</td>
<td>(-4.74)</td>
</tr>
<tr>
<td>( NI/TA )</td>
<td>-3.04***</td>
<td>-0.57</td>
<td>-3.04***</td>
<td>-0.57</td>
</tr>
<tr>
<td></td>
<td>(-5.77)</td>
<td>(-0.94)</td>
<td>(-5.77)</td>
<td>(-0.94)</td>
</tr>
<tr>
<td>( TL/TA )</td>
<td>0.70***</td>
<td>-0.20</td>
<td>0.70***</td>
<td>-0.20</td>
</tr>
<tr>
<td></td>
<td>(3.71)</td>
<td>(-0.49)</td>
<td>(3.71)</td>
<td>(-0.49)</td>
</tr>
<tr>
<td>( RE/TA )</td>
<td>0.29</td>
<td>0.18</td>
<td>0.29</td>
<td>0.18</td>
</tr>
<tr>
<td></td>
<td>(1.24)</td>
<td>(0.70)</td>
<td>(1.24)</td>
<td>(0.70)</td>
</tr>
<tr>
<td>( EBIT/TA )</td>
<td>-0.96</td>
<td>-0.20</td>
<td>-0.96</td>
<td>-0.20</td>
</tr>
<tr>
<td></td>
<td>(-1.45)</td>
<td>(-0.27)</td>
<td>(-1.45)</td>
<td>(-0.27)</td>
</tr>
<tr>
<td>( ME/TL )</td>
<td>-12.2***</td>
<td>-2.11</td>
<td>-12.2***</td>
<td>-2.11</td>
</tr>
<tr>
<td></td>
<td>(-9.63)</td>
<td>(-1.60)</td>
<td>(-9.63)</td>
<td>(-1.60)</td>
</tr>
<tr>
<td>( S/TA )</td>
<td>-1.51**</td>
<td>-1.34**</td>
<td>-1.51**</td>
<td>-1.34**</td>
</tr>
<tr>
<td></td>
<td>(-2.39)</td>
<td>(-2.19)</td>
<td>(-2.39)</td>
<td>(-2.19)</td>
</tr>
<tr>
<td>( \pi )</td>
<td>6.55***</td>
<td>2.15***</td>
<td>4.06***</td>
<td>2.16***</td>
</tr>
<tr>
<td></td>
<td>(9.60)</td>
<td>(3.01)</td>
<td>(5.23)</td>
<td>(2.91)</td>
</tr>
</tbody>
</table>

Pseudo-\( R^2 \) 0.49 0.10 0.50 0.17 0.51 0.43 0.52 0.43 0.51 0.48 0.53
This table reports proportional Cox hazard regressions of default. \( \frac{V}{B} \) is the market value of assets divided by the face value of debt. \textit{Cash shortage} is computed as \( \max\{1 - Q, 0\} \), where \( Q \) is the sum of cash and accounts receivable divided by current liabilities. Regressions (1) to (6) use the following proxies for financing constraints: In regression (1), it is the Headlock-Pierce (2010) measure of financing constraints; in (2), it is the number of bond covenant classes that restrict the firm’s ability to raise cash; in (3), the ratio of outstanding secured debt to fixed assets; in (4), one minus undrawn credit lines divided by current liabilities; in (5), one minus the normalized de-trended annual par amount of all new high-yield bonds by U.S. issuers in FISD; in (6), the difference between average Baa and Aaa bond yields. In each of these regressions, \textit{Constrained} and \textit{Unconstrained} are dummy variables that equal one if the proxy for constraint used in that regression is above (below) the sample median. Values of \( z \)-statistics 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 for the hypothesis that the coefficients for the two interaction terms are equal.

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \frac{V}{B} )</td>
<td>-4.88***</td>
<td>-4.89***</td>
<td>-5.11***</td>
<td>-4.59***</td>
<td>-5.23***</td>
<td>-4.98***</td>
</tr>
<tr>
<td></td>
<td>(-19.7)</td>
<td>(-19.9)</td>
<td>(-16.8)</td>
<td>(-13.4)</td>
<td>(-20.6)</td>
<td>(-19.6)</td>
</tr>
<tr>
<td>( \frac{H}{CL} \times \text{Constrained} )</td>
<td>2.13***</td>
<td>2.26***</td>
<td>2.68***</td>
<td>2.29***</td>
<td>2.03***</td>
<td>2.41***</td>
</tr>
<tr>
<td></td>
<td>(7.05)</td>
<td>(7.54)</td>
<td>(7.22)</td>
<td>(6.63)</td>
<td>(6.52)</td>
<td>(7.32)</td>
</tr>
<tr>
<td>( \frac{H}{CL} \times \text{Unconstrained} )</td>
<td>1.13***</td>
<td>1.22***</td>
<td>1.55***</td>
<td>0.58*</td>
<td>1.60***</td>
<td>1.04***</td>
</tr>
<tr>
<td></td>
<td>(3.59)</td>
<td>(4.12)</td>
<td>(5.95)</td>
<td>(1.74)</td>
<td>(6.09)</td>
<td>(5.08)</td>
</tr>
<tr>
<td>\text{Financing constraints}</td>
<td>0.040</td>
<td>0.014</td>
<td>0.000036</td>
<td>0.036</td>
<td>-0.27</td>
<td>-0.52***</td>
</tr>
<tr>
<td></td>
<td>(0.14)</td>
<td>(0.11)</td>
<td>(1.50)</td>
<td>(0.44)</td>
<td>(-1.11)</td>
<td>(-2.59)</td>
</tr>
<tr>
<td>\text{Pseudo-}R^2</td>
<td>0.42</td>
<td>0.43</td>
<td>0.43</td>
<td>0.35</td>
<td>0.43</td>
<td>0.42</td>
</tr>
<tr>
<td>( N )</td>
<td>38,989</td>
<td>39,238</td>
<td>24,807</td>
<td>8,783</td>
<td>39,238</td>
<td>39,238</td>
</tr>
<tr>
<td>\text{p-value } H_0: \text{Constr.}=\text{Unconstr.}</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.18</td>
<td>0.00</td>
</tr>
</tbody>
</table>
Table 7
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.

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