A Market-Based Study of the Cost of Default

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This article proposes a novel method of extracting the cost of default from the change in the market value of a firm's assets upon default. Using a large sample of firms with observed prices of debt and equity that defaulted over fourteen years, we estimate the cost of default for an average defaulting firm to be 21.7% of the market value of assets. The costs vary from 14.7% for bond renegotiations to 30.5% for bankruptcies, and are substantially higher for investment-grade firms (28.8%) than for highly levered bond issuers (20.2%), which extant estimates are based on exclusively. (*JEL* G21, G30, G33)

The cost of financial distress is among the most important factors thought to affect corporate financing decisions. It is a crucial parameter both in studies of capital structure and in models of corporate securities pricing. The costs of financial distress include both direct and indirect components. Direct costs, such as lawyers' fees in bankruptcy, are relatively straightforward to estimate, but they do not exceed a few percents of firm value. Indirect costs of financial distress are much more difficult to measure, but are also potentially much larger than direct costs.[1] As financial distress (the inability to meet required debt payments) typically occurs simultaneously with economic distress (deteriorating economic fundamentals), the effect of "pure" financial

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[1] Estimates of direct bankruptcy costs range from 3.1% (Weiss 1990) to 5.3% (Warner 1977) to 6% (Altman 1984) of firm value (see also Bris, Welch, and Zhu 2006). Indirect costs of distress may arise, for example, because of managerial distraction, distortions in the customer-supplier relationship (Titman 1984), losses from asset fire sales (Shleifer and Vishny 1992), and agency costs of debt due to asset substitution (Jensen and Meckling 1976) and debt overhang (Myers 1977).

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distress on firm value is difficult to identify empirically. As a result, quantitative estimates of the value loss due to financial distress are so rare that currently most if not all studies that make use of such estimates have to rely on just one systematic study of distress costs. That study is Andrade and Kaplan (1998; henceforth AK).

Based on thirty highly leveraged transactions (HLTs) that became distressed between 1987 and 1992, AK conclude that the total cost of financial distress for HLTs is likely to be in the 10% to 20% range. These estimates have been widely applied in different contexts.[2] Yet, as AK point out, the HLTs that their sample consists of may have chosen to become highly levered precisely because their distress costs were unusually low. As a result, for a typical firm, AK's estimates may be biased downward, and applying them to non-HLTs may be problematic.

Our article proposes a novel approach to estimating the cost of default that is not limited to HLTs. It is based on the idea that investors anticipate default only partially, so that the announcement of default contains an element of surprise. As a result, upon the announcement, the total market value of the firm's debt and equity changes, and the size of the change reflects both the cost of default and the degree to which it is unanticipated. Loosely speaking, if $D+E$ is the total market value of the firm's debt and equity, V is the value of assets in the absence of default, and $V-c$ is their "recovery" value in default (where c is the cost of default), then the predefault value of the firm is $D+E=(1-q)\times V+q\times(V-c)$, where q is investors' risk-adjusted estimate of the default probability. Upon default, the value of the firm decreases to $V-c$. The total firm-level price reaction to default equals $(1-q)\times c$, which is the cost of default scaled down because of investors' partial anticipation of default. We formalize this intuition in a dynamic setting and evaluate the conditional probability of default, q, from historical defaults and debt prices. This allows us to undo the effect of partial anticipation on the price reaction and compute the total cost of default, c.

We apply this approach to a sample of 175 firms that defaulted between 1997 and 2010, for which market prices of bonds, bank loans, and equity are observed both just prior to and shortly after default. For an average defaulting firm, we estimate the mean (median) cost of default to be 21.7% (22.1%) of the market value of assets. Looking at different types of default, we find the cost of a distressed bond exchange to be 14.7%, compared with the average cost of bankruptcy of 30.5%. Importantly, sample firms with lower default costs have lower ratings when they issue bonds. For highly levered (original-issue junk) firms, default costs average 20.2%, similar to AK's estimates for HLTs. However, the costs are substantially higher (28.8%) for fallen angels (firms originally rated investment grade), which may be more representative of a typical firm for the purposes of capital structure studies. Consistent with

2 Examples include studies of capital structure (Graham 2000; Molina 2005; Almeida and Philippon 2007; Elkamhi, Ericsson, and Parsons 2012), implementations of structural bond-pricing models (Eom, Helwege, and Huang 2004; Huang and Huang 2003), calibrations of dynamic models of the levered firm (Miao 2005), and studies of the effect of macroeconomic variables on asset prices (Bhamra, Kuehn, and Strebulaev 2010a,b).

Acharya, Bharath, and Srinivasan (2007), we find that default costs vary with industry conditions, as predicted by Shleifer and Vishny (1992).

Our estimation procedure can be viewed as a generalization of the event study methodology (e.g., Brown and Warner 1985). Event studies look at the price reaction to various corporate announcements. They typically deal with potential information leakages that can affect market prices before the event by extending the observation window backward. Unfortunately, this approach cannot be applied to studying the cost of default, because the *timing* of default itself is systematically related with the value of the firm. Our approach allows the timing of the event of interest (in our case, default) to depend endogenously on the quantity to be measured (in our case, the value of the firm's assets), and the possibility of the event to affect prices for an arbitrarily long time prior to the event. The procedure can be applied to any defaulted firm with observed market prices of debt and equity, including those distressed both economically and financially.

A potentially important confounding effect arises in many event studies because of investors' learning. If investors observe the value of assets only imperfectly, even an event that does not change the fundamental value can cause them to update their beliefs and thus trigger a price reaction. This effect has been studied in the context of mergers and acquisitions by Bhagat et al. (2005) and Hietala, Kaplan, and Robinson (2003), who investigate the extent to which takeover announcements convey information about stand-alone firm values. Similarly, in our setting, even a costless default can result in a negative price reaction if it makes investors realize that the true asset value is lower than thought. To evaluate the effect of learning on our estimates, we extend our procedure to allow for incomplete information about the value of assets. Our calibrations show that, although in many settings the bias due to learning can be large, for the average defaulting firm, under modest levels of investors' uncertainty suggested by Korteweg and Polson (2010), the effect of learning on our mean estimate does not exceed three percentage points.

A number of existing empirical studies focus on various components of distress costs, such as price discounts in asset fire sales (Pulvino 1998), risk shifting (Eisdorfer 2008), and the loss of market share in industry downturns (Opler and Titman 1994), but do not assess how they interact with each other. With the exception of Andrade and Kaplan (1998) and a case study by Cutler, and Summers (1988), most studies estimate total distress costs from the behavior of nondistressed firms, rather than the realized value loss in default. Based on the time-series behavior of market prices of debt and equity, Korteweg (2010) estimates expected distress costs for highly levered firms between 15% and 30%. Using structural estimation, Hennessy and Whited (2007) find implied bankruptcy costs between 8.4% and 15.1%. Glover (2011) finds that for observed leverage ratios to be consistent with the trade-off theory, the average cost of default must be as high as 45%. At the same time, as firms with low costs choose higher leverage ratios and default more often, the average cost among defaulting firms in his study is only 24.6%, which is comparable to what we observe empirically.

Overall, Andrade and Kaplan (1998) remains the main reference for numerical estimates of firm-specific ex post costs of financial distress. Compared with their approach, our procedure offers several potential advantages. First, our sample includes not only original-issue junk firms, but also fallen angels that were rated investment grade at the time of bond issuance, and these appear to have systematically higher default costs. Second, our estimates are based on the change in the observed market value of the firm around the announcement of default. By contrast, AK's estimates are based on the change in cash-flow margins from before the onset of distress to its resolution, multiplied by the industry median ratio of the firm value to cash flow, plus 2% that they add to account for direct costs of bankruptcy. Such an approach may be less accurate when changes in cash-flow margins are transitory and do not translate into a proportional shift in the market asset value; when cash-flow multiples differ across firms within an industry; or when the firm's direct costs of bankruptcy are unusually high or low. Third, most firms in our sample are distressed not only financially but also economically, which is a far more common situation than that of purely financial distress (Asquith, Gertner, and Scharfstein 1994). Because economic distress depletes firms' assets in the run-up to default, estimates of default costs are affected when expressed as a proportion of the value of assets at the time of default. Fourth, as debt pricing data sets become more readily available, our procedure can be applied to larger and more recent samples, reducing noise in the estimates and facilitating cross-sectional analysis.

A potential limitation of our estimates is that they are based on the price reaction to default, and as such cannot be directly applied to measure agency costs of financial distress incurred by nondefaulting firms. However, existing estimates indicate that such costs are unlikely to be substantial (Mello and Parsons 1992; Parrino and Weisbach 1999; Moyen 2007). Moreover, AK do not find the cost of distress for defaulting and nondefaulting firms to be statistically different. Given that even for highly levered firms our estimates are at the upper bound of AK's range, our results suggest that distress costs may be higher than previously thought.

The remainder of this article is organized as follows. Section 1 discusses our estimation procedure. Section 2 describes the data. Empirical results are reported in Section 3. Section 4 concludes. Technical details are given in the appendices.

1. Estimating the Costs of Default

In this section, we describe the approach used to estimate the unobservable cost of default from observed market prices of debt and equity before and after default. Our estimation procedure is based on the idea, first introduced in models of risky debt by Duffie and Lando (2001), that the information that investors have about firms' economic fundamentals is noisy and incomplete. As a result, investors generally cannot conclude with certainty whether or not any given firm is so distressed that it is about to default in the next instant. Indeed, if investors had enough information to replicate the timing of the managers' decision to default, then an announcement of default would never be a surprise. Hence, by the time the firm defaulted, its debt and equity prices would have gradually converged to their postdefault "recovery" values, and upon the announcement of default, prices would not move even if default involved deadweight value losses.

Empirically, however, it is well known that upon default firms' assets exhibit large abnormal returns. Clark and Weinstein (1983) and Lang and Stulz (1992) document abnormal stock returns at bankruptcy of around –20% to –30%, whereas Warner (1977) finds that prices of public bonds of bankrupt railroads fall by 9.2% in the month of bankruptcy. These large price reactions to default imply that default is not perfectly anticipated by investors. Duffie and Lando (2001), Jarrow and Protter (2004), and Giesecke (2006) argue that investors are only partially informed about crucial parameters that determine the timing of default. They show that under certain assumptions these information imperfections imply that the assets of the distressed firm can be priced as if, conditional on information available to investors, default were a random event with a hazard rate that is a function of the firm's economic conditions. Observed predefault debt and equity prices reflect both the "recovery" value that the firm's assets would have in default, and their "continuation" value in the absence of default, with the difference between the two arising because default is costly. By observing market values of firms immediately prior to default and their recovery values immediately after default, and by parameterizing the default hazard, one can solve for the implied continuation value that the firm's assets would have if default were never to occur. The net cost of default can then be found by subtracting the recovery value of the firm from the continuation value of assets.

1.1 A static illustration

To illustrate the key idea of our approach, consider a simple static example of a levered firm that has to make a single (and final) debt payment of B at time T. If the firm does not default on the debt payment, the value of its productive assets, also referred to as their "continuation" value, will be equal to V. If it defaults, the "recovery" value of the assets L will generally be different.[3] The net cost of default, c, is defined as the difference between the value of assets absent the possibility of default and their value in default: $c = V - L$. Default may be costly because of the transaction costs of arranging a distressed bond

[3] In structural models of risky debt, such as Merton (1974), V has a natural interpretation as the present value of assets or asset-generated cash flows in the absence of any financing imperfections.

exchange, legal fees in bankruptcy, lost sales due to customers' unwillingness to buy from a defaulted company, opportunity costs of management's time, expected asset fire-sale discounts, and other factors. For some firms, default may also be beneficial (its net cost may be negative) if it precipitates a value-increasing shake-up, like a sale of the firm to higher-value users, which self-serving managers may resist in the absence of default.

In the base case, we assume that investors observe both V and L[4] and use them in conjunction with an estimate of the risk-neutral probability of default, q, to calculate the value of the firm's financial claims, such as debt and equity. The value of the firm, M, is the total value of all such claims. If investors believe that default is possible but not certain, M will depend both on V and on L. As econometricians, we observe the value of the firm prior to the scheduled payment, M, and, in case of default, its recovery value, L. Unlike the investors, we do not know the continuation value, V. Our task is to estimate the cost of default, $c = V - L$, from observed prices of debt and equity.

Suppose that just prior to time T investors know both V and L but lack full information regarding some other factors that affect the firm's ability to make the required debt payment. For example, investors may be unsure if the firm has enough liquid assets to repay the debt, and if not, whether it will be able to raise the required cash from external sources. As a result of these information imperfections, up until the maturity of debt investors can neither be sure that the firm will make the debt payment nor know with certainty that it will not. They determine the market prices of debt and equity at T_{-} (i.e., just prior to time T) given their assessment of the risk-neutral probability of default, q, conditional on the information available to them. Investors' estimate of q may be based, for instance, on the distance-to-default (a volatility-adjusted measure of market leverage based on the Merton (1974) model) and the firm's accounting ratios (e.g., Altman's (1968) z-score).

In this setting, the market value of the firm at time T_{-}, that is, the total value of its debt and equity, is the probability-weighted average of the continuation and recovery values of its assets:

$$M = V \times (1-q) + L \times q. \tag{1}$$

Given this relationship, we can compute the cost of default implied by market prices as follows. First, we estimate investors' conditional default probability q, for example, from bond prices or from survival analysis of firms at risk of failure. Second, if the firm does default, we can measure its recovery value L and its predefault value M. These are, respectively, the total market value of the firm's debt and equity immediately after default and their value just prior. Third, we solve Equation (1) for the unobserved continuation value of assets V. The cost of default is then $c = V - L$.

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[4] As a robustness check, in Section 3.3 we generalize the model to allow for the possibility that investors cannot observe V perfectly.

Our approach can be interpreted as adjusting the observed firm price reaction upon default so as to undo the effect that partial anticipation of default has on predefault debt and equity prices. To see this, notice that Equation (1) can be rewritten as

$$M-L=c\times(1-q). \tag{2}$$

The left-hand side of this equation gives the (negative of the) jump in the firm value upon the announcement of default, that is, the firm-level price reaction to default. The right-hand side equals the cost of default, times one minus investors' conditional probability of default, which measures the extent to which default is a surprise. As long as default is partially anticipated, so that the conditional probability of default is positive, Equation (2) implies that (the negative of) the change in the firm value upon default is smaller than the cost of default. At the same time, the two are closely related, and the more surprising the default, the closer the price reaction is to the total default cost. The sign of the cost of default is always opposite that of the observed firm price reaction.

Our estimation procedure can be viewed as a generalization of the event study methodology (e.g., Brown and Warner 1985). If the event of interest (in our case, default) is partially anticipated by investors, the observed price reaction at the time of the event is the lower boundary for the total value effect of the event. Event studies deal with partial anticipation by extending the observation window backward. Unfortunately, this approach cannot be applied to studying the cost of default, because investors may be factoring in the possibility of default for a long time prior to the actual announcement. Moreover, the firm's decision to default may be systematically related to the value of assets, which summarizes the degree of the firm's economic distress. We overcome these difficulties associated with the event study design by explicitly evaluating investors' conditional probability of default, and adjusting predefault prices accordingly.

1.2 Base-case dynamic model

The static model discussed above ignores the fact that in reality debt payments are spread over time. As a result, if the firm does not default at time t, its value at t_+ still differs from the asset value V, as it is affected by the possibility of default in the future. To account for this effect, one needs to specify investors' expectations about the future dynamics of the asset value and the default process.

In this section, we describe the dynamic model that our base-case estimates are based on. The model merges important features of both reduced-form and structural models of credit risk. At the same time, our approach is structured so as to minimize the reliance on a number of debatable assumptions of such models, such as default boundary conditions used in structural models.

1.2.1 The default hazard. The central assumption behind our approach is that, because of information imperfections, investors cannot predict the timing of default perfectly. We assume that, as a result, there exists a default hazard rate, which is a function of investors' information.[5] Conditional on this information, default is a realization of a Poisson process stopped at its first jump. This approach to modeling default is common in reduced-form models of risky debt pricing (e.g., Duffie and Singleton 1999; Madan and Unal 1998). However, most reduced-form models also assume that the default hazard is driven by some latent risk factors, inferred from the time-series behavior of credit spreads. In contrast, we explicitly specify the hazard rate as a function of observed firm characteristics.

To focus on the most important salient information available to investors, we assume that the hazard rate is a function of the firm's asset value and its outstanding debt. Specifically, under the real probability measure $\mathbb{P}$, the default hazard $\lambda_t^{\mathbb{P}}$ is

$$\lambda_t^{\mathbb{P}} = e^{\beta_0 + \beta_1 \log \frac{V_t}{B}}, \tag{3}$$

where V_t is the market value of assets, B is the face value of debt, and β_0 and β_1 are fixed parameters. The ratio of the market value of assets to the face value of debt measures the firm's economic solvency and captures the degree of economic distress that the firm is in. The assumption that this ratio is a sufficient statistic for default is standard in many structural models of credit risk, beginning with Merton (1974) and Black and Cox (1976). This ratio is the main input for computing the distance-to-default and the Expected Default Frequency (EDF) by Moody's/KMV, both of which are now widely used by academics and practitioners as measures of default risk (e.g., Berndt et al. 2005). Empirically, Davydenko (2012) shows that the ratio of the market value of assets to the face value of debt is by far the most powerful variable explaining the timing of default. Its explanatory power exceeds that of most other default predictors (e.g., those entering Altman's (1968) z-score) put together, and in regression analysis such factors typically become insignificant in its presence.[6] Hence, we are unlikely to lose much in accuracy by following structural models and focusing on the asset-to-debt ratio exclusively.

To relate observed asset prices to investors' expectations about default, we need the mapping between the actual and the risk-neutral probability measures. For Poisson processes, the change of the probability measure affects the intensity of jump arrivals (see, e.g., Shreve 2004, as well as Gorbenko and Strebulaev 2010, for an application to finance). We therefore assume that under

5 Duffie and Lando (2001) are the first to introduce asymmetric information in a structural model. They show that the default process in their model can be described using a hazard rate. Giesecke (2006) generalizes the conditions under which a hazard rate exists in such models.

6 The only exception is measures of balance sheet liquidity, such as the current ratio, although their explanatory power is an order of magnitude lower than that of V_t/B. We control for liquidity in robustness checks, reported in Section 3.5, and find its effect to be small.

the risk-neutral measure $\mathbb{Q}$, default is also a doubly stochastic process, and that its intensity is a multiple of the real-measure intensity,

$$\lambda_t^{\mathbb{Q}} = \xi \lambda_t^{\mathbb{P}}, \tag{4}$$

where $\xi \geq 1$ is the risk premium associated with default, to be estimated from the data.[7]

At this point, several observations on our specification are in order. Our model combines the tractability of a reduced-form model with the economic intuition of structural models, which predict that default is driven by deteriorating economic fundamentals. At the same time, it does *not* rely on several common structural assumptions that are easiest to challenge on empirical grounds. First, in contrast to structural models, such as Black and Cox (1976), Leland (1994), and others, we do not assume that there is a sharp value-based default boundary separating defaulting and nondefaulting firms. Contrary to this assumption, Davydenko (2012) finds that some firms default while their asset value is still relatively high, and others manage to avoid default at very low asset values, so that the assumption of a sharp boundary known in advance is not very accurate. Second, we make no assumptions regarding managerial objectives in choosing when to declare default. Some models derive predictions about the optimal timing of default maximizing the value of equity (e.g., Leland 1994), whereas others assume that default is driven by covenants (e.g., Longstaff and Schwartz 1995).[8] In our setting, such theories would imply a particular form of the hazard function $\lambda(V)$, which determines the probability of default as a function of the firm's financial conditions. Instead of relying on any such theories, our approach allows us to estimate the hazard function directly from observed defaults, while remaining agnostic about why firms default when they do. Third, we do not need to specify how the firm's assets are divided between creditors and shareholders in default. Although most structural models assume that the absolute priority rule (APR) is enforced in default, empirical studies of distressed reorganizations find that the APR is often violated in practice (e.g., Franks and Torous 1989). Our approach is based on the aggregate value of the firm, and does not depend on its split between debt and equity.

1.2.2 The pricing equation. To relate the price reaction at default announcement to the cost of default, we proceed by specifying the risk-neutral dynamics of the continuation value of assets V_t and their recovery value, L_t. Following the standard assumptions in the literature on credit risk pricing, we

[7] Bhamra, Kuehn, and Strebulaev (2010a,b) show that this representation is general and that the risk premium is a function of the primitives of the economy, such as preferences.

[8] Moreover, managers may not maximize the value of equity and may have incentives to delay restructuring, whereas pressure from creditors can also affect the timing of default.

assume that V_t follows a geometric Brownian motion under the risk-neutral measure $\mathbb{Q}$:

$$dV_t = rV_t dt + \sigma V_t dW_t^{\mathbb{Q}}, \tag{5}$$

where r is the risk-free rate, σ is the volatility of assets, and $dW_t^{\mathbb{Q}}$ is a Brownian motion defined on a filtered probability space $(\Omega, \mathcal{F}, \mathbb{Q}, (\mathcal{F}_t)_{t\geq 0})$. All parameters, as well as the face value of debt, B, are known constants. We also follow the literature (e.g., Leland 1994) in assuming that the recovery value of the firm is a constant fraction of the asset value:

$$L_t = (1-\alpha)V_t, \tag{6}$$

where α is the proportional cost of default.

Investors observe both V_t and L_t, and also evaluate the conditional risk-neutral default intensity $\lambda_t^{\mathbb{Q}}$. As shown in Appendix 1, at any time t up to default (or maturity T, whichever comes first), the value of the firm can be expressed as

$$M_t = L_t + (V_t - L_t)\mathbb{E}_t^{\mathbb{Q}}\left[\frac{V_T e^{-r(T-t)}}{V_t} e^{-\int_t^T \lambda_u^{\mathbb{Q}} \mathrm{d}u}\right], \tag{7}$$

where the expectation $\mathbb{E}^{\mathbb{Q}}$ is conditional on all information available to investors.

This equation relates the market value of the firm to the continuation value of its assets and their recovery value. For a firm that defaults at time $t=\tau$, M_τ can be observed as the market value of the firm just prior to the announcement of default and L_τ as its value immediately after. Thus, we can solve Equation (7) for V_τ and compute the cost of default as $c = V_\tau - L_\tau$.

It is important to emphasize the economic meaning of V and its implications for interpreting our empirical results. In our model, V is the value of a copycat firm, identical to the firm that we observe, but for which default does not affect the firm value (i.e., it is costless). Note that, in general, V may not coincide with the value of unlevered assets of the firm for two reasons. First, tax benefits of debt are incorporated in V but not in the unlevered firm value.[9] Second, even if default per se does not change the total value of the firm, it can still result in wealth redistributions among the various stakeholders. This gives rise to agency conflicts, which may affect the value of the firm. For example, the levered firm may underinvest ("debt overhang" of Myers 1977) or overinvest in risky projects ("asset substitution" of Jensen and Meckling 1976). To the extent that such activities are costly, V could be below the unlevered value of assets, and default costs could be lower than the full cost of financial distress.

Although we cannot ascertain the quantitative impact of such factors, it is unlikely to be substantial. Mello and Parsons (1992) and Parrino and Weisbach

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9 Given that both before and after default most firms are loss-making with high debt levels (Gilson 1997), and thus the expected present value of income taxes is very low, the effect of taxes in our sample is likely to be small.

(1999) estimate the effect of agency costs on firm value to be below 2%, which is small in comparison with total distress costs. Andrade and Kaplan (1998), whose estimates of distress costs presumably incorporate agency costs, do not find significant differences between the costs for defaulting and nondefaulting firms. Moreover, our estimates of default costs are similar to or higher than AK's.

Similar to the static case of the previous subsection, Equation (7) implies a relationship between the cost of default $c = V_\tau - L_\tau$ and the firm-level price reaction to the default announcement, $M_\tau - L_\tau$:

$$M_\tau - L_\tau = c \times \mathbb{E}_\tau^{\mathbb{Q}}\left[\frac{V_T e^{-r(T-\tau)}}{V_\tau} e^{-\int_\tau^T \lambda_u^{\mathbb{Q}} \mathrm{d}u}\right], \tag{8}$$

where the expectation term on the right-hand side parallels the "surprise" component of the default announcement in Equation (2) of the static model. Essentially, this term is the probability of no default until maturity, adjusted for the expected growth in the firm's assets between τ and T.

1.2.3 Identifying the risk premium. We estimate the default risk premium parameter, ξ, from the market prices of debt before default and observed debt recovery rates. Consider a generic firm financed with a zero-coupon bond with a promised payment of one dollar at maturity. If the firm defaults, creditors receive R dollars at the time of default, where R is the recovery rate, assumed to be constant. As shown in Appendix 1, the market value of the bond can be found from

$$D_t = e^{-r(T-t)}\mathbb{E}_t^{\mathbb{Q}}\left[e^{-\xi\int_t^T \lambda^{\mathbb{P}}(V_u)\mathrm{d}u}\right] + \xi\int_t^T \mathbb{E}_t^{\mathbb{Q}}\left[Re^{-\int_t^s [r+\xi\lambda^{\mathbb{P}}(V_u)]\mathrm{d}u}\lambda^{\mathbb{P}}(V_s)\right]\mathrm{d}s. \tag{9}$$

For firms that are about to default, we observe the market value of debt immediately prior to default, as well as debt recovery rates following default. Given an estimate of the value of assets at that time, V_τ, we can evaluate the physical default hazard, $\lambda^{\mathbb{P}}(\cdot)$, from Equation (3) and solve Equation (9) for ξ. The idea is similar to solving Equation (7) for V_t based on the value of the firm before and after default. The main difference is that, to treat the risk premium as a market-wide parameter, in implementing the model we do not solve Equation (9) for each individual firm. Instead, we solve it once for an "average" firm in each year, using as inputs the average values of the parameters over all firms that defaulted in that year. We thus obtain time-varying estimates of the risk premium.[10]

[10] Several articles estimate the jump-to-default risk premium by comparing risk-neutral default probabilities implied by bond or CDS spreads with physical probabilities implied by credit ratings or the EDF (Driessen 2005; Berndt et al. 2005; Hull, Predescu, and White 2005).

1.3 Implementation

Our estimation procedure involves the following steps. First, using a sample of defaulting and nondefaulting firm-months, we estimate the parameters of the hazard function under the real measure using survival analysis. Second, we compute the risk premium from observed debt prices and use it to transform the hazard rate to the risk-neutral measure. Third, we solve Equation (7) for V.

A complicating factor is that $\lambda_t^{\mathbb{Q}}$ in Equation (7) is a function of V_t, which we do not know initially. To estimate jointly the parameters of the risk-neutral default hazard function, the default risk premium, and the continuation value of assets, we employ the following iterative procedure.

1.3.1 The iterative estimation procedure.

Step 1. As an initial approximation for V_t, we choose $V_t^{(1)} = M_t$, that is, we use the observed firm value as an initial guess for the continuation value of assets.

Step 2. We apply standard tools of parametric survival analysis (see, e.g., Kalbfleisch and Prentice 2002; Shumway 2001) to estimate the parameters of the hazard function $\lambda_t^{\mathbb{P}}\left(V_t^{(1)}\right)$ specified in Equation (3), using maximum likelihood for the whole sample of firms, including firm-month observations that do not correspond to default. This yields parameter estimates $\beta_0^{(1)}$ and $\beta_1^{(1)}$.

Step 3. Next, we estimate the default risk premium. For each year in the sample, we select firms that defaulted in that year. Based on the current approximation, we find the average market value of assets for these firms at default, $\overline{V_\tau^{(1)}}$. We also compute the average price of debt just before default, $\overline{D}$, and the average recovery rate, $\overline{R}$, as well as average volatility, debt maturity, and risk-free rate (these parameters do not change from iteration to iteration). We plug these inputs into Equation (9). Using 1,000 value path simulations, we solve the equation for ξ, and obtain an approximation of the risk-neutral hazard function in year i as $\lambda_t^{\mathbb{Q}\,(1)} = \xi_i e^{\beta_0^{(1)}} \left(V_t^{(1)}/B\right)^{\beta_1^{(1)}}$. For years in which we have less than ten defaults, we estimate ξ using the characteristics of an average firm in the sample.

Step 4. For firm-month observations that correspond to default, we solve Equation (7) for V_t using 1,000 value path simulations per firm.[11] This yields $V_\tau^{(2)}$, where $t = \tau$ is the month of default. The implied proportional default cost for each defaulted firm is thus $\alpha^{(2)} = 1 - L_\tau / V_\tau^{(2)}$.

[11] The details of our simulation algorithms are available upon request.

Step 5. For all firm-month observations that do not correspond to default, we find $V_t^{(2)}$ from a modification of Equation (7) that uses α instead of L_t as an input:

$$M_t = (1-\alpha)V_t + \alpha \mathbb{E}_t^{\mathbb{Q}}\left[V_T e^{-r(T-t)} e^{-\int_t^T \lambda_u^{\mathbb{Q}} \mathrm{d}u}\right]. \tag{10}$$

To do so, for nondefaulting firms we assume that the proportional cost of default is equal to the sample average of $\alpha^{(2)}$. For firm-month observations of defaulting firms prior to default, we use the firm-specific estimates of $\alpha^{(2)}$.

Step 6. We return to step 2 and reestimate the hazard rate coefficients using $V_t^{(2)}$. We repeat steps 2 through 5 until $\beta_0^{(k)} - \beta_0^{(k-1)}$, $\beta_1^{(k)} - \beta_1^{(k-1)}$, and $V_\tau^{(k)} - V_\tau^{(k-1)}$ all become less than $\epsilon = 10^{-5}$.

1.3.2 The choice of the model inputs. The variables that the model uses as inputs are computed as follows. Prior to default, the market value of the firm M_t is estimated as the total value of all bonds, bank debt, and common and preferred equity, as described in Appendix 2. Because of data limitations, these estimates are only available on a monthly basis. Hence, the value of the firm at default, denoted M_τ in Equation (8), is approximated by its value at the end of the last calendar month prior to default. Similarly, the recovery value of the firm L_τ is observed at the end of the calendar month of default. To separate the price reaction to default from the general market movement in the month of default, we subtract the market return from the defaulted firm's return and adjust the recovery value of assets accordingly.

We calculate the volatility of assets, σ, as the standard deviation of monthly asset returns for the median firm in the industry, as follows. First, we estimate the standard deviation of each firm's monthly returns, as in Choi and Richardson (2008), excluding postdefault months and firms with fewer than ten consecutive monthly firm value observations. Second, we find the median asset volatility for Fama-French's fifty industries. The use of industry, rather than firm-specific, volatility estimates increases the number of usable observations and reduces noise. Moreover, because the median firm in the industry is typically not distressed, its firm and asset values are very close. Therefore, asset volatility can be estimated as the volatility of the firm, which is much easier to measure, as it does not have to be adjusted for unobserved expected default costs.

Debt maturity, $T-t$, is the weighted average of maturities of all debt instruments, assuming that all bank debt has a maturity of one year. The face value of debt, B, is the total debt outstanding at the end of the previous fiscal quarter, as reported in Compustat. Finally, the risk-free rate r is the five-year constant-maturity Treasury rate, matching the average maturity at default (5.3 years).

2. Data Description

2.1 Data sources and sample selection

Our estimation procedure is based on debt and equity prices before and after default. Accordingly, our sample construction involves merging data on firm defaults and on bond, loan, and equity prices, as well as accounting information and details of firms' debt structure.[12]

According to the definition of default used by the rating agency Moody's, bond defaults comprise bankruptcy filings, distressed bond exchanges, and missed or delayed bond payments. Thus, default events include both bankruptcies and out-of-court renegotiations with bondholders.[13] Covenant violations, failed bond exchange offers, and renegotiations of bank loans do not alter bondholders' cash flow and hence do not constitute events of default.

Our main source of information on defaults is the Default & Recovery Database (DRD) from Moody's, which includes all defaults on rated bonds between 1970 and 2010. We amend these data in several ways. For distressed exchanges, DRD reports the date of completion as the date of default. Yet the price reaction we want to study is realized at the time of the announcement of the exchange, which DRD does not report. For this reason, we collect information on announcement dates for distressed exchange offers from Factiva. We also use Factiva to determine the outcomes of defaults not available in DRD. Not all defaults in DRD are independent events, both because firms often default together with their wholly owned subsidiaries and because DRD often reports multiple default events within a short period of time. We deal with these issues by focusing on defaults by parent companies only and by looking at the first default event during our sample period. Finally, we classify defaults as "formal bankruptcies" and "out-of-court renegotiations" as follows. If the default event is a missed bond payment or a distressed exchange offer not followed by bankruptcy in the same calendar month, we classify it as a (de facto) renegotiation of the bond contract.[14] Default events involving a bankruptcy filing in the same calendar month are classified as bankruptcy reorganizations.

Our procedure calls for the estimation of the total market value of the firm's debt and equity in the month prior to and in the month following default. To estimate the market value of bonds, we use monthly bond prices from

[12] To increase the precision of estimated hazard function coefficients, in survival analysis we also use nondefaulting firms included in the Merrill Lynch indices (see the previous subsection). For each month, we estimate values of these firms by applying the same procedures as for defaulting firms.

[13] Moody's defines bond default as "any missed or delayed disbursement of interest and/or principal, bankruptcy, receivership, or distressed exchange, where (1) the issuer offered bondholders a new security or package of securities that amount to a diminished financial obligation (such as preferred or common stock, or debt with a lower coupon or par amount), and (2) the exchange had the apparent purpose of helping the borrower avoid default"(Keenan, Shtogrin, and Sobehart 1999, p. 10). Standard & Poor's adopts a similar definition; the minor differences pertain to grace period defaults and defaults on preferred stock.

[14] This definition of renegotiation does not preclude the firm from filing for bankruptcy in the next calendar month. However, such cases are infrequent in the sample. Where renegotiations are followed by bankruptcy, the median time period between default and filing in the sample is 130 days.

Merrill Lynch. These are available since December 1996 for constituents of the Merrill Lynch U.S. Investment Grade Index and the High Yield Master II Index. Consequently, our sample period extends from January 1997 to December 2010.[15] Bank loan prices are based on quotes from the LSTA/LPC Mark-to-Market Pricing Database. The database includes monthly secondary-market loan quotes, each obtained from several dealers. These data are available for 69% of defaulting firms but only for 40% of defaults. For the remaining firms that borrow from banks, we compute loan prices as a function of bond prices, as described in Appendix 2. Where available, equity prices are obtained from CRSP. However, firms are often delisted from the exchange some time prior to default. For such cases, we search CapitalIQ for OTC equity price quotes. Also, whereas accounting information is primarily from quarterly Compustat, we use debt structure data from CapitalIQ to compute the proportion of debt that is owed to banks. For descriptive information on bonds, we use Mergent's Fixed Income Securities Database (FISD). We use bond, loan, and equity prices in conjunction with the debt structure data to estimate market values of total debt and equity at the end of the month preceding default and in the month of default, as described in Appendix 2.

We select the sample as follows. The DRD lists 2,675 defaults between January 1997 and December 2010. We first exclude non-U.S. firms and retain only defaults by industrial, transportation, and utility companies. We also remove dividend omissions and other events other than public bond defaults. After combining repeated defaults and defaults by firms related through parent-subsidiary relationships, we are left with 727 unique defaulting firms. We manually merge these to FISD and the Merrill Lynch data and obtain bond prices for 514 of them.[16] We manually merge these firms with CRSP and also search for equity prices from CapitalIQ. Share prices are available in the month prior to default for only 240 of the 514 firms. They are missing for many defaulting firms because a large majority of them are original-issue speculative-grade firms (i.e., highly levered bond issuers) and many of those are post-LBO and other private firms, especially in the latter part of the sample. Finally, we require that bond and equity prices be available both in the month prior and in the month following default, which further reduces the sample to 183 firms.

Our estimation procedure assumes that investors observe the value of assets at default. (In robustness checks, we also allow for the possibility that the value of assets can only be observed with noise, but assume that the noise is unbiased.) However, if the information that investors have about the firm is systematically biased because of fraud, then the price reaction upon default may be primarily due to investors' learning about the fraud, rather than due to

15 Schaefer and Strebulaev (2008) describe the Merrill Lynch data in detail.

16 The Merrill Lynch indices include neither bonds with par amounts of less than $100 million nor those with remaining maturity below one year. For firms that have such bonds outstanding at the time of default, we approximate their market value based on prices of other bonds of the same issuer.

Table 1
Sample composition

	No. of defaults	% of sample
Panel A: Number of defaults by year		
1997	5	2.9
1998	13	7.4
1999	24	13.7
2000	19	10.9
2001	50	28.6
2002	28	16.0
2003	19	10.9
2004	5	2.9
2005	7	4.0
2008	2	1.1
2009	2	1.1
2010	1	0.6
All	175	100
Panel B: Industry composition		
Consumer goods	24	13.7
Business equipment	7	4.0
Steel	9	5.1
Other manufacturing	21	12.0
Telecommunications	34	19.4
Wholesale and retail trade	27	15.4
Transportation	8	4.6
Energy and utilities	14	8.0
Other industries	31	17.7
All	175	100

This table reports the number of defaults in the sample, by year of default (Panel A) and by industry (Panel B). The sample consists of nonfinancial U.S. public firms that defaulted on their public bonds between January 1997 and December 2010. Default events are bond payment omissions (including those rectified within the grace period), distressed bond exchanges, and bankruptcy filings.

default costs. As a result, our estimates could also be biased. For this reason, we exclude firms that allegedly were involved in fraud within two years of default, using the list of large corporate fraud cases compiled by Dyck, Morse, and Zingales (2010). After removing Enron and seven other firms with alleged fraud, we are left with our final sample of 175 defaulted firms.[17]

2.2 Descriptive statistics

The composition of the sample by year of default and broad industry group is shown in Table 1. Although the sample spans fourteen years, it is dominated by firms that defaulted during the dot-com crash of the early 2000s. As many as 28.6% of sample firms defaulted in 2001, when the rate of default was one of the highest since the Great Depression (Giesecke et al. 2011). By contrast, there are relatively few defaults from 2008–2010, as a large majority of defaults

[17] For the eight fraud cases, both the price reaction at default and the estimated cost of default are about twice the sample average, consistent with bias in investors' perception of the value of assets. When these firms are included in the sample, the average estimate of the cost of default increases by one percentage point.

Table 2
Default events, bankruptcy filings, and outcomes

	First default event			
	Bankruptcy filing	Distressed exchange	Payment default	Total
Panel A: First default events				
All defaults	66 37.7%	19 10.9%	90 51.4%	175 100%
Panel B: Renegotiations and immediate bankruptcies				
Bankruptcy	66 100%	–	11 12.2%	77 44.0%
Renegotiation	–	19 100%	79 87.8%	98 56.0%
Panel C: Eventual outcomes of default				
Creditors paid in full	–	–	7 7.8%	7 4.0%
Bond exchange completed	–	13 68.4%	2 2.2%	15 8.6%
Emerged from bankruptcy	55 83.3%	4 21.1%	69 76.7%	128 73.1%
Acquired or liquidated	10 15.2%	2 10.5%	11 12.2%	23 13.1%
Other	1 1.5%	–	1 1.1%	2 1.1%

This table reports the incidence of bankruptcy filings and the eventual outcomes 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, following default, there was a bankruptcy filing in the same calendar month. Panel C reports the eventual outcomes of default.

by nonfinancials during this period were by private, postbuyout firms with no traded equity. The sample also covers "calm" periods with low default rates, which allows us to study the effect of macroeconomic conditions on the cost of default. Panel B shows the sample composition by industry: (1) Telecommunications, (2) wholesale and retail trade, and (3) consumer goods are the best-represented industries in the sample (19.4%, 15.4%, and 13.7%, respectively).

Table 2 reports the number of sample defaults by the type and outcome of default. As Panel A shows, 37.7% of firms default by filing for bankruptcy, 10.9% complete a distressed bond exchange, and 51.4% miss or delay a bond payment. Panel B reports the incidence of bankruptcy in the calendar month of default. It shows that 12.2% of bond payment defaults are quickly followed by a bankruptcy filing. We refer to the rest of the payment delays and omissions, as well as to successful bond exchanges, as "renegotiations" or "workouts."[18]

[18] Thus, "workouts" include bond exchange offers, which are bona fide bond contract renegotiations, as well as missed or delayed bond payments not followed by a bankruptcy filing within the same month. Payment defaults reduce the value of creditors' cash flow compared to that specified in the bond contract, and as such constitute a de facto out-of-court debt restructuring.

Table 3
Descriptive statistics

	Mean	Median	SD	N
% Original-issue junk firms	87.1			171
Total assets ($ Mil.)	3,271	1,034	7,856	175
Book leverage	0.803	0.747	0.383	175
Market leverage	0.851	0.906	0.161	175
Sales/Book assets	0.240	0.190	0.237	172
EBIT/Total assets	−0.109	−0.024	0.282	163
% Negative net income	90.1			172
Interest coverage ratio	−3.151	−0.169	7.343	162
Industry asset volatility	0.276	0.279	0.048	175
Quick ratio	0.575	0.397	0.616	164
Current ratio	0.977	0.770	0.830	164
Short-term/Total debt	0.200	0.029	0.309	173
Debt maturity	5.27	4.63	2.90	175
Debt interest rate	8.8%	8.8%	2.3%	172
Bonds/Total debt	0.762	0.842	0.258	175
Number of bond issues	4.63	2.00	10.41	175

This table reports descriptive statistics for firms at default. *Original-issue junk firms* are those which had a speculative-grade rating at the most recent bond issuance. *Book leverage* is the ratio of total debt to book assets. *Market leverage* is the ratio of the market value of debt to the market value of the firm. *EBIT* is the sum of pretax income and interest expenses. *Interest coverage ratio* is the ratio of EBITDA, calculated as the sum of pretax income, interest expense, and depreciation to interest expense. *Industry asset volatility* is the annualized median standard deviation of monthly firm returns in the industry, using Fama-French's fifty industries. *Quick ratio* is the sum of cash and accounts receivable divided by current liabilities. *Current ratio* is the ratio of current assets to current liabilities. *Debt maturity* is the weighted average of maturities of all outstanding debt instruments, assuming that all bank debt has a maturity of one year. *Debt interest rate* is interest expense in the last quarter divided by the average outstanding debt in that quarter. Accounting variables are observed at the end of the last fiscal quarter preceding default. All other variables are as of the end of the last calendar month preceding default.

In untabulated analysis, we find that an additional 75.5% of payment defaults and 15.8% of bond exchanges result in bankruptcy within two years. Overall, as many as 84.6% of bond defaults are followed by bankruptcy either immediately or after some time within two years of the first default event. Finally, Panel C shows eventual outcomes of default, with successful emergence from Chapter 11 being the most common outcome by far.

Table 3 reports general descriptive statistics for defaulted firms. As many as 87.1% of them are original-issue junk-bond issuers, meaning that they had a speculative grade rating when they last issued bonds. The remaining 12.9% are "fallen angels," that is, firms that are rated investment grade at the time of bond issuance and later downgraded to junk. Thus, although our sample is not limited to highly levered bond issuers by design, it is nonetheless dominated by them, as is any random sample of firms that default on their bonds. The firms in the sample are naturally larger in size than a typical Compustat firm because all of them issue public bonds. They appear distressed based on measures of leverage, profitability, and liquidity. About 76% of their debt is in bonds. The weighted average debt maturity is 5.3 years, and the median firm has two bonds outstanding.

Table 4
Asset returns at default and debt recovery rates

	Mean	Median	SD	10%	90%	Return > 0
Panel A: All defaults, N = 175						
Total return	−12.2%	−9.9%	22.4%	−43.3%	12.4%	0.30
Equity return	−21.2%	−24.7%	43.2%	−72.7%	23.7%	0.24
Debt return	−10.8%	−7.8%	22.6%	−39.9%	11.8%	0.30
Bond return	−16.2%	−13.8%	28.6%	−55.0%	14.0%	0.29
Bank debt return	−4.9%	−3.7%	13.1%	−19.8%	7.9%	0.32
Debt recovery rate	43.5%	40.8%	22.7%	14.0%	76.0%	
Panel B: Renegotiations, N = 99						
Total return	−7.3%	−6.3%	22.1%	−37.9%	17.4%	0.38
Equity return	−11.5%	−14.7%	43.5%	−57.3%	35.3%	0.29
Debt return	−6.5%	−4.7%	22.9%	−35.6%	17.6%	0.38
Bond return	−8.7%	−6.8%	26.9%	−44.4%	26.9%	0.38
Bank debt return	−4.0%	−3.2%	12.1%	−19.2%	7.9%	0.38
Debt recovery rate	47.4%	44.8%	22.9%	18.4%	79.4%	
Panel C: Bankruptcy filings, N = 76						
Total return	−18.5%	−14.5%	21.3%	−51.0%	6.4%	0.18
Equity return	−33.7%	−33.9%	39.7%	−78.0%	12.4%	0.17
Debt return	−16.3%	−12.7%	21.0%	−50.5%	8.0%	0.20
Bond return	−26.0%	−24.6%	28.0%	−64.6%	4.8%	0.16
Bank debt return	−6.0%	−3.9%	14.3%	−23.0%	9.1%	0.24
Debt recovery rate	38.4%	36.7%	21.4%	11.4%	66.6%	

This table reports statistics on market-adjusted returns for different asset classes in the month of default, as well as debt recovery rates. *Total return* is the weighted-average return on equity, loans, and bonds in the calendar month of default, less the return on S&P 500. *Debt return* is the weighted-average return on loans and bonds, calculated similarly. Returns on bonds, bank debt, and equity are also adjusted for the market return. *Debt recovery rate* is the weighted-average market value of all of the firm's outstanding debt instruments at the end of the calendar month of default, expressed as a proportion of the face value of total debt.

3. Empirical Results

3.1 Asset returns at default

As discussed in Section 1, the cost of default is proportional to (the negative of) the change in the market value of the firm upon default. The observed firm-level price reaction to default announcements is at the heart of our estimates of the cost of default. Table 4 summarizes the firm price reaction in the month of default, as well as returns on specific asset classes over the same month. The returns are adjusted by subtracting the return on S&P 500 over the same month.

For a typical firm, the announcement of default triggers a large value loss. The mean (median) firm-level market-adjusted return in the month of default is –12.2% (–9.9%). The value of the firm falls much more for bankruptcies (by 18.5% on average) than for nonbankruptcy bond defaults (7.3%). Such large price reactions to default imply that, although investors might anticipate it to a certain degree, the announcement of default nonetheless contains a significant element of surprise, which in turn means that predefault prices are informative about the continuation value of assets.

Returns on individual security classes (bonds, loans, and equity) in Table 4 is inversely related to the seniority of the asset: For an average firm, the equity return in the month of default is –21.2%, the loan return is only –4.9%, and the return on bonds falls in between at –16.2%. This ranking is to be expected, given that payoffs in default are increasing with seniority. For very distressed firms that have not yet defaulted, the value of junior claims such as equity comes mostly from the option value on the firm's recovery, which is greatly reduced in default. In contrast, banks usually have a senior claim on the firm's assets in bankruptcy, and hence loan prices do not fall nearly as much.

Table 4 also shows that asset returns at default are highly heterogeneous, ranging from –43.3% to +12.4% between the first and last deciles. Moreover, adjusted for the market return, the value of the firm *increases* upon default for 30% of defaults, including 18% of bankruptcies and as many as 38% of nonbankruptcy bond defaults. Similarly, Andrade and Kaplan's (1998) estimates of distress costs are also negative for 8 out of 30 firms, or 27% of their sample. A positive price reaction at default means that, even though there may be administrative costs of renegotiation and bankruptcy, the net cost of default is nonetheless negative for these firms. In the absence of default and reorganization, the status quo for such firms likely involves value destruction in ongoing operations, which makes default good news for investors. Consistent with this conjecture, Andrade and Kaplan (1998) find that an important component of costs of financial distress is firms' tendency to delay reorganization, and Davydenko and Rahaman (2011) find that a large number of firms that are worth more dead than alive are able to avoid reorganization or delay it for years, while financing ongoing losses by liquidating assets. For such firms, default may increase value, as documented by Hotchkiss and Mooradian (1997) for reorganizations involving vulture investors, and by Taillard (2011) for asbestos-related bankruptcies.

3.2 Estimates of the cost of default

Table 5 reports the main results of the article—our estimates of the cost of default. The mean (median) cost for all bond defaults in the sample is 21.7% (22.1%) of the market value of assets. Default costs are highly heterogeneous, varying from –22.5% at the first decile to +65.6% at the tenth decile. Figure 1 shows the distribution of the cost estimates.

The total cost of bankruptcy is on average more than twice as large as the cost of a nonbankruptcy default, 30.5% versus 14.7%. Our estimates of bankruptcy costs are much larger than direct costs of bankruptcy, such as lawyers' fees, which are typically found to be within several percentage points of the (book) value of the firm (e.g., Altman 1984; Weiss 1990).[19] The following factors

[19] It should be noted that previous studies express bankruptcy costs as a proportion of the book value of assets, whereas our estimates are normalized by market asset values, which at default average only 45.2% of the book value. Nonetheless, even after adjusting for the differences in the denominator, our estimates of total bankruptcy costs far exceed the direct costs found in aforementioned studies.

Table 5
Estimates of the cost of default

	Mean	Median	SD	10%	90%	N
Panel A: By type of default						
All defaults	21.7%	22.1%	33.0%	−22.5%	65.6%	175
Renegotiations	14.7%	11.4%	33.9%	−27.2%	69.2%	98
Bankruptcy filings	30.5%	30.7%	29.8%	−11.6%	65.6%	77
Panel B: By outcome of default						
Acquired or liquidated	41.4%	43.1%	27.1%	9.4%	76.7%	23
Emerged from bankruptcy	23.1%	25.4%	31.8%	−22.5%	64.3%	128
Bond exchange completed	−7.4%	−10.3%	25.6%	−44.4%	28.8%	15
Creditors paid in full	5.2%	−8.5%	34.9%	−27.2%	74.7%	7
Panel C: By industry						
Consumer goods	23.6%	27.6%	28.7%	−27.2%	50.2%	24
Business equipment	9.7%	−5.9%	51.9%	−51.1%	83.6%	7
Steel	48.5%	44.8%	23.9%	6.9%	76.7%	9
Other manufacturing	24.9%	30.6%	32.3%	−21.8%	59.5%	21
Telecommunications	18.4%	16.5%	35.3%	−17.9%	74.1%	34
Wholesale and retail trade	27.5%	30.7%	35.9%	−28.2%	69.2%	27
Transportation	19.5%	13.4%	22.9%	−5.2%	61.7%	8
Energy and utilities	25.1%	16.9%	22.1%	8.4%	54.8%	14
Other industries	10.4%	6.3%	32.2%	−22.5%	50.1%	31

This table reports estimates of the cost of default, expressed as a proportion of the market value of assets at the end of the last calendar month prior to default. Panel A reports the statistics for all sample firms, and separately for firms that do and do not file for bankruptcy in the calendar month of default. Panels B and C report default costs by the eventual outcome of default and by industry.

contribute to the substantial size of these estimates. First, default usually occurs at advanced stages of insolvency, so that the market value of assets just prior to default on average is only 66% of the face value of debt (Davydenko 2012). This implies that the denominator of our estimated cost-to-value ratio is substantially lower than that in AK's study of firms that are not economically distressed. Second, on average, the value of the bankrupt firm falls by 18.5% in the month of bankruptcy alone, which provides a lower bound on total bankruptcy costs. Third, bankruptcy filings are usually at least partially anticipated by investors, which means that firm values prior to default already incorporate some of the bankruptcy costs, so that the price reaction to the bankruptcy announcement is only a fraction of the total cost of bankruptcy. Indeed, our estimates imply that the observed price reaction is only about half of the total costs of default, whereas the other half is already incorporated in the predefault firm value. Overall, our evidence suggests that indirect costs of financial distress are much larger than direct costs.

Panel B of Table 5 compares default costs for different outcomes of default. Although the eventual outcome is not known with certainty at the time of default, investors' perceptions of the likely scenarios should affect the price reaction to default, and hence we expect our estimates to be correlated with the outcome. The most interesting result in this panel is the contrast between default costs for firms that eventually emerge from bankruptcy (23.1%) and

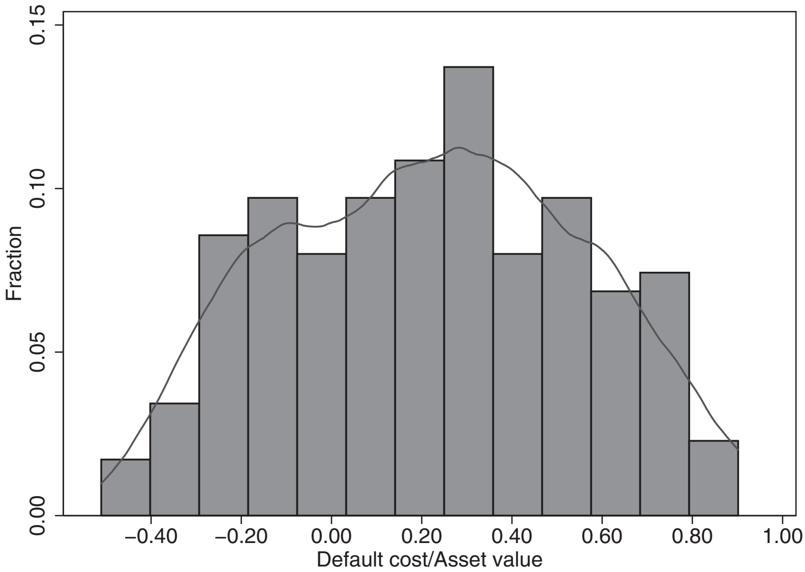

Figure 1
Distribution of default costs
This graph presents the histogram of default cost estimates, expressed as a proportion of the market value of assets.

those that are eventually liquidated or sold (41.4%). One interpretation of these estimates is that liquidations are substantially costlier than going-concern reorganizations. An alternative possibility is that the way the firm is reorganized in bankruptcy is endogenous, so that firms that are costlier to reorganize end up in liquidation, whereas those for which reorganization is feasible are preserved as going concerns and subsequently emerge from bankruptcy. Interestingly, the average estimated net cost of a bond exchange that is not followed by bankruptcy within two years is negative, indicating that successful renegotiations are value-increasing overall. Finally, Panel C suggests that there is more heterogeneity in default costs within industries than across industries.

An important question concerns the applicability of estimates obtained from observed defaults to other nondefaulting firms. For example, Andrade and Kaplan (1998) warn that their estimates of the cost of financial distress may be biased downward because the HTLs that constitute their sample may have chosen to become highly levered precisely as a result of their lower-than-usual distress costs. Glover (2011) calibrates a structural model under the assumption that firms follow the trade-off theory of capital structure, and shows that average distress costs among defaulting firms could be substantially lower than the population average.

We investigate this issue by splitting the sample based on the rating that the firm had the last time it issued bonds. Under the self-selection hypothesis,

Table 6
Default costs by original rating

	Mean	Median	SD	10%	90%	N
Panel A: All firms						
A	26.0%	26.0%	40.8%	−2.8%	54.8%	2
BBB	29.1%	22.6%	23.6%	−2.0%	57.5%	20
BB	25.9%	27.6%	26.9%	−29.9%	60.5%	18
B	21.4%	25.6%	33.4%	−22.4%	65.0%	100
CCC	15.9%	8.3%	37.1%	−28.8%	76.2%	28
CC	−16.6%	−20.6%	12.3%	−26.3%	−2.8%	3
All fallen angels	28.8%	22.6%	24.2%	−2.8%	55.5%	22
All original-issue junk firms	20.2%	21.9%	33.5%	−24.9%	65.6%	149
Panel B: Excluding utilities						
BBB	31.0%	30.7%	25.5%	−9.5%	59.5%	15
BB	25.9%	27.6%	26.9%	−29.9%	60.5%	18
B	21.1%	25.7%	34.1%	−22.5%	64.3%	93
CCC	15.9%	8.3%	37.1%	−28.8%	76.2%	28
CC	−16.6%	−20.6%	12.3%	−26.3%	−2.8%	3
All fallen angels	31.0%	30.7%	25.5%	−9.5%	59.5%	15
All original-issue junk firms	19.9%	21.9%	33.9%	−24.9%	64.3%	142

This table reports estimates of the cost of default, expressed as a proportion of the market value of assets at the end of the last calendar month prior to default, by firm rating as of the date of the most recent bond issuance. Panel A reports statistics for all firms. Panel B excludes energy and utility firms. *Fallen angels* and *original-issue junk firms* are firms that were rated investment grade and speculative grade, respectively, at the time of the last bond issuance preceding default.

we expect firms with lower costs of default to be more willing to issue high-yield bonds. By contrast, high-default-cost firms would reduce their expected losses from default by choosing lower leverage. Table 6 presents evidence to this effect. Consistent with self-selection, firms with lower ratings at the time of bond issuance generally have lower default costs. The average cost for original-issue high-yield firms is 20.2%, which is at the higher end of—but close to—the 10% to 20% range found by Andrade and Kaplan (1998) for distressed HLTs. However, for investment-grade firms (which in our sample later become fallen angels), the mean cost is 28.8%. Our subsample of fallen angels includes a disproportionate number of regulated utilities, which may default for idiosyncratic reasons and may not be representative of other investment-grade issuers. Panel B shows that when we exclude such firms, the mean (median) estimate for investment-grade firms increases to 31% (30.7%). The correlation between the cost of default and the at-issuance firm rating (coded as 1 for AAA, 2 for AA, etc.) is –0.16%, significant at the 5% level. Thus, low-default-cost firms do seem to be over-represented among risky firms that are more likely to default.

These findings have important implications for the interpretation of sample statistics obtained from defaulting firms. Consistent with Andrade and Kaplan's (1998) conjecture, their 10% to 20% range—found based on HLTs—may have to be revised upward when evaluating the cost of default for a typical investment-grade firm. Similarly, one has to be selective when applying our sample averages, which are also tilted toward original-issue junk firms, which comprise a large majority of firms observed to default. As a rough guide, if our estimates are to be used to compute ex ante expected default costs for nondistressed investment-grade firms, it may be more appropriate to use average costs of about 30% instead of 20%.

3.3 The effect of learning from default

Our model assumes that investors know with certainty the continuation value of assets, V. But, what if the value of assets is not observed perfectly? In this case, the default announcement itself may cause investors to update their beliefs about the value of assets, most likely downward. For a given cost of default, this learning-from-default effect could increase the observed price reaction. More generally, the total price reaction is the sum of two parts, one due to learning and the other due to default costs. Hence, our estimates of default costs, which assume away the first component, could be biased upward. In this section, we explore the effect that learning from default has on our estimates. To illustrate the mechanism intuitively, we first analyze a static model with unobserved asset value. Then, we develop a dynamic model, which allows us to evaluate the effect quantitatively.

3.3.1 Static model with unobserved asset value. To clarify the intuition on how learning may affect our estimates, consider the following modification of the static model from Section 1.1. As before, the firm can either default or survive in the next period, but now investors are uncertain about the value of assets. Assume that, given all the information available to them just prior to default, investors believe that with probability q the value of assets is equal to V_b, and with probability $1-q$ it is strictly higher than V_b. Assume further that the firm defaults in the next instant if $V=V_b$ (so that V_b can be thought of as the default-triggering value of assets, or the "default boundary"). Upon default, the asset value drops to $L<V_b$ because of default costs, and creditors receive a recovery payment of $R<1$. Conversely, if $V>V_b$, then the firm survives and creditors receive one dollar.

The value of the firm and the value of its debt per dollar of face value satisfy:

$$M=qL+(1-q)\mathbb{E}[V|V>V_b], \tag{11}$$

$$D=qR+(1-q). \tag{12}$$

Equation (12) implies that investors' conditional default probability is $q=\frac{1-D}{1-R}$. The pricing equation (Equation (11)) can then be used to find the value of assets for the defaulting firm consistent with the observed M and to compute the cost of default as $\alpha=1-L/V_b$.

It is easy to see that for firms that are about to default, investors' estimate of the value of assets is biased upward. Indeed, in this model the true asset value conditional on default is always equal to V_b, which is its lowest possible value. As long as there is information asymmetry, the investors' estimate of the asset value prior to default is strictly greater than the true value: $\mathbb{E}[V] = qV_b + (1-q)\mathbb{E}[V|V > V_b] > V_b$. As a result, even if default is costless ($L = V_b$), the announcement of default results in a negative price reaction as investors infer that the asset value is lower than they thought. This intuition holds in more general settings without a default boundary, as long as the probability of default is decreasing in the value of assets.

Importantly, not all types of investors' beliefs are compatible with observed firm values, and this limits the effect that learning can have on our estimates for a given level of uncertainty. Notice that, according to Equations (11) and (12), a combination of M, L, D, and R implies a unique value for $\mathbb{E}[V|V > V_b]$, which severely restricts the set of admissible distributions of V that investors may have conditional on their information.

As a specific example, assume that investors' distribution for $V > V_b$ is uniform between V_b and $V_b(1+2x)$, and is zero for $V > V_b(1+2x)$, for some positive constant x. The total variance of this distribution is proportional to x^2, so that x summarizes investors' uncertainty ("noise") about the true asset value.

Figure 2 shows three admissible distributions for different levels of noise x: intermediate, low, and high. As x increases, the set of possible values for V becomes larger, but the conditional mean $\mathbb{E}[V|V > V_b] = V_b(1+x)$ remains constant. For the pricing equation to hold, V_b must become smaller, which in turn implies a lower value of $\alpha = 1 - L/V_b$.

To illustrate, in Figure 2b the uncertainty about the value of assets is very low (x is close to zero). In the limiting case of $x = 0$, investors are confident that $V = V_b$, which corresponds to the largest possible value of α. At the other extreme, Figure 2c shows that for very large levels of uncertainty the true asset value V_b can coincide with L, implying the cost of default equal to zero. Therefore, a given price reaction can be fully due to default costs when there is no learning, as in Figure 2b, or fully due to learning when there are no default costs, as in Figure 2c. For intermediate levels of noise, corresponding to Figure 2a, the observed price reaction is explained partly by default costs and partly by investors learning that the value of assets is lower than thought.

For this distribution, the pricing equation becomes

$$M = qL + (1-q)(1+x)V_b,$$

which after a little algebra implies that the cost of default satisfies

$$\alpha = \left(1 - \frac{1-\omega}{\omega}(1-q)x\right)\alpha_0, \tag{13}$$

where $\omega = 1 - L/M$ denotes the negative of the price reaction to default and $\alpha_0 = \frac{\omega}{1-q(1-\omega)}$ is the full-information estimate that obtains in the absence of noise

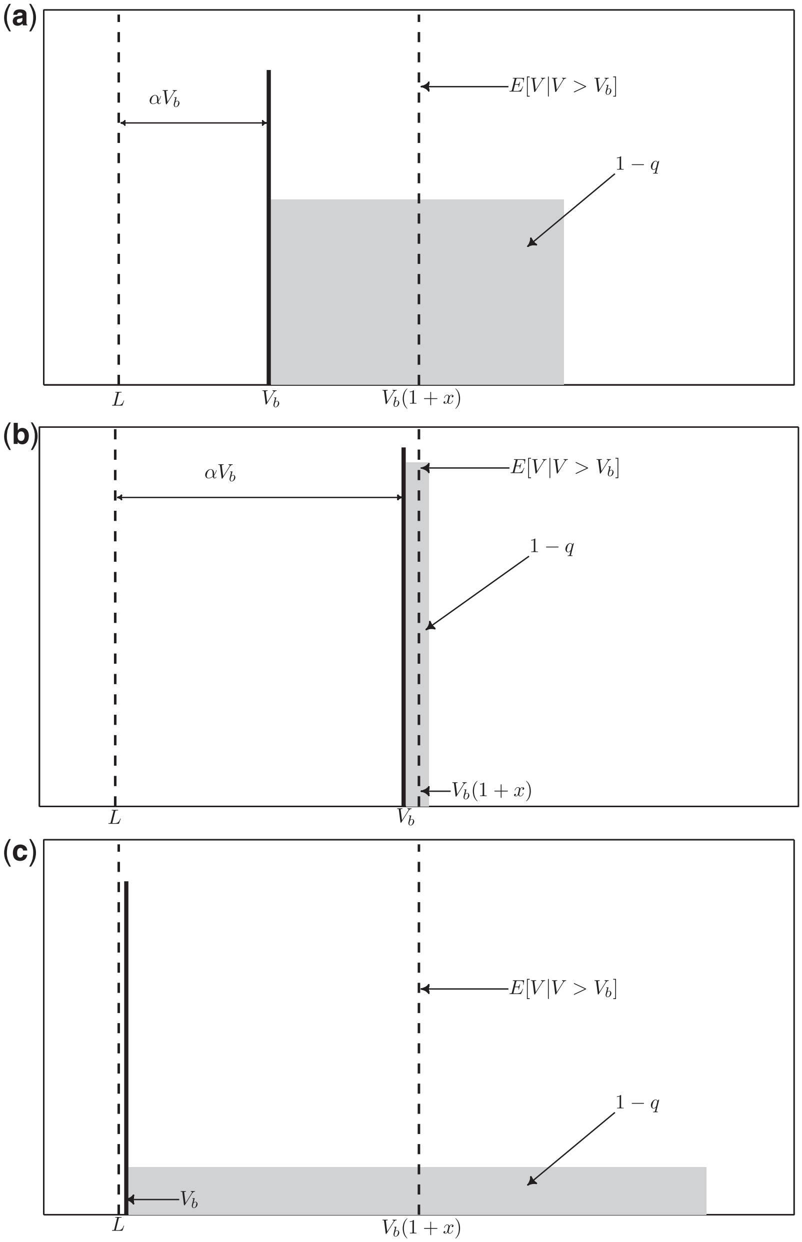

Figure 2
Unobserved asset value in the static model
This graph shows different admissible distributions of the asset value in the static model with uncertainty.

($x = 0$). Equation (13) shows that the estimated cost of default is decreasing in x.

Equation (13) also predicts that for a given base-case estimate α_0 the effect of noise is decreasing both in ω and in q. Thus, one group of firms for which the estimates are sensitive to the information structure are firms for which default is a big surprise (q is small). Intuitively, default is particularly surprising when investors overestimate the value of assets substantially. Another situation in which uncertainty may have a large effect on our estimates is when the price reaction ω is small. The reason is that in this case even a small learning effect may explain a large part of ω and thus change the implied α substantially.

As this discussion suggests, the impact of investors' uncertainty about the value of assets can vary in the cross-section. For the average firm in our sample, $\omega = 0.126$, $D = 0.483$, $R = 0.435$, and this model implies that a 1% increase in the standard deviation of investors' conditional distribution corresponds roughly to a 1% decrease in α. Thus, for levels of uncertainty below 10% (see Korteweg and Polson 2010), the effect of learning for the average firm in this static model is modest. In the next subsection, we confirm this prediction using a more realistic, dynamic model.

To understand intuitively what limits the effect for the average firm, notice that substantial overestimation of the asset value by investors would imply a low probability of default and a large surprise when default is announced. Yet, given the average recovery rate of 0.435, the average debt price of 0.483 implies that the risk-neutral probability of default is quite high (91% for this static model, and 81% for the dynamic model described in the next subsection). As the default probability is decreasing in the asset value, this implies in turn that investors are rather pessimistic about the value of assets even before default is announced. Hence, for the average firm, the observed price reaction to default is more likely to be caused by the realization of default costs than by investors' correcting their expectations of the asset value. Next, we proceed to quantify the role of learning in a dynamic setting.

3.3.2 Quantitative estimates of the impact of learning. In this subsection, we introduce investors' uncertainty about the value of assets into our hazard model of Section 1.2. All probabilities discussed below are under the risk-neutral measure. As before, the asset value follows a geometric Brownian motion as in Equation (5), and, conditional on knowing the true asset value, default is a Poisson process with the hazard rate specified in Equations (3) and (4). However, investors do not observe the true asset value. Instead, they have a prior distribution for V_t, which we denote $f(V_t)$, and a signal about the value of assets, denoted $\tilde{V}_t$. If the firm defaults, its value drops to $L_t = (1-\alpha)V_t$. Here, we study how our estimates of α depend on the level of investors' uncertainty (characterized by the variance of the prior distribution f) as well as on the reliability of available information (characterized by the variance of the signal $\tilde{V}$).

To be specific, we assume that the prior distribution is log-normal with variance s_0^2 and mean $\mathbb{E}[V_t]=e^{u_0+s_0^2/2}$. Following Duffie and Lando (2001), we also assume that the signal is unbiased given V_t and takes the form $\tilde{V}_t=V_t e^{a\epsilon-a^2/2}$, where $\epsilon\sim N(0,1)$ and a is the volatility of noise in the signal. Having received the signal, investors evaluate the market value of the firm $\tilde{M}(\tilde{V}_t)$ by integrating the function $M(V_t)$, given by Equation (10), over the posterior distribution of assets given their signal, $f(V_t|\tilde{V}_t)$.

As econometricians, we observe a sample of defaulted firms but not the individual signals. The distribution of the asset value for these firms is given by

$$f(V_t|d_t=1)=\frac{\lambda(V_t)f(V_t)}{\int\lambda(V)f(V)\mathrm{d}V}, \tag{14}$$

where $d_t=1$ denotes default. Under the above assumptions, this distribution is log-normal with variance s_0^2 and mean $\mathbb{E}[V_t|d_t=1]=e^{u_0+s_0^2/2+\beta_1 s_0^2}=\mathbb{E}[V_t]e^{\beta_1 s_0^2}<\mathbb{E}[V_t]$. Thus, low-value firms are over-represented in the defaulted subsample, which gives rise to investors' learning from default.

For the defaulted subsample, the average value of the firm before and after default can be found by averaging over different realizations of the signal as follows:

$$\bar{M}|_{d_t=1}=\mathbb{E}\left[\tilde{M}(\tilde{V}_t)|d_t=1\right],$$

$$\bar{L}|_{d_t=1}=(1-\alpha)\mathbb{E}[V_t|d_t=1]=(1-\alpha)e^{u_0+s_0^2/2+\beta_1 s_0^2}.$$

For given values of s_0 and a, these two equations include two unknowns, α and u_0.[20] We solve them using the parameters of the average firm in the sample[21] and study how the implied α depends on the uncertainty parameters, s_0 and a.[22]

The results are presented in Figure 3, which plots the ratio of the implied cost of default, α, to the base-case estimate α_0 that ignores learning. The estimates are given as a function of the volatility of noise, a, for three levels of investor's uncertainty, measured by s_0. Using a structural model, Korteweg and Polson (2010) estimate the standard deviation of noise in the value of assets for speculative-grade firms to be about 5%–7%. As Figure 3 shows, at $a=7\%$ the estimate of the cost of default is lower than in the base case by 4.3%, when $s_0=0.1$, and by 6.1%, when $s_0=0.3$. It also shows that when investors'

[20] In our implementation, we also use a third equation, one specifying the value of debt, to find the implied risk premium, ξ, as described in Section 1.2.3 for the base case.

[21] In principle, the equations can be solved for individual firms to yield firm-specific estimates of the cost of default for a given combination of the uncertainty parameters. In practice, statistics on such firm-specific estimates would be difficult to interpret, given that investors' uncertainty and the noisiness of value signals are likely to differ sharply across firms, and prior literature offers little guidance on how to choose firm-specific uncertainty parameters. Applying our approach to individual firms is an interesting avenue for future research.

[22] A detailed description of the estimation procedure is available from the authors upon request.

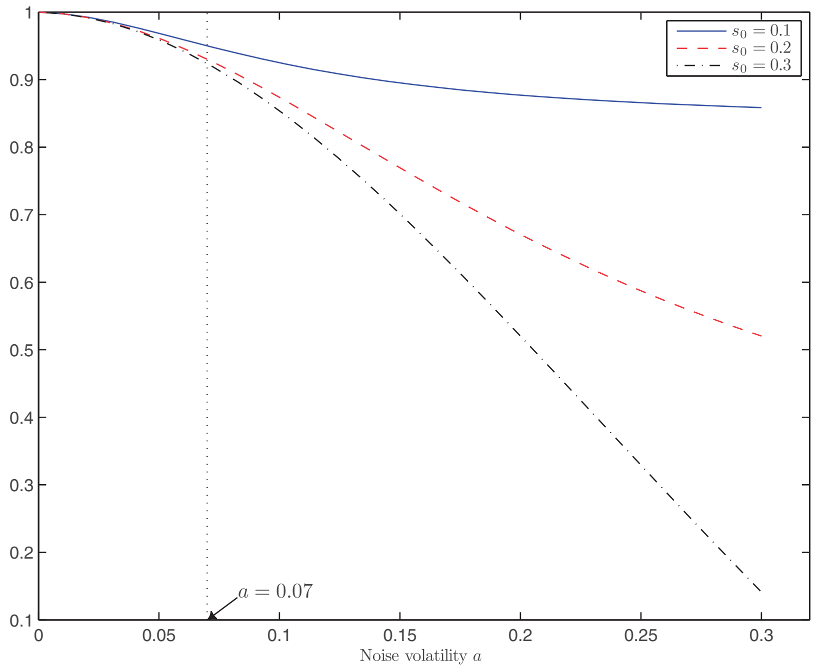

Figure 3
The effect of learning on the estimate of the cost of default
This graph illustrates the effect of learning for the average firm, estimated from the dynamic model with asset value uncertainty. The three lines correspond to different standard deviations of investors' prior distribution of V. The standard deviation of noise in the signal that investors receive about V is along the horizontal axis. For each combination of the uncertainty parameters, the graph shows the ratio of the implied cost of default α to the base-case estimate α_0 that obtains when V is observable without noise.

uncertainty is limited ($s_0 = 0.1$), the effect of learning does not exceed 15% even for very noisy signals, which corresponds to a bias in our mean estimate of about three percentage points. Thus, although the effect of learning on our estimates can be dramatic if investors are very uncertain about the value of assets, for plausible levels of noise the learning effect is likely to be modest.

3.4 Possible reverse causality

An important concern arising from our use of monthly prices is the possibility of "reverse causality." The argument is as follows. We observe default and a change in the value of the firm in the same calendar month and interpret the latter as a price reaction to the former. But, what if the value of assets drops first in response to some negative news, and then the firm defaults in response? In this case, the drop in the asset value that we estimate would be due to economic distress rather than the cost of default, and our approach would not work.

We note as a point of reference that in the twelve months preceding the month of default, the cumulative abnormal return on assets for the mean (median) firm is –68% (–61%). Thus, firms accumulate large losses due to economic distress over a substantial period of time prior to default, which far exceed the drop in the asset value in the month of default. Based on this observation, default is unlikely to be driven solely by any negative developments in the last month. Nonetheless, it is possible that recent bad news is the last drop that tilts the balance and triggers default.

To investigate this possibility, we take a closer look at the dynamics of market prices during the month of default. As we do not have daily debt prices, we focus on the share price instead. Daily equity prices in the month of default are available from CRSP for 100 sample firms. We find that the mean (median) cumulative abnormal return on equity over the calendar month of default for these firms is –12.2% (–12.8%). At the same time, the mean (median) cumulative abnormal return over the period [–5, +1] days, where 0 is the day of default, is –11.2% (–10.3%). Thus, almost all of the value drop seems to occur in a very short period around default when extrapolating the equity dynamics to the whole firm. However big its impact on the asset value, it is highly unlikely that more than a trivial number of firms default within just a few days of any negative development. After all, even though the events of 9/11 clearly had a large and immediate negative effect on major U.S. airlines, they did not start to file for bankruptcy until almost a year later.

Based on this analysis, the drop in the asset value appears to be caused by the firm's decision to default, rather than the other way around.

3.5 Additional robustness checks

In this section, we investigate the robustness of our results. First, we look into the possibility that debt of defaulting firms may be illiquid, making our value estimates unreliable. Second, we look at whether our results are likely to be affected by our use of monthly prices. Third, we show that our estimates are insensitive to the specifics of our hazard model setup.

3.5.1 Debt illiquidity. Our estimates are based in large measure on the market price of bonds. One may be concerned that bonds of firms near default may be illiquid and hence our bond price quotes may not reflect the true market value of debt accurately. In reality, the opposite is likely to be true: Because defaulted bonds attract certain types of investors (such as vulture funds) and are shunned by others, as investors actively adjust their portfolios, defaulting bonds are likely to be traded more actively compared with those of other speculative-grade firms. To verify this conjecture, we download information on all bond transactions from the Trade Reporting and Compliance Engine (TRACE) database between July 2002 (the earliest available date) and 2010. For each high-yield nonfinancial U.S. issuer, we compute the total number of bond trades in each calendar month. The mean (median) number of trades across all firm-months is 112 (27). We merge these data with our data on defaults and find that the mean (median) number of trades in the month of default is 287 (84), much higher than during normal periods. Unreported regression analysis confirms that the number of trades is significantly higher in the month of default even after controlling for bond issue size and rating fixed effects. These results, available upon request, suggest that bonds of defaulting firms are more liquid than those of nondefaulting high-yield firms. Moreover, Huang and Huang (2003) show that for credit spreads of low-rated firms, the nondefault component of the spread, including that attributable to illiquidity, is substantially smaller than that of higher-rated firms. Thus, debt illiquidity is unlikely to be a major factor affecting our estimates.

3.5.2 Robustness to the use of monthly prices. One potential source of bias in our estimates is the use of monthly prices instead of shorter observation windows around default. If values of defaulting firms decrease systematically prior to default, they will be lower immediately before default. As a result, the asset return in the month of default may be systematically higher than the price reaction to the default announcement.

To investigate this possibility, we compare price reactions and cost estimates for defaults occurring within the first fourteen days of the month with those happening in the remainder of the month. If the decline in firm value since the end of the last calendar month systematically inflates observed asset returns, we would expect this bias to be higher for defaults that happen late in the month. In untabulated tests, we find no evidence of this effect in the data: The average cost of default for the first half of the month is actually slightly higher than that for the second half (23.6% vs. 20.0%), although the difference is not statistically significant. Thus, our use of monthly data is unlikely to bias our estimates significantly.

3.5.3 Robustness to assumptions of the hazard model. A potential concern is that, although rooted in default-predicting studies, our specification for the default hazard is necessarily to some degree ad hoc. We therefore investigate whether our estimates are sensitive to various specific assumptions of our hazard model. Table 7 reports the results of this exercise. First, we use a different functional form of the hazard function, assuming that $\lambda_t^{\mathbb{P}} = \xi e^{\alpha_0 + \alpha_1 \frac{V_t}{B}}$. Second, time-varying risk premium estimates may be noisy for years in which only a handful of firms default. Therefore, we also use a common value for ξ, estimated from Equation (9), based on the characteristics of an average firm in the whole sample.

An important assumption of the model is that the ratio of the market value of assets to the face value of debt, V_t/B, can be used as a sufficient statistic for investors' conditional default hazard. Davydenko (2012) shows that, although this ratio is far and away the most powerful predictor of default, balance sheet liquidity also has incremental predictive power. As a result, ignoring liquidity may bias the hazard rate and affect the estimates of the cost of default. We assess the robustness of our estimates by adding liquidity as a second factor

Table 7
Robustness to model assumptions

	Mean	Median	SD	10%	90%
Base-case model	**21.7%**	**22.1%**	**33.0%**	**−22.5%**	**65.6%**
Exponential hazard function	21.7%	22.4%	33.2%	−23.0%	68.7%
Constant risk premium	22.2%	23.7%	33.2%	−22.3%	65.7%
Liquidity in default hazard	21.1%	22.2%	33.7%	−26.0%	66.3%

This table reports estimates of the cost of default for different functional forms of the default hazard, $\lambda_t^{\mathbb{P}}$, and different assumptions about the default risk premium, ξ. The base-case uses $\lambda_t^{\mathbb{P}}=e^{\beta_0+\beta_1 \log \frac{V_t}{B}}$ and year-specific risk premium estimates. In the second row, the hazard function is assumed to be exponential: $\lambda_t^{\mathbb{P}}=e^{\alpha_0+\alpha_1 \frac{V_t}{B}}$. The third row uses a constant risk premium, ξ, estimated based on the characteristics of an average firm in the sample. In the fourth row, the hazard function is assumed to depend on balance sheet liquidity, as follows: $\lambda_t^{\mathbb{P}}=e^{\gamma_0+\gamma_1 \log \frac{V_t}{B}+\gamma_2 QR}$, where QR is the quick ratio, defined as cash and receivables over current liabilities, assumed constant for each firm. The number of observations in each row is 175.

that can affect the default hazard: $\lambda_t^{\mathbb{Q}}=\xi e^{\gamma_0+\gamma_1 \log \frac{V_t}{B}+\gamma_2 QR}$, where QR is the quick ratio (cash and accounts receivable over current liabilities). We assume that to price assets at time t, investors expect QR to stay constant at its current level QR_t until the debt matures. With this modification, liquidity affects the baseline hazard for each firm but not its expected future dynamics. As Table 7 shows, our reported estimates are not sensitive to any of these changes in the specification of the default hazard.

3.6 Regression results

In this section, we explore the determinants of default costs, focusing in particular on the effect of economy-wide and industry distress. Shleifer and Vishny (1992) identify asset fire sales as a potentially important source of financial distress costs. They argue that when a financially distressed firm needs to sell assets, other firms in the same industry are likely to be distressed at the same time. As a result, assets may have to be sold at a discount to deep-pocketed industry outsiders who are not their most efficient users, resulting in value losses.

Given the dearth of empirical estimates of distress costs, the effect of industry conditions has been studied either for particular industries, such as airlines (Pulvino 1998), or indirectly by observing debt recovery rates in default (Acharya, Bharath, and Srinivasan 2007). Andrade and Kaplan (1998) regress their distress cost estimates on industry equity returns and find the correlation between the two to be negative as expected, but not statistically significant.

Using our sample of defaulted firms, which is both much larger and covers a longer time period, we test the Shleifer-Vishny fire-sale hypothesis by regressing our default cost estimates on measures of economy-wide and industry distress. Our macroeconomic proxies include the annual rate of default on rated bonds reported by Moody's (Ou, Chlu, and Metz 2011), the return on the S&P 500 over the previous year, and the rate of GDP growth. Industry-specific proxies include the median profitability and the median equity return over the previous year for firms in the same three-digit SIC industry. Under the fire-sale hypothesis, these variables are expected to be negatively correlated with default costs, with the exception of the rate of default, which is expected to be positively correlated. We report regressions for the whole sample, as well as separately for bankruptcies, for which we expect the effect of fire sales to be particularly strong.

The results are presented in Table 8. For bankruptcy filings, both macroeconomic and industry-specific distress measures are significant and have the predicted sign. When we look at all defaults, the macro factors become insignificant, but industry-specific distress measures remain strongly significant. Importantly, our evidence corroborates the findings of Acharya, Bharath, and Srinivasan (2007) that industry-level variables dominate economy-wide distress measures: Columns (11) to (13) show that when both types of proxies are included simultaneously, industry variables remain significant but macroeconomic factors do not. Overall, these findings support Shleifer and Vishny's (1992) prediction that industry distress makes financial distress costlier.

In untabulated tests, we also estimate cross-sectional regressions of default costs on various firm-specific factors used by Andrade and Kaplan (1998), including measures of debt structure complexity, such as the number of outstanding bonds; firm size; and proxies for asset tangibility, such as the ratio of fixed to total assets. Similar to AK, few of these variables are significant determinants of the size of our default cost estimates. The only exception is the ratio of bank to total debt, for which the regression coefficient is negative and generally statistically significant at the 5% level for the bankrupt subsample. The negative correlation with the fraction of bank debt may suggest that banks reduce bankruptcy costs by facilitating restructuring of bankrupt firms. An alternative interpretation is that the composition of debt is endogenous, and that banks prefer borrowers with high-quality collateral, for which default costs are low. Yet another possibility is that the presence of banks may be factored in investors' conditional probability of default and thus in the price reaction to default. Our specification of the default hazard may not fully capture this cross-sectional variation in the probability of default, as well as the effect of other firm-specific variables. Such a dependence could make our cross-sectional comparisons unreliable, and for this reason we do not attempt to conduct a detailed cross-sectional analysis of the estimated default costs.

3.7 The expected cost of default

Many applications, such as studies of optimal capital structure, are concerned with the expected risk-adjusted present value of default costs, which affect firm value prior to default. We compute these costs as the difference between the market value of assets and the value of the firm in each month up to default. Our estimates are reported in Table 9. Just prior to default, the expected cost for the median firm is 10.0%, which is 45% of the total median cost of default.

Table 8
The effect of macroeconomic and industry conditions

	All defaults					Bankruptcies							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Const.	0.20***	0.22***	0.20***	0.23***	0.22***	0.17**	0.31***	0.42***	0.30***	0.30***	0.20**	0.31***	0.37***
	(3.16)	(8.66)	(3.58)	(9.05)	(8.59)	(2.05)	(9.29)	(5.62)	(9.03)	(9.19)	(2.37)	(9.10)	(4.75)
Default rate	0.005					0.054*					0.042		
	(0.22)					(1.77)					(1.30)		
Market return		0.0003					−0.004**					−0.001	
		(0.26)					(−2.02)					(−0.63)	
GDP growth			0.004					−0.024*					−0.014
			(0.40)					(−1.72)					(−0.96)
Industry profitability				−0.008***					−0.010***		−0.009**		
				(−2.67)					(−2.78)		(−2.18)		
Industry return					−0.002**					−0.0026***		−0.002**	−0.002**
					(−2.41)					(−2.96)		(−2.35)	(−2.64)
N	175	175	175	167	167	77	77	77	75	72	75	72	72
R^2	0.000	0.000	0.001	0.042	0.034	0.040	0.051	0.038	0.096	0.111	0.117	0.116	0.123

This table presents OLS regressions of the cost of default. Columns (1) to (5) are for all firms, and Columns (6) to (13) are for bankruptcies only. *Default rate* is the proportion of rated bonds that default in each calendar year, as reported by Moody's. *Market return* is the return on S&P 500 over the year preceding default. *GDP* is the percentage increase in the GDP in the year of default. *Industry profitability* is the profit margin of the median firm in the same 3-digit SIC industry. *Industry return* is the equity return of the median firm in the same 3-digit SIC industry. Values of t-statistics are reported in parentheses. Coefficients marked ***, **, and * are significant at the 1%, 5%, and 10% significance level, respectively.

Table 9
Ex ante (expected) costs of default

	Mean	Median	SD	10%	90%	N
A	0.5%	0.6%	0.6%	−0.2%	1.0%	3
BBB	3.0%	1.2%	4.4%	−0.6%	8.9%	18
BB	4.5%	2.0%	8.4%	−1.3%	9.5%	44
B	4.6%	4.6%	9.2%	−5.7%	15.9%	135
CCC	10.3%	9.0%	19.1%	−14.4%	35.2%	122
CC	12.8%	7.3%	22.4%	−11.9%	47.7%	40
C	19.6%	6.0%	28.2%	1.3%	72.8%	6
Firms at default	14.0%	10.0%	20.9%	−10.2%	42.8%	171
All investment grade	2.6%	1.0%	4.1%	−0.2%	7.5%	21
All high yield	7.8%	4.8%	15.8%	−8.1%	28.9%	347

This table reports expected default costs prior to default, defined as the difference between the continuation value of assets and the market value of the firm, and expressed as a proportion of the market value of assets. For each firm, the sample consists of all firm-month observations since December 1996 and up to default. The reported statistics are calculated using firm means for each firm-rating combination.

Thus, by the time a firm declares default, its debt and equity prices already incorporate almost half of the total cost of default, whereas the other half is realized as the price reaction upon the announcement.

For firms that are far away from default, expected costs of default are much lower. For investment-grade firms, the sample mean is 2.6% of the asset value, and the median is only 1%. Moreover, even these estimates in all likelihood are biased upward, as our investment-grade subsample is dominated by future defaulters with ratings barely above junk. If we assume that a typical investment-grade firm is like the three A-rated firms in our sample, then the expected default cost is only about 0.5% of the firm value. These numbers are similar to those of Elkamhi, Ericsson, and Parsons (2012), who use AK's estimates of total ex post costs and find that ex ante expected costs are generally below 1% of firm value.

Finally, in untabulated tests, we also calculate the default-driven marginal cost of debt, defined as the decrease in the firm value when the face value of debt increases by one dollar. We find that the mean (median) marginal cost of default is 6.5% (5.6%) for investment-grade firms and slightly higher for high-yield firms.[23] Overall, consistent with the conclusions of Elkamhi, Ericsson, and Parsons (2012) and Graham (2000), our findings suggest that ex ante default costs are small in comparison with typical estimates of the tax advantage of debt.

4. Conclusions

By combining a novel estimation approach with unique data on market values for a large sample of defaulted firms, this article obtains market-implied estimates of the total cost of default, which are not limited to highly levered

23 In a recent article, van Binsbergen, Graham, and Yang (2010) estimate the all-in marginal cost of debt and find it to be substantially above the marginal cost of default.

firms. Although the average default cost in the sample is in the region of 20%, the cost for investment-grade firms is closer to 30%. This number may be more applicable to high- and medium-grade firms than estimates obtained on samples limited to highly levered firms. As debt prices of distressed firms become more readily available, our procedure can be applied to firms that are rarely seen to default. This would allow for more precise estimation of the ex ante cost of debt and thus for better understanding of financing choices that a typical firm faces.

Our estimation procedure adjusts the price reaction to default for the effect that partial anticipation has on predefault prices. It would be interesting to extend our model to allow for more precise cross-sectional identification of the probability of default, which could facilitate cross-sectional comparisons and provide new insights into the nature and the determinants of distress costs. The idea behind the approach can also be applied to other settings in which the market reaction to a corporate event may be dampened by its partial anticipation. For example, Bhagat et al. (2005) and Hietala, Kaplan, and Robinson (2003) account for investors' expectations and learning in the context of mergers and acquisitions. Our approach has the potential to enhance the accuracy of such estimates without relying on extranous events or particular subsamples for identification. Applying it in such settings could advance our understanding of the full effect that various corporate events have on firm value beyond the capabilities of traditional event studies.

Appendix 1. Derivation of the Pricing Equation

In what follows, all probabilities and expectations are under the risk-neutral measure $\mathbb{Q}$. We assume that

1. the market value of the firm's productive assets, V_t (i.e., the continuation value of the firm), follows a geometric Brownian motion

$$dV_t = rV_t dt + \sigma V_t dW_t, \tag{A1}$$

2. default follows a doubly stochastic process: conditional on knowing the history of the risk factor, default time is the first jump of a heterogeneous Poisson process with conditional risk-neutral intensity λ_t,
3. the "recovery" value of the firm L_t (i.e., its value in a hypothetical default at time t) is a constant fraction of its continuation value:

$$L_t = (1-\alpha)V_t, \text{ and} \tag{A2}$$

4. the firm is financed with a single discount bond that promises to pay one dollar at maturity. If the firm defaults, the bondholders receive a recovery payment of R at the time of default.

If the firm does not default by the maturity date T, its value at maturity equals the all-equity asset value, V_T. If the firm defaults some time prior to maturity, the value of assets at maturity is $L_T = (1-\alpha)V_T$. Conditional on no prior default, the market value of the firm M_t for $t \le T$ can be expressed as

$$M_t = e^{-r(T-t)}\mathbb{E}_t\left[V_T 1_{\{\tau \ge T\}} + (1-\alpha)V_T 1_{\{\tau < T\}}\right]. \tag{A3}$$

Rearranging the above equation and using the fact that $V_t = e^{-r(T-t)}\mathbb{E}_t[V_T]$ yields

$$\begin{aligned}
M_t &= e^{-r(T-t)}\mathbb{E}_t\left[V_T 1_{\{\tau\geq T\}} + (1-\alpha)V_T(1-1_{\{\tau\geq T\}})\right] \\
&= e^{-r(T-t)}\mathbb{E}_t[(1-\alpha)V_T] + \mathbb{E}_t\left[\alpha V_T e^{-r(T-t)} 1_{\{\tau\geq T\}}\right] \\
&= (1-\alpha)V_t + \alpha\mathbb{E}_t\left[V_T e^{-r(T-t)}\mathbb{E}_T[1_{\{\tau\geq T\}}]\right] \\
&= (1-\alpha)V_t + \alpha\mathbb{E}_t\left[V_T e^{-r(T-t)} e^{-\int_t^T \lambda_u(V_u)\mathrm{d}u}\right], \qquad \text{(A4)}
\end{aligned}$$

which is Equation (10) of the main text. The last step uses the fact that at time t we know $\tau > t$ and, conditional on the information up to T, the default process is a nonhomogeneous Poisson process stopped at its first jump. Hence, $\mathbb{E}_T[1_{\{\tau\geq T\}}]$ is the nondefault probability, and we have

$$\mathbb{E}_T[1_{\{\tau\geq T\}}] = e^{-\int_t^T \lambda_u(V_u)\mathrm{d}u}. \qquad \text{(A5)}$$

Since $L_t = (1-\alpha)V_t$, Equation (A4) can be rearranged as

$$M_t = L_t + (V_t - L_t)\mathbb{E}_t\left[\frac{V_T e^{-r(T-t)}}{V_t} e^{-\int_t^T \lambda_u(V_u)\mathrm{d}u}\right], \qquad \text{(A6)}$$

which is Equation (7) of the main text.

Similarly, the value of debt can be found as

$$\begin{aligned}
D_t &= \mathbb{E}_t\left[e^{-r(T-t)} 1_{\{\tau > T\}} + R e^{-r(\tau-t)} 1_{\{\tau\leq T\}}\right] \\
&= e^{-r(T-t)}\mathbb{E}_t^{\mathbb{Q}}\left[e^{-\xi\int_t^T \lambda^{\mathbb{P}}(V_u)\mathrm{d}u}\right] + \xi\int_t^T \mathbb{E}_t^{\mathbb{Q}}\left[R e^{-\int_t^s [r+\xi\lambda^{\mathbb{P}}(V_u)]\mathrm{d}u}\lambda^{\mathbb{P}}(V_s)\right]\mathrm{d}s, \qquad \text{(A7)}
\end{aligned}$$

where we have used the fact that the conditional distribution of the default time in the doubly stochastic framework is given by

$$f_\tau(s|V_T) = e^{-\int_t^s \lambda(V_u)\mathrm{d}u}\lambda(V_s). \qquad \text{(A8)}$$

This yields Equation (9) of the main text.

Appendix 2. Computing the Market Value of the Firm

For each sample firm, we estimate monthly market values of the firm as the sum of market values of bonds, bank debt, and equity. The firm's bond structure is inferred from the history of outstanding bond amounts in the FISD database for each bond issued by the firm and its wholly owned subsidiaries. The market value of bonds included in the Merrill Lynch 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 \$100 million are not included in the MLI. The market value of these bonds is calculated assuming that their yield equals the weighted-average yield of all quoted bonds of the same issuer on each date. If 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 database provides a mean price quote from three dealers. When there are several loans outstanding for a firm, we use their mean price, resulting in 7.5 dealer quotes per bank debt price on average (the median is four). 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:

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

where P_{bank} and P_{bond} are average loan and bond prices in cents on the dollar, respectively, and t-statistics adjusted for firm clustering are reported in parentheses. The quadratic term controls for nonlinearities that arise because of 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, we 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 our 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, we assume that all such debt obligations are similar to bank debt and have the same price-to-par ratio. These types of debt are not frequently used by risky firms that dominate our sample, so this approximation affects only a small fraction of the firms.

Where available, we 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, we use OTC equity prices from on CapitalIQ. Finally, we 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.

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