Default, Recovery, and the Macroeconomy

William Waller

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Approved by:

Gregory W. Brown

Charles M. Jones

Chotibhak (Pab) Jotikasthira

Christian T. Lundblad

Adam V. Reed

ABSTRACT

WILLIAM WALLER: Default, Recovery, and the Macroeconomy.
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While recent theoretical research has highlighted the importance of time-series variation in the cost of financial distress in explaining well-document corporate debt puzzles, empirical research has found that estimates of firm recovery rates are unrelated to overall market conditions. This paper answers the question: do default costs vary across the business cycle or are aggregate measures of default costs simply picking up differences in asset quality? Specifically by jointly estimating a model of ex-ante recovery rates and default probabilities, I find that a one standard deviation increase in the level of interest rates is associated with a 0.3% increase in the cost of default (decrease in recovery rate) and with firms liquidated 13 months earlier than the case of no change in interest rates. Moreover, a one standard deviation increase in the slope of interest rates is associated with a 0.7% decrease in the cost of default (increase in recovery rate) and with firms delaying the default decision 45 months than in the case of no change in interest rates.

For my brother, Robert D. Waller.

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1 DEFAULT, RECOVERY, AND THE MACROECONOMY

1.1 Introduction

Variation in the credit costs of the firm across the business cycle has broad implications for both asset prices and corporate financing decisions. This variation can stem from either changes in recovery rates through time or changes in the probability of a firm defaulting, due in part to managerial incentives and liquidity demands by bondholders, across macroeconomic conditions. Time-variation in recovery rates helps explain the magnitude and variability of the credit spread taking into account the observed rate of default. Countercyclical movements in default costs are also crucial in explaining the low levels of leverage in firms despite the relatively large tax benefits of debt. Moreover, this variation introduces the potential for strategic timing of default as managers of distressed firms face a tradeoff between the possibility of the firm as an ongoing concern and the payback to creditors of the firm.

Academics have long puzzled over the "under-leverage" of firms. Given the relatively small present value of expected losses from default, firms have too little leverage to take full advantage of the tax benefits of debt. (Miller 1977) Specifically, Graham (2000) estimates the tax benefits of debt to be as high as 5% of firm value, much larger than conventional estimates for the values of expected default losses. Almeida and Philippon (2007) extract risk-adjusted default probabilities from observed credit spreads to calculate expected default losses and find the values much larger than the tra- ditional estimates. Their findings highlight the importance of incorporating systematic risk stemming from macroeconomic conditions in evaluating firm financing decisions.

Similarly, the bond pricing literature identifies the importance of considering systematic risk. The credit spread puzzle posits that default spreads are too high to be explained solely by expected costs of default, especially in investment grade bonds (e.g. Collin-Dufresne et al. (2001); Elton et al. (2001); Huang and Huang (2012); Longstaff et al. (2005)). However, Giesecke et al. (2011) argues that systematic risk in bonds is largely related to bond-market liquidity and is not significantly associated with changes in aggregate default rates.

If aggregate cyclicality in default costs or the probability of default represents systematic risk, then these risks also should be priced in equity markets. This relationship has been born out in the literature as correlation with aggregate failure probability is in part responsible for the asset pricing ability of size and book-to-market factors (e.g. Vassalou and Xing (2004); Kapadia (2011)). However, firms with higher probability of failure earn abnormally low returns relative to their healthier counterparts (e.g. Dichev (1998); Griffin and Lemmon (2002); Campbell et al. (2008)). Ogneva et al. (2014) concludes that the lack of a distress risk-return tradeoff is tied to the idiosyncratic nature of distress risk.

Observed cyclicality in recovery rates may be due to a variety of factors. Firms whose assets provide poor insurance, low payoffs during bad economic times, have relatively low recovery rates compared to firms that default during economic upswings. Thus during economic downturns, these firms with poor growth options, or low quality assets, declare bankruptcy driving aggregate recovery rates to be lower during recessions. In this case, aggregate trends in recovery rates are due to sample composition effects. Alternatively, a given firm's assets may be priced differently across the business cycle. Such time-varying recovery rates could drive trends in aggregate recovery rates apart from the sample composition phenomenon. The question then becomes, do default costs vary across the business cycle or are aggregate measures of default costs simply picking up differences in asset quality (sample composition)?

Recent research has highlighted the importance of time-series variation in the cost of financial distress in explaining well-document corporate debt puzzles. For example, Chen

(2010) builds a dynamic model of capital structure in which countercyclical movements in the cost of default help drive the credit risk premium in investment grade firms. While this model sheds light on the credit spread puzzle and the under-leverage puzzle, business cycle variation in recovery rates is calibrated using aggregate recovery rates, which ignores time-series variation in the sample of defaulted firms. However, this variation has not been documented in cross-sectional studies of the cost of default. Davydenko et al. (2012) find that their estimates of firm recovery rates are unrelated to overall market conditions and are instead related to measures of industry health. These estimates are recovered by assuming that the costs of default are constant for a given firm and that macroeconomic conditions do not vary.

Similarly, time-variation in default probabilities may explain portions of the credit spread unrelated to default costs explicitly but instead related to credit costs through a bondholder liquidity channel. Recent theoretical work by Chen et al. (2013) shows that bondholder liquidity demands drive managers to delay bankruptcy despite the erosion of bondholder value during insolvency. This implication fits the empirical observation of Davydenko (2012) that the average firm is insolvent for one year prior to declaring bankruptcy, and that during that time bondholder value is eroded by 33% on average. However, this bondholder liquidity story differs from the firm liquidity channel espoused by Davydenko (2012).

This paper augments the event-study methodology of Davydenko et al. (2012) to study the effect of business cycle risk on default costs and the decision to default. Specifically, I find that a one standard deviation increase in the level of interest rates is associated with a 0.3% increase in the cost of default (decrease in recovery rate) and with firms liquidated 13 months earlier than the case of no change in interest rates. Moreover, a one standard deviation increase in the slope of interest rates is associated with a 0.7% decrease in the cost of default (increase in recovery rate) and with firms delaying the default decision 45 months than in the case of no change in interest rates. These findings are broadly consistent with firms facing time-varying recovery rates rather than trends in aggregate recovery rates being driven solely by a sample composition effect where firms with low quality assets face financial distress costs during economic downturns. However, the economic effects are relatively small compared to the economic effects of the delay in bankruptcy when facing poor macroeconomic conditions. This strategic bankruptcy story is consistent with the theoretical model of Chen et al. (2013) in which bondholder liquidity demands incentivize the firm to remain an ongoing concern. Specifically as investors demand more liquid, shorter-maturity bonds the slope of the term structure increases and firms delay bankruptcy in order to provide bondholders liquidity.

These findings are robust to a variety of additional tests. First, I consider sequential estimates which allow controls for additional aggregate and firm-specific controls. Next, I consider the case in which the jump intensity of default arrival varies through time and the case in which firm asset volatility is time varying. Then, I consider the relationship between aggregate and industry-level distress and the default probability.

The paper proceeds as follows. Section 2 discusses dataset construction in detail. Section 3 explains the methodology. Section 4 presents the main results. Section 5 provides additional tests and Section 6 concludes.

1.2 Data

1.2.1 Constructing the Market Value of the Firm

For our tests, we are interested in estimating the cost of financial distress for a broader sample than the highly leveraged transactions of Andrade and Kaplan (1998). To this end, we employ the strategy of Davydenko et al. (2012) which involves constructing the market value of firm assets in each month by combining firm data from a variety of sources including: equity and bond prices; accounting information; details on the capital structure of the firm; and information on firm defaults. This approach has the added benefit of providing a monthly time-series of firm characteristics prior to default rather than simply relying on quarterly financial statements. This higher frequency data provides insight in the firm's health and changes to the firm's capital structure just prior to default. As shown in Davydenko (2012), the median defaulting firm in a similarly constructed sample continues to operate with a negative net worth for approximately eight months prior to default before eventually defaulting when asset values reach 61.6% of the face value of firm debt. This lengthy insolvency hints at a possible strategic motive to default, which benefits from a higher frequency time-series relative to quarterly or annual data from financial statements. While the construction of the panel of firm market values follows the procedure of Davydenko et al. (2012) closely, we detail the specifics below.

The most restrictive constraint placed on firm-months[1] in our sample is the availability of bond prices. Bond prices are monthly quotes from Merrill Lynch's bond trading desks for constituents in the Bank of America Merrill Lynch (BoA ML) U.S. High Yield Master II (H0A0) and U.S. Corporate Master (C0A0) Indices from their inception in December 1996 through December 2012. These indices cover bonds with face value exceeding $100 million and remaining maturity in excess of one year. We supplement these prices with amounts outstanding from the Mergent Fixed Income Securities Database (FISD) in order to calculate the total market value of bonds for each firm-month. Bonds, which are not constituents of either BoA ML index, are priced assuming that their yield is equal to the weighted-average yield of the bonds of the same issuer at the same date for which pricing data is available. If no bond prices are observed for a given firm-month, that observation is excluded from the sample. While the BoA ML indices only cover 52.2% of the outstanding debt in the intersection of the Mergent FISD/CompuStat universes for a given month on average, we are able to compute the market value of 96.7% of outstanding debt in the intersection of the Mergent FISD/CompuStat universes by inferring prices based on

[1] We define a firm (company) as in CompuStat and use CompuStat GVKEY as our primary firm identifier.

available yields. To account for potential mismatches between the total face value of debt from Mergent FISD and CompuStat, we rescale the face value of debt to equal the long-term liabilities (CompuStat variable: *LLTQ*) from the firm's most recent quarterly financial statement. Similarly, the rescaled market value of debt is equal to the market-to-book ratio of debt from Mergent FISD times the face value of debt from CompuStat.

The remainder of the firm's capital structure is treated as follows. The remaining total liabilities as reported by CompuStat (*LTQ – LLTQ*) are treated as bank debt and are priced as follows:

$$P_{bank} = 40.18 + 1.045 \times P_{bond} - 0.00461 \times P_{bond}^2,$$

where P_{bank} and P_{bond} are weighted-average loan and bond prices in cents on the dollar, respectively.[2] Preferred stock (*PSTKQ*) is priced based on the findings of Varma (2003) that mean recovery rates for preferred stock are 15.3% versus 36.1% for senior unsecured debt. Thus, we set the price of preferred stock to the constant fraction $0.153/0.361 = 0.424$ of the firm's current bond price. Finally, stock prices and the amount of equity outstanding are primarily from CRSP. The exception is when firm equity is delisted just prior to the firm's default. In these cases, we supplement the data from CRSP with OTC prices from Capital IQ and Bloomberg. The market value of the firm's assets is then equal to the sum of the market values of the firm's common and preferred stock and the outstanding debt of the firm.

1.2.2 Sample of Defaults

The primary firm-months of interest for our tests are those in which a firm defaults. We supplement the market value of firm assets with information on firm defaults included in

[2] Davydenko et al. (2012) use this quadratic function to infer the market price of bank debt for firm-months not included in the LSTA/LPC Mark-to-Market Pricing Service by fitting the regression for firm-months in which they have prices for both bank debt and bonds. Their "regression produces an R^2 of 75.5% and is not substantially improved by the inclusion of additional firm-specific or macroeconomic controls." (Davydenko et al. 2012, p. 38)

Moody's Default & Recovery Database (DRD). DRD provides information on over 5,000 default events[3] (over 16,000 defaulted securities) for U.S. firms between 1920 and 2012. Specifically, DRD provides data such as date of default, default type, and 30-day post default pricing.

Over our sample period, DRD reports 1,752 firm defaults, excluding dividend omissions, for U.S. firms from January 1997 to December 2012. We are able to match 357 of these defaults to non-financial firms in CompuStat, representing 33.4% of the face value of defaulted debt. After removing firm-months following a firm's first default and thus eliminating subsequent defaults by a given firm, we are left with 283 defaults. After losing observations for which we do not observe prices both at the month-end just prior to default and the month-end for the month in which default occurs, we are left with a final sample of 173 firm defaults.

1.2.3 Sample of Non-defaulting Firms

We supplement our sample of firm defaults with firm-months in which a default does not occur. These observations include firms which will eventually default as well as firms which do not default in our sample period. These observations play two roles: (i) they serve as a control group in a variety of our tests, and (ii) they increase the precision of the hazard model portion of our joint estimation by serving as censored observations. As before, we exclude financial firms from our analysis. All told we have 123,287 firm-months in which no default occurs in our panel. These observations come from 1,499 unique firms with an average of 82 firm-month observations per firm. Firms that default in sample occur less frequently in our panel with an average of 72 firm-month observations per firm.

Compared to the standard intersection of the CRSP/CompuStat universes, coverage in

[3] Moody's defines bond default as "any missed or delayed disbursement of interest and/or principal, bankruptcy, receivership, or distressed exchange, where (i) the issuer offered bondholders a new security of package of securities that amount to a diminished financial obligation (such as preferred or common stock, or debt with a lower coupon or par amount), and (ii) the exchange had the apparent purpose of helping the borrower avoid default" (Keenan et al. 1999, p. 10).

our sample is on average 59.4% of equity market capitalization for a given month, ranging from 44.6% in February of 2000 to 67.0% in December of 2012. However, this number is biased downward due to our requirement that firms in our sample have a single debt issue with a face value in excess of $100 million (for inclusion in the BoA ML indices). If we consider only CRSP/CompuStat firms with greater than $100 million in long-term liabilities, we arrive at a more realistic, albeit still conservative since a firm's long-term liabilities are likely to be split up over multiple debt issues, measure of the coverage of our sample. In this case, coverage increases to an average 65.2%, ranging from 55.9% in June of 2000 to 71.3% in March of 2003.

1.2.4 Descriptive Statistics

We conclude this section by considering descriptive statistics comparing the set of defaulting firms both to themselves 12 months prior to default and the set of non-defaulting firms. *Recovery Rate* is the equally-weighted average price relative to par for defaulting issues 30 days after default. *Market Value of Assets / Total Debt* is the ratio of the market value of firm assets to total face value of debt (*LTQ*). *Total Assets / Total Debt* is the ratio of the total book value of assets (*ATQ*) to total face value of debt. *Total Assets* is the total book value of assets in billions of dollars. *Tangible Assets* is the the ratio of plants, property, and equipment (*PPEGTQ*) to total book value of assets. *Capital Expenditures* is total of the previous 4 quarters of capital expenditures[4] scaled by total assets. *Profitability* is the sum of the previous 4 quarters of operating income before depreciation (*OIBDPQ*) divided by the sum of the previous 4 quarters of net sales (*SALEQ*). *Profit Volatility* is the 5-year centered standard deviation of *Profitability*. *Cash / Total Assets* is the ratio of cash and short-term investments (*CHEQ*) to total assets. *Debt Maturity* is the ratio of long-term liabilities (*LLTQ*) to total liabilities (*LTQ*).

Table I presents these descriptive statistics. Using both *Market Value of Assets / Total*

[4]CompuStat reports the year-to-date capital expenditures (*CAPXY*).

Debt and *Total Assets / Total Debt*, defaulting firms are closer to insolvency compared either to themselves 12 months prior to default or to the set of non-defaulting firms. Over the 12 months leading up to default, *Market Value of Assets / Total Debt* falls roughly three times as much *Total Assets / Total Debt*, 73.2% versus 22.4%. The *Market Value of Assets / Total Debt* ratio of defaulting firms of 72.6% implies that roughly 30% of bondholder value has been eroded by the firm remaining in business. This measure is broadly consistent with Davydenko (2012) who finds that approximately $1/3$ of bondholder value is depleted by shareholders prior to default and hints at a strategic motive behind default timing. Over this period leading up to default, assets fall and firms write-down, or begin selling off, intangible assets. Moreover, defaulting firms display cut backs in capital expenditures by 1.2% of firm assets and 3.3% lower profitability. Interestingly, firms do not deplete their cash reserves in the 12 months leading up to default. They do, however, display a shift away from long-term liabilities and toward short term liabilities as debt maturity falls 20.9%. Compared to the sample of non-defaulting firms, defaulting firms are smaller, less profitable, and have more tangible assets. There is no statistically significant difference in the cash on hand between defaulting firms and their non-defaulting counterpart.

1.3 Methodology

This section outlines the model and underlying assumptions used to estimate my main results. I begin with an overview of a simple static model. Then, I build on that intuition to develop a general dynamic model, which nests the model of Davydenko et al. (2012). Next, I describe the estimation procedure to recover the parameters of interest. Finally, I provide details on the empirical proxies that I use for the non-free parameters in the model.

1.3.1 Static Model

To develop intuition for my model, consider a simple one-period model of a firm's market value of assets just prior to default. In this case,

$$M = V \times (1 - q) + L \times q, \tag{1.1}$$

where M is the market value of the firm, V is the value of the firm's assets, L is the recovery value of the firm (ex-post), and q is the risk-neutral default probability. Simply put, the market value of the firm is a convex combination of the continuation value of the firm and the recovery value of the firm given default. This approach can be viewed as an event study where the empiricist observes the market value of the firm just prior to default and the market value of the firm just after default (the recovery value of the firm).

Thus for a given firm just prior to default, the market value of the firm's assets, M, is observed. Moreover, the ex-post recovery value of the firm, L, can be observed. Given an estimate of the default probability of the firm, q, the continuation value of the firm, V, can be calculated. Additionally, the cost of default is given by $c = V - L$.

As in Davydenko et al. (2012), identification in this model hinges on the assumption that information about the firm's fundamentals is incomplete, such that investors cannot know with certainty that a firm will default in the next instant. In this setting as default occurs, investors incorporate this information into prices and prices converge to their postdefault recovery values. This identifying assumption is consistent with the large abnormal returns observed empirically in papers such as Altman (1969); Clark and Weinstein (1983); and Lang and Stulz (1992) who document shareholder losses of 20-30% following a firm's bankruptcy. In this imperfect information environment, Duffie and Lando (2001); Giesecke (2006); and Jarrow and Protter (2004) show that a firm's assets can be priced as though default were a random event with a hazard rate that is a function of the firm's economic conditions. We review these dynamic pricing equations in the following subsection.

1.3.2 General Model

Consider the continuation value of a firm's assets, V_t, which evolves following a geometric Brownian motion,

$$dV_t = r_t V_t dt + \sigma_t V_t dW_t,$$

where both the drift term and the volatility term can be time-varying. Moreover, let default follow a heterogenous Poisson process with conditional risk-neutral intensity, λ_t. Assuming that the recovery value of the firm, L_t, is a fraction of its continuation value, such that

$$L_t = (1 - \alpha_t)V_t,$$

the value of assets at time $t^* \geq \tau$, where τ is the instant of default occurring prior to maturity, is given by:

$$L_{t^*} = (1 - \alpha_\tau)V_\tau \mathbb{E}_\tau[e^{\int_\tau^{t^*} r_s ds}].$$

Denote T as the maturity date of the firm and $f(\tau) = \lambda_\tau(V_\tau)e^{-\lambda_\tau}$ as the instantaneous hazard at time τ. Under the risk-neutral measure, $\mathbb{Q}$, the market value of the firm, M_t, for $t \leq T$ can be written as follows

$$\begin{aligned}
M_t &= \mathbb{E}_t[e^{-\int_t^T r_s ds}(V_T \mathbb{1}_{\{\tau \geq T\}} + \int_t^T (1-\alpha_\tau)V_\tau \mathbb{E}_\tau[e^{\int_\tau^T r_s ds}]f(\tau)d\tau)] \\
&= \mathbb{E}_t[e^{-\int_t^T r_s ds}(V_T \mathbb{E}_T[\mathbb{1}_{\{\tau \geq T\}}] + \int_t^T (1-\alpha_\tau)V_\tau \mathbb{E}_\tau[e^{\int_\tau^T r_s ds}]f(\tau)d\tau)] \\
&= \mathbb{E}_t[e^{-\int_t^T r_s ds}(V_T e^{-\int_t^T \lambda_s(V_s)ds} + \int_t^T (1-\alpha_\tau)V_\tau \mathbb{E}_\tau[e^{\int_\tau^T r_s ds}]f(\tau)d\tau)] \\
&= \mathbb{E}_t[e^{-\int_t^T r_s + \lambda_s(V_s)ds}V_T + e^{-\int_t^T r_s ds}\int_t^T (1-\alpha_\tau)V_\tau \mathbb{E}_\tau[e^{\int_\tau^T r_s ds}]f(\tau)d\tau] \qquad (1.2) \\
&= \mathbb{E}_t[e^{-\int_t^T r_s + \lambda_s(V_s)ds}V_T + \int_t^T e^{-\int_t^T r_s ds}(1-\alpha_\tau)V_\tau \mathbb{E}_\tau[e^{\int_\tau^T r_s ds}]f(\tau)d\tau] \\
&= \mathbb{E}_t[e^{-\int_t^T r_s + \lambda_s(V_s)ds}V_T + \int_t^T e^{-\int_t^\tau r_s ds}(1-\alpha_\tau)V_\tau f(\tau)d\tau] \\
&= \mathbb{E}_t[e^{-\int_t^T r_s + \lambda_s(V_s)ds}V_T + \int_t^T e^{-\int_t^\tau r_s ds}(1-\alpha_\tau)V_\tau \lambda_\tau(V_\tau)e^{-\lambda_\tau(V_\tau)}d\tau].
\end{aligned}$$

This equation mirrors the static case given by Equation 1. The market value of a firm's assets, M_t, is a combination of the discounted value of the terminal value of the firm's assets, V_T, times the probability that the firm does not default and the discounted value of the instantaneous liquidation value, $(1-\alpha_\tau)V_\tau$, times the probability that the firm defaults in the next instant.

In order to investigate cyclicality in the probability of default and default costs, I consider a $k \times 1$ vector of factors, $\mathbf{x_t}$, which govern the macroeconomy. These factors evolve according to a general transition equation

$$d\mathbf{x}(t) = \kappa(\mu - \mathbf{x}(t))dt + \Sigma dW(t). \tag{1.3}$$

These factors feed into both the default hazard and the recovery value of the firm. Specifically, I make the following assumptions:

- The default hazard under the real probability measure is:

$$\lambda_t^{\mathbb{P}} = e^{-\beta_0 - \beta_1 \log \frac{V_t}{B} - \beta_2 \mathbf{x_t}}. \tag{1.4}$$

  Under this specification, the default hazard is a function of both some factors (possibly latent risk factors) and observed firm characteristics. The default hazard specification extends the default hazard model used in Davydenko et al. (2012) to include a set of common economy-wide factors which impact the probability of a firm defaulting. Davydenko et al. (2012) use a firm's economic solvency as a sufficient statistic for default arguing that their assumption is common in structural models of credit risk, such as Black and Cox (1976) and Merton (1974). Additionally, they argue that firm solvency is a primary input in measures of default used by academics and practitioners[5], such as distance-to-default and Expected Default Frequency by Moody's/KMV, and is a strong predictor of firm default as shown empirically in

[5] See for example Berndt et al. (2008).

Davydenko (2012).

- The recovery value of the firm is a function of the underlying interest rate process:

$$\alpha_t = \phi_1 + \phi_2 \mathbf{x_t}. \tag{1.5}$$

I make two additional assumptions for simplicity. However in Section 1.5, I confirm that my results are not driven by either a constant default risk premium, ξ, or constant volatility, σ.

- The intensity of the Poisson arrival process under the risk neutral measure is:

$$\lambda_t^{\mathbb{Q}} = \xi \lambda_t^{\mathbb{P}} \tag{1.6}$$

- The value of the firm's assets follows a geometric Brownian Motion with time-varying drift under the risk neutral measure:

$$\mathrm{d}V_t = \mathbf{r_t} V_t \mathrm{d}t + \sigma V_t \mathrm{d}W_t^{\mathbb{Q}} \tag{1.7}$$

The dynamic model I estimate is similar in spirit to the model proposed by Davydenko et al. (2012) except that I relax several key assumptions that they make in order to test the relationship between macroeconomic conditions and the joint determination of the probability of default and default costs. When firms face constant recovery rates and drift in asset growth, Equation 2 further reduces to

$$M_t = L_t + (V_t - L_t)\mathrm{E}_t^{\mathbb{Q}}\left[\frac{V_T e^{-r(t-t)}}{V_t} e^{-\int_t^T \lambda_u^{\mathbb{Q}} \mathrm{d}u}\right] \tag{1.8}$$

giving the pricing equation in Davydenko et al. (2012).

1.3.3 Factor Model

While my estimation allows for any of a broad class of general factors, I operationalize the factors governing aggregate conditions using a standard two factor Gaussian model given by:

$$\begin{aligned} r(t) &= \varphi(t) + x(t) + y(t) \\ dx(t) &= -ax(t)dt + \sigma dW_1(t) \\ dy(t) &= -by(t)dt + \eta dW_2(t) \\ dW_1(t)dW_2(t) &= \rho \end{aligned}$$

This model is convenient for several reasons. First, it ties the underlying factor model to the time-varying drift. Second, the factors can be estimated outside the model using the term structure of US interest rates thus avoiding the additional computational burden of using a Kalman filter within my estimation procedure.

Moreover, prior literature has emphasized the link between the term structure and the macroeconomy. For example, Ang et al. (2006); Estrella and Mishkin (1998); and Harvey (1988) provide evidence that term structure factors predict future economic activity (output). Similarly, Mishkin (1991) and Stock and Watson (2005) link information embedded in the term structure to future inflation. Diebold et al. (2006) document that the term structure effects future macro variables. Finally, Bekaert et al. (2010) ties the informational content of the yield curve to inflation targeting and monetary policy within a New Keynesian framework.

These factors also carry important information regarding the liquidity preferences of investors. In theoretical work by Chen et al. (2013), bondholder liquidity demands drive managers to delay bankruptcy despite the erosion of bondholder value during insolvency. Both theoretical (for example, Brunnermeier and Pedersen (2009) and Chordia et al. (2001)) and empirical (for example, Amihud and Mendelson (1991); Krishnamurthy (2002); and

Longstaff (2004)) literature confirm the relationship between the term structure and bond market liquidity. Specifically as investors demand more liquid, shorter-maturity bonds the slope of the term structure increases.

1.3.4 Estimation

The estimation procedure follows Davydenko et al. (2012). Specifically, I employ an expectation-minimization (E/M) algorithm to recover estimates for the parameters of interest. The algorithm is as follows:

1. Set $V_t^{(1)} = M_t$.
2. Estimate hazard model given in Equation 4 using $V_t^{(1)}$.
3. Simulate new values of $V_\tau^{(2)}$ for firm-months that correspond to default and use to calculate $\alpha^{(2)} = 1 - L_\tau / V_\tau^{(2)}$.
4. Estimate the ϕ parameters by regressing $\alpha^{(2)}$ on x_t and y_t and simulate $V_t^{(2)}$.
5. Iterate until parameters and V_τ converge.

Since the expectations given in Equation 2 have no analytical solution, I numerically solve for these expectations by simulating the path of the firm's asset value over 10,000 draws.

1.3.5 Model Inputs

I compute the other variables that serve as model inputs 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 Section 2. The unit of observation is firm-month due to data limitations. The value of the firm at default, M_τ, 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, I subtract the market return from the defaulted firms return and adjust the recovery value of assets accordingly.

The volatility of assets, σ, is the standard deviation of monthly asset returns for the median firm in the industry, as follows. First, I estimate the standard deviation of each firms monthly returns, as in Choi and Richardson (2009), excluding postdefault months and firms with fewer than ten consecutive monthly firm value observations. Second, we find the median asset volatility for the Fama French 17 Industry Classification. 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.

The factors underlying the risk-free rate r_t are extracted from a two-factor Gaussian term-structure model using the US Treasury yield curve and the no-arbitrage conditions.

1.4 Results

This section begins with some full sample tests in order to motivate the analysis and highlight some of the identification problems that I face. These simple tests have the advantage of utilizing a broader sample of defaults for which market prices of bonds are not available. After these tests, I present my main results.

1.4.1 Full Sample Tests

Table II presents the differences in defaulting firms across the business cycle as defined by NBER recession dates. Two primary differences between these two sets of defaulting firms stand out. First, recovery rates are 14% lower in recessions than in expansions despite the characteristics of defaulting firms being quite similar. While firms defaulting in recessions are smaller than those firms defaulting during expansions, both sets of firms have similar profitability, levels of tangible assets and profit volatility. This finding is consistent with the notion that recovery rates vary through time rather than differences in the quality of the firms defaulting in both states driving differences in sample composition between the two groups of defaulting firms. Second, bankruptcies occur more frequently during downturns despite the bankruptcy trigger being the same across the business cycle. Similarly, cash on hand, a simple proxy for liquidity, does not differ significantly across the two samples.

An alternative measure to assess the similarity of firms defaulting in good versus bad economic states is to look at the industry composition of defaulting firms across the business cycle. Panel A of Table III shows the percentage of defaulting firms by the 17 Fama and French industries for the full sample of defaults and during both expansions and recessions. On the whole, industry composition of defaulting firms is similar across the business cycle providing further evidence that sample composition between the two groups of defaulting firms, firms defaulting in recessions and firms defaulting in expansions, is unlikely the primary culprit in aggregate differences in recovery rates across the business cycle.

Insomuch as firms within a given industry are of a similar quality, differences in average recovery rates within an industry across different economic states are informative about time-variation in recovery rates. While firm may differ in quality within an industry, asset composition and exposure of those assets to aggregate productivity shocks are likely to be similar within industry. Panel B of Table III presents the differences in average recovery rate within industry classification across the business cycle. Unlike in the industry composition of defaulting firms, recovery rates are consistently lower during economic downturns within industry classification. For all firms within this broader sample of defaults, recovery rates are 10.91% lower during recessions than in expansions. Statistically significant differences in recovery rate range from a high of 24.14% lower recovery rates during recessions in Mining and Minerals to a low of 10.65% lower recovery rates during recessions in firms classified as Other Industries. The one industry in which recovery rates are not lower during economic downturns is Oil and Petroleum Products; however, this difference is not significantly different from zero.

I next turn to a multivariate analysis of recovery rates and default probabilities in order to better control for differences in firm characteristics and sample composition through time. For this analysis, I incorporate a continuous measure of the business cycle by focusing on the *Level* and *Slope* factors of the term structure of interest rates rather than the binary NBER recession indicator. These continuous variables help me identify the transition between recessions and expansions and provide a concise model for aggregate economic conditions in my main empirical analysis. Table IV presents parameter estimates from regressions of these two factors on aggregate output and inflation. In the specifications using both aggregate output and inflation, both the *Level* and *Slope* factor are positively related to output and negatively related to inflation. Moreover, these two macroeconomic variables do a relatively good job in explaining the variation in the two term structure factors. These two macroeconomic variables explain 82.6% of the variation in the *Level* factor and 34.3% of the variation in the *Slope* factor. All told, macroeconomic conditions are highly related to the continuous proxies I utilize in my analysis consistent with the more rigorous empirical evidence of Ang et al. (2006); Estrella and Mishkin (1998); Harvey (1988); Mishkin (1991); Stock and Watson (2005); and others.

Table V presents the estimates from the regression of recovery rates on macroeconomic conditions and a variety of controls. Consistent with time-varying recovery rates where recovery rates fall during economic downturns, *Level* is negatively and statistically significantly related to recovery rates. A one standard deviation increase in level is associated with a 31.1% decrease in recovery rates. This relationship is present despite controlling for aggregate and industry-levels of distress, *Credit Spread* and *Industry Profitability* respectively. These controls help to rule out an asset fire sale story to cyclicality in recovery rates at either an aggregate-level, as in Altman et al. (2005), or at the industry-level, as in Shleifer and Vishny (1992). Furthermore, firm characteristics meant to proxy for the quality of a firm are not significantly related to recovery rates. This finding provides evidence against sample composition being a primary driver in observed cyclicality in recovery rates.

In order to examine the relationship between the business cycle and default probabilities, it is important to examine only a set of firms likely to default in order to better isolate the marginal impact of the variables of interest on default. To this end, I match the set of defaulting firms to a control set of three non-defaulting firms per defaulting firm. The match is made 12 months prior to default by minimizing the sum of the squared differences in percentile face value of debt, percentile *Total Assets / Total Debt*, and percentile debt maturity. Non-defaulting firms are also required to be in the same industry as the defaulting firm. Table VI presents the match quality between the defaulting and non-defaulting firms. Along the dimensions of the match, defaulting and non-defaulting firms are quite similar with the only statistically significant difference between the two groups being along the dimension of debt maturity. In this case, non-defaulting firms have a shorter maturity of debt, and thus as evidenced in Table I, be more likely, if anything, to default. Turning to the capital structure of the defaulting firms versus that of the non-defaulting control group, both groups exhibit a similar market value of assets and distribution of those assets between equity, bonds, and bank notes.

While these simple tests provide preliminary evidence of the relationship between macroeconomic conditions and recovery rates, it is important to note several shortcomings of this approach. First, these straightforward tests use ex-post recovery data that combines losses due to financial and economic distress. Second, these tests ignore that recovery rates and the default decision is jointly determined. To this end, I follow the approach of Davydenko et al. (2012) in the next set of results. This methodology avoids these problems by backing out the cost of default after observing the market value fo the firm just before and just after bankruptcy is declared. Thus, the expectation of the recovery rate at the time of default is recovered in this event study-like approach.

1.4.2 Estimates from Full Model

I now present the estimates from the full model detailed in Section 3.2. This analysis overcomes many of the shortcomings of the prior analyses in order to better identify the effects of macroeconomic conditions on both default probabilities and default costs. As with the estimation framework of Davydenko et al. (2012), this methodology addresses the joint estimation problem and recovers ex-ante estimates of default costs, which represent the costs of financial distress rather than economic distress. Additionally, this estimation procedure relaxes several key assumptions made in the Davydenko et al. (2012) case. First, firm assets grow at a stochastic rate. Second, a firm's default probability is a function of its solvency as well as aggregate conditions. Third, a firm's default costs are allowed to be time varying within the estimation.

Estimates of both the baseline (Davydenko et al. (2012)) model and the extended model are provided in Table VII. I begin with a discussion of the hazard model estimates, which map firm solvency and macroeconomic conditions into the probability of a firm's default. Both proxies for macroeconomic conditions, *Level* and *Slope*, are statistically significantly related to the probability of default. A one standard deviation in the level of interest rates is associated with firms liquidating 13 months earlier than in the case where *Level* is at the mean. The slope of interest rates has an opposite effect on the survival probability of a firm. A one standard deviation in the *Slope* is associated with a delay of 45 months in the firm's default decision relative to the case where the slope of interest rates is at the mean. This finding comports with the idea that bondholders prefer the option value of holding a bond, despite the destruction of bondholder value during insolvency, to the uncertainty regarding the timing of cashflows from recovery due to asset lockup during bankruptcy proceedings. When liquidity demands rise, investors buy more liquid, shorter-maturity bonds tilting the slope of the yield curve up. Managers of insolvent firms postpone default relative to periods in which the yield curve is flatter in order to provide liquidity to bondholders.

Figure I provides information on the fit of the hazard model augmented to control for macroeconomic conditions. This figure plots the receiver operating characteristic (ROC) curve to quantify the improvement in this model versus the baseline case where firm solvency, as measured by the natural logarithm of firm value to the face value of debt, is a sufficient statistic for characterizing the probability of a firm's survival. This figure plots the proportion of true positives classified correctly as such for a given threshold of false positives and aids in assessing model fit. For example allowing for 35 percent false positives, the extended model that incorporates macroeconomic factors in addition to firm solvency classifies 63 percent of the true positives correctly relative to 51 percent classified correctly in the baseline model that uses firm solvency as a sufficient statistic to predict firm default. Moreover, a statistically test of the area under the curve (AUC) for the two models rejects the null of equal coverage at the 10 percent level. Taken together, the incremental effect of including macroeconomic factors in the hazard model is statistically and economically significant highlighting the importance of including factors related to aggregate bond market liquidity in addition to firm characteristics when predicting firm default.

Now I turn to a discussion of the estimates of recovery rates as a function of macroeconomic conditions in the full model. Again, both proxies for macroeconomic conditions are statistically significantly related to default costs. A one standard deviation in *Level* is associated with a 0.3% increase in the cost of default (decrease in recovery rate). Conversely, a one standard deviation increase in *Slope* is associated with a 0.7% decrease in the cost of default (increase in recovery rate). Thus as macroeconomic conditions worsen and a recession looms, cost of default rises as *Level* falls and *Slope* decreases. Then as the economy begins to recover and the term structure becomes upward sloped, cost of default falls. This evidence is broadly consistent with the aggregate trends which motivate the theoretical work by Chen (2010). Moreover insomuch as the quality of defaulting firms is similar across the business cycle, as argued in Section 1.4.1, these results provide evidence of time-variation in the cost of default. However, the magnitudes of these macroeconomic effects are much smaller than the trends apparent from aggregate data, hinting that the quality of assets of defaulting firms may still play a role. Additionally, these tests provide little evidence as to the drivers of this time-variation in recovery. For example, aggregate distress or industry-specific distress that is tied to macroeconomic conditions may lead to asset fires sales as in Altman et al. (2005) or Pulvino (1998), and the full model estimates are simply picking up these effects. In the next section, we explore a battery of additional tests designed to rule out these and other potential alternative explanations for these findings. Among other tests, we better control for the quality of defaulting firms as well as provide evidence that distress in non-defaulting firms/asset fire sales are not the primary drivers of these results.

1.5 Additional Tests

In this section, I address the robustness of my findings to several potential concerns. First, I consider sequential estimates which allow controls for additional aggregate and firm-specific controls. Next, I consider the case in which the jump intensity of default arrival varies through time and the case in which firm asset volatility is time varying. Then, I consider the relationship between aggregate and industry-level distress and the default probability. I conclude this section by examining the effects of time-varying recovery rates on the timing of a firm's default and examining the bond pricing implications of time-varying recovery rates.

1.5.1 Sequential Estimates

Unfortunately, the inclusion of additional variables in my estimation requires specifying a law of motion for each variable so that investors can form expectations of the future values of these variables. Instead of harnessing my estimation procedure with this additional complexity, I address the problem of omitted variables that are correlated with my proxies for macroeconomic conditions by performing a sequential estimation procedure. Specifically in this subsection, I follow the approach of Davydenko et al. (2012) and estimate a nested case of the full model in which assets grow at a constant rate, firm solvency is a sufficient statistic for estimating default probabilities, and firms face constant default costs. This model is the baseline model presented in Table VII. I then examine the relationship between these first-stage estimates and the battery of macroeconomic variables, firm-characteristics, and aggregate and industry-level controls used in Tables V. While this approach faces a number of unrealistic assumptions, estimates from these results are consistent with the results from the full sample of defaults. Moreover, these results address the use of ex-post recovery rate data and the joint determination of the default decision and recovery rates.

Table VIII presents the analogue of Table V within the Davydenko et al. (2012) estimation framework. In this table, the dependent variable are firm-level estimates of *Default Costs* $= (1-$ *Recovery Rate*$)$ recovered from the estimation procedure described in Section 3.2. Similar to the OLS results presented in Table V, *Level* is positively (negatively) and statistically significantly related to default costs (recovery rates). After controlling for the expectation of default costs rather than the ex-post realization of financial distress costs and the joint estimation problem, the impact of macroeconomic conditions on default costs is roughly a third lower with a one standard deviation increase in *Level* corresponding to a 20.7% increase versus the 31.1% increase estimated in the OLS regressions. Thus, roughly one third of default costs estimated in the OLS case are attributable to the costs of economic, rather than financial, distress. As before, aggregate distress, as measured by *Credit Spread*, is positively and statistically significantly related to default costs. However, these estimates are roughly two-thirds smaller than in the OLS case. Again, this finding is consistent with a large portion of OLS estimates of default costs (recovery rates) attributable to economic versus financial distress costs. Within this estimation framework, several variables proxying for asset quality are statistically significantly related to default costs. Firms with more profitable assets face lower expected default costs with a one standard deviation increase in profitability being associated with an almost 4% decrease in default costs. Firms with higher industry-level asset volatility interestingly exhibit lower default costs as well. A one standard deviation increase in asset volatility is associated with a roughly 6% decrease in default costs. Finally, firms with higher asset tangibility face higher expected default costs. A one standard deviation increase in asset tangibility is associated with a roughly 16% increase in default costs.

1.5.2 Time-varying Jump Intensity

One potential concern of my estimates is that the inclusion of macroeconomic conditions in the hazard model simply captures variation through time in the mapping of the Poisson arrival process for firm default between the real probability ($\mathbb{P}$) measure and the risk neutral ($\mathbb{Q}$) measure. To address this concern, I allow the jump intensity measure presented in Equation 5 to vary through time. Thus,

$$\lambda_t^{\mathbb{Q}} = \xi_t \lambda_t^{\mathbb{P}}.$$

In order to identify ξ_t, I estimate the Volatility Risk Premium for each month in the spirit of Bollerslev et al. (2009) and Drechsler and Yaron (2011). Specifically, ξ_t is equal to the ratio of the model-free expected volatility as measured by the VIX index and the realized volatility as measured by the square root of the sum of the squared S&P 500 daily returns. I then rescale this measure to ensure that the jump intensity is greater than one in all months. This proxy provides a time-varying measure of jump intensity that may helps alleviate concerns that significant loadings on macroeconomic conditions in the hazard model for firm default, β_2 and β_3, are simply picking up variation in jump intensity through time. Results from this specification are presented in the second set of results in Table IX. The estimates of cyclicality in default probabilities and recovery rates are quantitatively similar to the main results presented in Section 5.3.

1.5.3 Time-varying Volatility

A rich literature has developed regarding time-variation in firm volatility, for example Engle (1982); Bollerslev (1986); Bakshi et al. (1997); Chernov and Ghysels (2000) and cites therein. Systematic measurement error in firm volatility may distort estimates of the probability of default and the costs of default. For example, volatility may be systematically high during economic downturns as in Nelson (1991). As the economy recovers, firm volatility may drift downward to an expected long-term mean. Thus in the estimation, firm volatility is overstated leading to estimates of firm default probabilities that are biased upward and correlated with recessionary conditions. Similarly, estimates of firm default costs are biased downward and correlated with recessionary conditions.

To account for this time-variation in firm asset volatility, I allow the value of the firm's assets to follow the geometric Brownian motion under the risk neutral measure below:

$$\begin{aligned} \mathrm{d}V_t &= \mathbf{r_t} V_t \mathrm{d}t + \sigma_t V_t \mathrm{d}W_t^{\mathbb{Q}} \\ \sigma_t &= (1-\alpha)\bar{\sigma} + \alpha\sigma_{t-1} \end{aligned}$$

This concise representation of time-varying firm volatility follows the spirit of the GARCH literature of Engle (1982) and Bollerslev (1986), while minimizing the number of extra parameters to be included in the model. Specifically, I estimate a centered 24-month standard deviation for each industry-month and fit a simple AR(1) model for each industry series.

These industry estimates provide firm-level α and $\bar{\sigma}$. σ_t for a given firm-month is calculated as in the main results.

Specifying volatility in this manner allows firm volatility to return to the level of long-run expected volatility for the industry to which the firm belongs despite temporary movements away from this long-term mean of volatility and should reduce the potential for volatility-related biases in the probability of default and default cost estimates. Results for this time-varying volatility specifications are presented in the third set of estimates in Table IX and are quantitatively similar to the main results.

1.5.4 Aggregate and Industry-level Distress

Similar to the above concerns, time variation in the level of aggregate distress as in Altman et al. (2005) or in the level of industry distress as in Shleifer and Vishny (1992) that is correlated with macroeconomic conditions may distort estimates of the cyclicality of default probabilities and default costs. To address this concern, I control for this distress within the estimation by augmenting the default cost specification to include the aggregate or industry-level default probability as a proxy for the level of distress. Specifically, a firm's recovery rate is

$$\alpha_t = \phi_1 + \phi_2 x_t + \phi_3 y_t + \phi_4 \lambda_{-i,t},$$

where

$$\lambda_{-i,t} = \frac{1}{n} \sum_{j \in -i} \lambda_{j,t} = \frac{1}{n} \sum_{j \in -i} e^{-\beta_0 - \beta_1 \log \frac{V_{j,t}}{B_j} - \beta_2 x_t - \beta_3 y_t}.$$

This sum is taken over all firms in the sample excluding firm i to proxy for aggregate distress or over all firms in the same industry as firm i excluding firm i to proxy for industry-level distress. The primary advantage of this proxy for distress is that it is internal to the estimation procedure. Thus, its law of motion is consistent with the model as a whole.

Table IX presents the results from this estimation. Again, parameter estimates are similar to those obtained from the estimation, which does not explicitly control for distress at the aggregate or industry-level. This evidence is broadly consistent with time-variation in a given firm's recovery rate that is related to macroeconomic conditions rather than asset liquidity or fire sales.

1.6 Conclusion

My study attempts to provide an answer to the following question: do default costs vary across the business cycle or are aggregate measures of default costs simply picking up differences in asset quality (sample composition)? While this time variation is apparent in simple multivariate regressions of firm default and recovery rates on macroeconomic conditions and a battery of industry and firm-specific characteristics, it is important to strip out the cost of economic distress by focusing on investor's expectations of recovery rates rather than ex-post measures of recovery. Additionally, the default decision and recovery rates are jointly determined, which may induce bias in parameter estimates from simple regressions. By exploiting changes in the market value of a firm's assets around default events, I estimate the role of business cycle conditions on the joint determination of ex-ante default costs and the default probability of the firm.

I find evidence that is consistent with time-variation in default costs within a given firm. Specifically, a one standard deviation increase in the level of interest rates is associated with a 0.3% increase in the cost of default (decrease in recovery rate) and with firms liquidated 13 months earlier than the case of no change in interest rates. Moreover, a one standard deviation increase in the slope of interest rates is associated with a 0.7% decrease in the cost of default (increase in recovery rate) and with firms delaying the default decision 45 months than in the case of no change in interest rates.

These findings are broadly consistent with firms facing time-varying recovery rates rather than trends in aggregate recovery rates being driven solely by a sample composition effect where firms with low quality assets face financial distress costs during economic downturns. However, the economic effects are relatively small compared to the economic effects of the delay in bankruptcy when facing poor macroeconomic conditions. This strategic bankruptcy story is consistent with the theoretical model of Chen et al. (2013) in which bondholder liquidity demands incentivize the firm to remain an ongoing concern. Specifically as investors demand more liquid, shorter-maturity bonds the slope of the term structure increases and firms delay bankruptcy in order to provide bondholders liquidity.

Moreover, my findings are robust to a variety of additional tests. First, I consider sequential estimates which allow controls for additional aggregate and firm-specific controls. Next, I consider the case in which the jump intensity of default arrival varies through time and the case in which firm asset volatility is time varying. Then, I consider the relationship between aggregate and industry-level distress and the default probability.

Future research should explore the pricing implications of these micro-level findings. Spreads from corporate structural models incorporating both time-variation in recovery rates and in default probabilities can be compared to spreads observed in the data. One natural extension of this work is to incorporate the estimates of the time-variation in distress risk to further explore the panel of bond returns in the context of a constant credit cost component, a time-varying credit cost component, and firm-specific COAS.

Similarly, additional research should explore the relationship between the components of distress risk I explore, probability of default and default costs, as they relate to equity returns. While a host of papers explore the pricing of distress risk in equities (Kapadia (2011); Ogneva et al. (2014); among others), some puzzling findings still remain, which the decomposition of time-varying distress risk into time-variation in the probability of default and time-variation in default costs can likely shed light on.

Figure 1.1: Receiver Operating Characteristic Curve

This figure plots the receiver operating characteristic curve for the hazard model estimated in Table VII. For a given threshold of false positives, the percentage of true positives identified by the fitted model is plotted. The baseline model, in which firm solvency is a sufficient statistic for default, is plotted in red. The extended model, in which firm solvency is augmented with macroeconomic factors, is plotted in green.

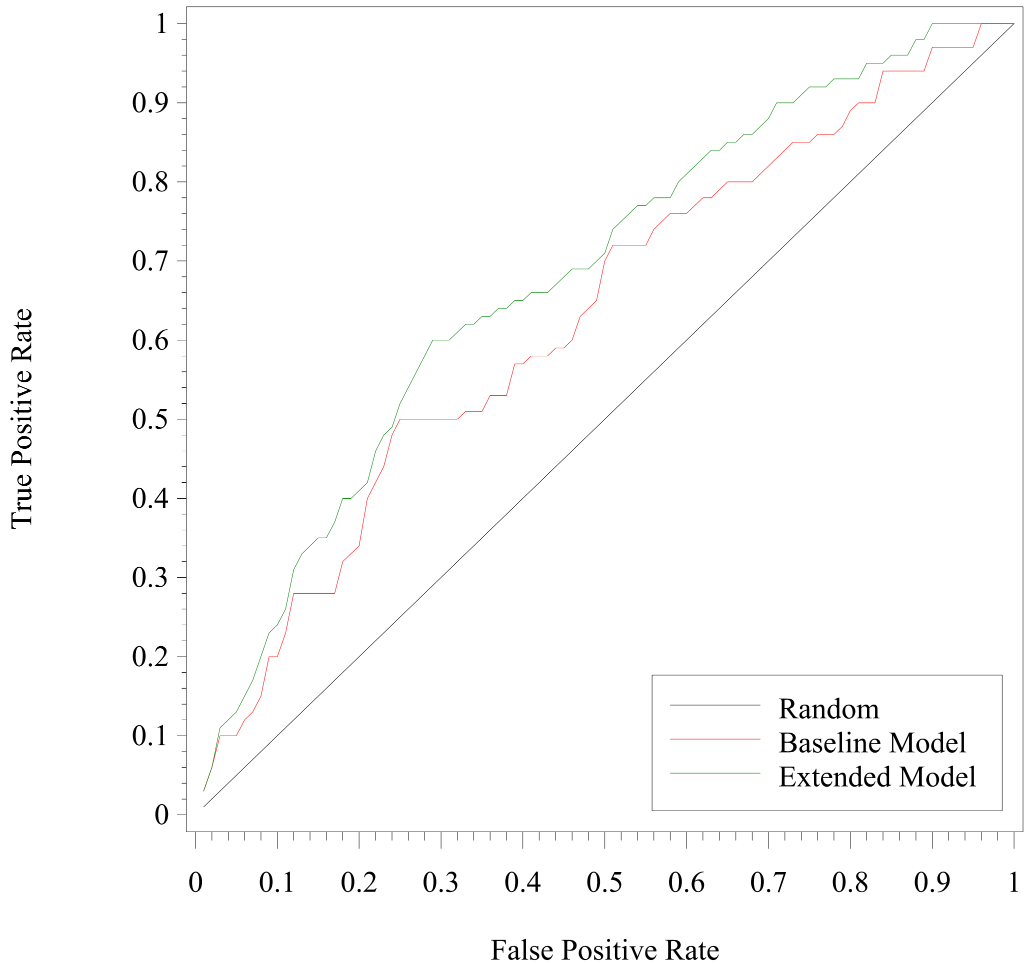

Table 1.1: Summary Statistics

This tables presents summary statistics for the sample of defaulting firms in the month of default, the sample of defaulting firms twelve months prior to default, and the sample of non-defaulting firms. For the sample of non-defaulting firms, I present the cross-sectional mean of the time-series median of the firm characteristic. *Recovery Rate* is the equally-weighted average price relative to par for defaulting issues 30 days after default. *Market Value of Assets / Total Debt* is the ratio of the market value of firm assets to total face value of debt (*LTQ*). *Total Assets / Total Debt* is the ratio of the total book value of assets (*ATQ*) to total face value of debt. *Total Assets* is the total book value of assets in billions of dollars. *Tangible Assets* is the the ratio of plants, property, and equipment (*PPEGTQ*) to total book value of assets. *Capital Expenditures* is total of the previous 4 quarters of capital expenditures[6] scaled by total assets. *Profitability* is the sum of the previous 4 quarters of operating income before depreciation (*OIBDPQ*) divided by the sum of the previous 4 quarters of net sales (*SALEQ*). *Profit Volatility* is the 5-year centered standard deviation of *Profitability*. *Cash / Total Assets* is the ratio of cash and short-term investments (*CHEQ*) to total assets. *Debt Maturity* is the ratio of long-term liabilities (*LLTQ*) to total liabilities (*LTQ*). For the test of the difference in means, *, **, and *** denote significance at the 10 percent, 5 percent and 1 percent levels, respectively.

	Default Sample		12 mos. Prior		Non-default Sample	
	Mean	Std. Dev.	Mean	Diff.	Mean	Diff.
Recovery Rate	42.03%	26.59%				
Market Value of Assets / Total Debt	0.726	0.753	1.458	−0.732***	2.849	−2.123***
Total Assets / Total Debt	1.093	0.431	1.317	−0.224***	1.652	−0.559***
Total Assets	6.262	17.253	7.156	−0.894***	10.759	−4.497**
Tangible Assets	0.885	0.495	0.761	0.124***	0.626	0.260***
Capital Expenditures	0.081	0.093	0.094	−0.012*	0.067	0.015
Profitability	0.054	0.173	0.087	−0.033**	0.147	−0.094**
Profit Volatility	0.094	0.105	0.098	−0.004	0.079	0.015
Cash / Total Assets	0.068	0.080	0.079	−0.011	0.076	−0.008
Debt Maturity	0.563	0.327	0.772	−0.209***	0.684	−0.121***
Number of Firms	173		173		1,499	

Table 1.2: Differences in Defaulting Firms Across the Business Cycle

This tables presents differences in the characteristics of defaulting firms conditional on whether default occurs during an NBER recession. *Recovery Rate* is the equally-weighted average price relative to par for defaulting issues 30 days after default. *Market Value of Assets / Total Debt* is the ratio of the market value of firm assets to total face value of debt (*LTQ*). *Total Assets / Total Debt* is the ratio of the total book value of assets (*ATQ*) to total face value of debt. *Total Assets* is the total book value of assets in billions of dollars. *Tangible Assets* is the the ratio of plants, property, and equipment (*PPEGTQ*) to total book value of assets. *Capital Expenditures* is total of the previous 4 quarters of capital expenditures[7] scaled by total assets. *Profitability* is the sum of the previous 4 quarters of operating income before depreciation (*OIBDPQ*) divided by the sum of the previous 4 quarters of net sales (*SALEQ*). *Profit Volatility* is the 5-year centered standard deviation of *Profitability*. *Cash / Total Assets* is the ratio of cash and short-term investments (*CHEQ*) to total assets. *Debt Maturity* is the ratio of long-term liabilities (*LLTQ*) to total liabilities (*LTQ*). For the test of the difference in means, *, **, and *** denote significance at the 10 percent, 5 percent and 1 percent levels, respectively.

	Expansion		Recession		
	Mean	Std. Dev.	Mean	Std. Dev.	Diff.
Recovery Rate	0.455	0.272	0.315	0.215	-0.140^{**}
Total Assets / Total Debt	1.082	0.354	1.080	0.603	-0.002
Total Assets	5.735	15.573	2.859	3.097	-2.876^{**}
Tangible Assets	0.896	0.551	0.946	0.525	0.050
Capital Expenditures	0.081	0.101	0.103	0.112	0.022
Profitability	0.049	0.167	0.053	0.197	0.004
Profit Volatility	0.103	0.112	0.092	0.108	-0.011
Cash / Total Assets	0.064	0.066	0.076	0.112	0.011
Debt Maturity	0.580	0.314	0.492	0.365	-0.088

Table 1.3: Default Statistics by Industry - Full DRD Sample

This tables presents default statistics by industry. Expansionary and recessionary periods are classified using the NBER recession dates. Panel A provides the distribution of defaults across 17 Fama and French industries. Panel B presents the mean recovery rate by Fama and French 17 Industry Classification. *Recovery Rate* is the equally-weighted average price relative to par for defaulting issues 30 days after default. For the test of the difference in means between defaults occuring within recessionary periods versus those occuring during periods of expansion, *, **, and *** denote significance at the 10 percent, 5 percent and 1 percent levels, respectively.

Panel A: Frequency of Defaults

	Full Sample	Expansion	Recession
Automobiles	2.28%	1.67%	3.04%
Chemicals	2.64%	1.93%	3.52%
Construction and Construction Materials	5.78%	4.50%	7.36%
Consumer Durables	5.21%	5.15%	5.28%
Drugs, Soap, Perfumes, and Tobacco	0.86%	0.64%	1.12%
Fabricated Products	1.43%	1.29%	1.60%
Financials	9.84%	9.52%	10.24%
Food	2.78%	3.35%	2.08%
Machinery and Business Equipment	5.99%	5.66%	6.40%
Mining and Minerals	1.78%	1.67%	1.92%
Oil and Petroleum Products	3.50%	4.89%	1.76%
Retail Stores	10.56%	12.23%	8.48%
Steel Works	3.28%	2.70%	4.00%
Textiles, Apparel, and Footware	3.99%	4.25%	3.68%
Transportation	5.35%	7.08%	3.20%
Utilities	2.07%	2.32%	1.76%
Other	32.67%	31.15%	34.56%
Total Number of Defaults with SIC Codes	1,402	777	625
Total Number of Defaults	3,004	1,869	1,135

Table 1.3: Default Statistics by Industry - Full DRD Sample (cont.)

Panel B: Average Recovery Rate

	Full Sample	Expansion	Recession	Diff.
Automobiles	48.80%	50.48%	47.58%	−2.89%
Chemicals	34.03%	49.68%	25.84%	−23.84%**
Construction and Construction Materials	38.15%	45.93%	33.26%	−12.67%
Consumer Durables	38.68%	44.17%	31.36%	−12.82%**
Drugs, Soap, Perfumes, and Tobacco	39.41%	45.40%	34.42%	−10.98%
Fabricated Products	39.08%	50.79%	30.30%	−20.49%
Financials	35.60%	36.56%	34.49%	−2.08%
Food	51.36%	56.06%	43.41%	−12.66%
Machinery and Business Equipment	37.99%	40.62%	34.87%	−5.75%
Mining and Minerals	41.21%	53.28%	29.14%	−24.14%*
Oil and Petroleum Products	47.77%	46.55%	52.35%	5.80%
Retail Stores	43.95%	48.58%	36.38%	−12.20%*
Steel Works	38.35%	45.21%	32.40%	−12.81%
Textiles, Apparel, and Footware	43.94%	49.38%	34.14%	−15.25%*
Transportation	44.24%	46.40%	38.01%	−8.39%
Utilities	55.92%	60.90%	43.85%	−17.05%
Other	42.81%	47.95%	37.30%	−10.65%***
No SIC Code	42.72%	46.66%	35.22%	−11.43%***
All Firms	42.13%	46.72%	35.81%	−10.91%***

Table 1.4: Term Structure and Output

This tables presents parameter estimates from the regression of the *Level* and *Slope* factor on *Aggregate Output* and *Inflation*. *Level* is the first factor extracted from fitting a two-factor Gaussian term structure model to the US Treasury yield curve. *Slope* is the second factor extracted from fitting a two-factor Gaussian term structure model to the US Treasury yield curve. *Aggregate Output* is the natural logarithm of real GDP. *Inflation* is the year-over-year log change in CPI. Standard errors are robust to heteroskedasticity. *, ** and *** denote significance at the 10 percent, 5 percent and 1 percent levels, respectively.

	Estimate	Estimate	Estimate
Level Factor			
Aggregate Output	0.915		0.951***
Inflation		−0.147***	−0.145***
R^2	0.033	0.783	0.826
Slope Factor			
Aggregate Output	1.788***		1.803***
Inflation		−0.058***	−0.061***
R^2	0.164	0.163	0.343

Table 1.5: Simple Regressions

The first two columns of this table present the parameter estimates from the regression of recovery rates on macroeconomic variables, industry characteristics and firm characteristics. The last two columns of this table present the parameter estimates from the logit regression modeling the probability of default for defaulting firms and the matched sample of non-defaulting firms. *Recovery Rate* is the equally-weighted average price relative to par for defaulting issues 30 days after default. *Level* is the first factor extracted from fitting a two-factor Gaussian term structure model to the US Treasury yield curve. *Slope* is the second factor extracted from fitting a two-factor Gaussian term structure model to the US Treasury yield curve. Other variables are defined in the text. Marginal effects are the change in the dependent variable for a one standard deviation change in the independent variable. Standard errors are robust to firm-level heteroskedasticity. *, ** and *** denote significance at the 10 percent, 5 percent and 1 percent levels, respectively.

	Recovery Rates		Default Probabilities	
	Estimate	MFX	Estimate	MFX
Intercept	73.260^{***}		-0.609	
Level	-3.974^{***}	-0.311	-0.182^{***}	-0.140
Slope	-1.090	-0.050	0.016	0.004
Credit Spread	-7.014^{***}	-0.301	-0.044	-0.010
Industry Beta	10.163	0.080	-0.837^{**}	-0.063
Industry Asset Vol.	-39.938	-0.142	0.809	0.019
Industry Profitability	-3.453	-0.012	0.009	-0.007
Assets (log)	-1.558	-0.090	0.115^{***}	0.105
Asset Tangibility	2.434	0.024	1.131^{***}	0.105
Profitability	6.716	0.053	-2.405^{***}	-0.174
Profit Vol.	-2.639	-0.017	-0.820	-0.020
Debt Maturity	-2.649	-0.029	0.008	-0.006
Financial	-8.112^{*}		0.130	0.002
Number of Observations	560		2,538	
Adj. R^2	0.100		0.079	

Table 1.6: Match Quality

This table presents the match quality between the sample of defaulting firms and the matched sample of non-defaulting firms. Each defaulting firm is matched 12 months prior to default to four non-defaulting firms in the same Fama and French 17 Industry Classification by minimizing the sum of the square differences of percentile *Face Value of Debt*, percentile *Total Assets / Total Debt*, and percentile *Debt Maturity*. These firm characteristics are defined in the text. For the test of the difference in means, standard errors are robust to firm-level heteroskedasticity, and *, **, and *** denote significance at the 10 percent, 5 percent and 1 percent levels, respectively.

	Default Sample		Control Sample		
	Mean	Std. Dev.	Mean	Std. Dev.	Diff.
Match Characteristics					
Percentile Face Value of Debt	41.609	28.253	41.734	26.807	−0.125
Percentile Total Assets / Total Debt	29.594	24.948	30.711	23.973	−1.117
Percentile Debt Maturity	69.156	25.334	66.898	23.116	2.258*
Market Measures					
Total Market Value	6.816	15.025	7.820	14.475	−1.004
Market Value of Equity	2.904	7.668	2.879	5.389	0.026
Market Value of Debt	2.594	4.470	3.477	7.784	−0.884
Market Value of Bank Notes	0.840	2.000	1.317	3.498	−0.477

Table 1.7: Joint Estimation Results

This table presents the parameter estimates from the model described in Section 3.2. The baseline model is the model of Davydenko et al. (2012), which is a nested case of the extended model in which assets grow at a constant rate, firm solvency is a sufficient statistic for estimating default probabilities, and firms face constant default costs. The extended model relaxes these assumptions. Details underlying the assumptions of the model and the estimation procedure are provided in the text.

	Baseline Model		Extended Model		
	Estimate	Std. Err.	Estimate	Std. Err.	MFX
Hazard Model					
Constant	3.325	0.319	3.298	0.336	
$\ln(V/B)$	0.520	0.147	0.497	0.146	
Level			−17.215	5.516	−13.49
Slope			26.607	7.939	45.28
Pseudo-R^2	0.045		0.059		
Default Cost Model					
Constant	0.247	0.010	0.247	0.025	
Level			0.294	0.142	0.003
Slope			−0.476	0.223	−0.007
Adj. R^2			0.038		

Table 1.8: Davydenko et al. (2012) Regressions

The first two columns of this table present the parameter estimates from the regression of recovery rates on macroeconomic variables, industry characteristics and firm characteristics. The last two columns of this table present the parameter estimates from the logit regression modeling the probability of default for defaulting firms and the matched sample of non-defaulting firms. *Default Costs* are the ex-ante default costs recovered from the baseline estimation in Table VII. *Level* is the first factor extracted from fitting a two-factor Gaussian term structure model to the US Treasury yield curve. *Slope* is the second factor extracted from fitting a two-factor Gaussian term structure model to the US Treasury yield curve. Other variables are defined in the text. Marginal effects are the change in the dependent variable for a one standard deviation change in the independent variable. Standard errors are robust to firm-level heteroskedasticity. *, ** and *** denote significance at the 10 percent, 5 percent and 1 percent levels, respectively.

	Default Costs		Default Probabilities	
	Estimate	MFX	Estimate	MFX
Intercept	-0.371		-4.433	
Level	0.098^{**}	0.207	-0.264^{***}	-0.042
Slope	0.018	0.023	0.286^{*}	0.020
Credit Spread	0.097^{**}	0.109	0.709^{***}	0.069
Industry Beta	0.180	0.039	0.787	0.019
Industry Asset Vol.	-0.638^{*}	-0.063	0.002	-0.002
Industry Profitability	0.029	0.003	-1.460	-0.008
Assets (log)	-0.004	-0.006	-0.476^{***}	-0.053
Asset Tangibility	0.601^{***}	0.158	0.715	0.017
Profitability	-0.187^{*}	-0.039	-1.181	-0.017
Profit Vol.	0.272	0.046	1.634	0.012
Debt Maturity	0.002	0.001	-0.407	-0.007
Financial	0.172^{*}		-9.084^{***}	0.002
Number of Observations	248		15,641	
Adj. R^2	0.057		0.098	

Table 1.9: Robustness

This table presents the parameter estimates from the supplementary models described in Sections 5.2 and 5.3. For comparison, I also provide the parameter estimates from the extended model presented in Table VII. Details underlying the assumptions of the model and the estimation procedure are provided in the text. *, ** and *** denote significance at the 10 percent, 5 percent and 1 percent levels, respectively.

	Extended Model	w/ TV Price of Risk	w/ TV Vol.	w/ Agg. Distress	w/ Ind. Distress
Hazard Model					
Constant	3.298***	3.330***	3.288***	3.313***	3.325***
$\ln(V/B)$	0.497***	0.541***	0.513***	0.478***	0.483***
Level	−17.215***	−16.967***	−17.517***	−17.155***	−17.323***
Slope	26.607***	26.204***	26.102***	25.831***	26.022***
Pseudo-R^2	0.059	0.057	0.061	0.059	0.060
Default Cost Model					
Constant	0.247***	0.251***	0.246***	0.310***	0.322***
Level	0.294**	0.301**	0.283**	0.273**	0.282**
Slope	−0.476**	−0.483**	−0.494**	−0.464*	−0.453*
Distress Proxy				−2.114*	−2.324**
Adj. R^2	0.038	0.036	0.035	0.041	0.043

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