ISSN 1936-5330

THE FEDERAL RESERVE BANK *of* KANSAS CITY
RESEARCH WORKING PAPERS

Creditor Recovery: The Macroeconomic Dependence of Industry Equilibrium

Nada Mora

June 2013; Revised December 2014
RWP 13-06

RESEARCH WORKING PAPERS

Creditor Recovery: The Macroeconomic Dependence of Industry Equilibrium

NADA MORA*

This version: December 2014
First draft: June 2013

ABSTRACT

This paper reconciles the state of the economy with industry conditions in driving asset liquidation values and, therefore, recovery rates on defaulted debt securities. Evidence to date downplays the economy-wide effect on recoveries in favor of industry-, bond-market-, and control-rights-specific explanations. This paper shows that macroeconomic effects are important but operate differentially at the industry level. I find that industries whose sales growth is more correlated with GDP growth recover less during recessions. And industries that are more dependent on external finance recover less when the stock market falls. These findings expose how economy-wide shocks transmit to industry downturns; providing a framework for the role of aggregate risk in recovery risk and for macroeconomic stress testing.

JEL Codes: G33, G32, G12, E32
Keywords: Recovery rate; Loss given default; Credit risk; Business cycle; Fire-sales.

* Federal Reserve Bank of Kansas City. *E-mail:* nada.mora@kc.frb.org. The views expressed herein are those of the author and do not necessarily reflect the positions of the Federal Reserve Bank of Kansas City or the Federal Reserve System. I thank Viral Acharya, Jose Berrospide, Mark Carey (discussant), Michael Gordy, seminar participants at the International Finance Division of the Federal Reserve Board, the 2014 Global Finance Conference, the 2014 Interagency Risk Quantification Forum, colleagues at the Kansas City Fed, and former colleagues at the Bank of England for helpful comments on this research. Any remaining errors are my own.

I. Introduction

One important cost of a firm's default comes from industry-wide downturns. First, times of depressed prospects in a firm's industry are invariably reflected in lower asset liquidation values. Intuitively, creditor recoveries will depend on the value of the debt collateral. But the collateral, and the economic worth of the defaulted firm's assets more generally, are expected to be revised downward in line with an industry downturn. Second, an industry downturn can impose an additional fire-sales discount on the assets of the defaulted firm, over and above its effect on fundamental value. In this view, the would-be buyers of liquidated assets are likely to be industry peers of the defaulted firm, who may not have the capacity to buy the liquidated assets because they are financially distressed too. Therefore, distress in the firm's industry limits its peers from bidding on the defaulted firm's assets up to their "value in best use" when managed by industry specialists. Shleifer and Vishny (1992) first developed this market equilibrium approach and described the difference between the price and the best-use value of an asset as "asset illiquidity".[1]

Both of these effects (industry fundamentals and distress) limit the amount that creditors are able to recover from realized or *anticipated* liquidations of a firm's assets. If the adverse shock hitting the firm were purely idiosyncratic in nature – not industry-wide – then creditors would be better able to pool the costs of default. Thus, recovery risk – the chance of recovering less than the full amount of principal and accrued interest due given a default event – and its relation to industry conditions influences the ex-ante debt capacity of borrowing firms.[2] Ex post,

[1] As reviewed in Shleifer and Vishny (2011), while corporate finance theory models of the 1980s began to describe securities in terms of control rights, the liquidation value of collateral was held exogenous, irrespective of constraints affecting the industry-cohort.
[2] Even when recovery is known with certainty, the debt capacity of firms appears to be conservative because of distress risk premia as discussed in Almeida and Philippon (2007). That is, to the extent that default is more likely to occur in bad times, ex-ante measures of financial distress costs are understated.

significantly larger losses than anticipated by creditors can lead to a situation in which the hypothesized initial industry-wide shock makes the credit system itself more vulnerable to failure. Indeed, Pesaran, Schuermann, Treutler, and Weiner (2006) maintain that credit risk is the leading source of risk for banks. And much of risk management is (should be) on the possibility of large losses (Duffie and Singleton, 2003).

As motivated so far, the possibility of large losses stems from industry-wide shocks. And there is considerable supportive evidence in the literature reviewed in the next section. Many of these studies focus on the effects of fire-sales, whether of real assets or financial assets. Such forced asset sales at "dislocated" prices are found to occur because either the industry of the real-sector firm is financially constrained, or alternatively, because financial arbitrageurs that specialize in the trade of particular financial securities are encumbered.

A logical course that follows from this industry-specific starting point is to question whether industry shocks are exogenous as assumed and consider instead whether economy-wide shocks induce industry downturns and possibly distress. Therefore, the purpose of this paper is to investigate whether creditor recoveries depend on the macroeconomy in an economically important manner. The impact of the macroeconomy can be transmitted through either or both the economic-worth channel and the fire-sales channel. For example, an economy-wide recession reduces business opportunities, lowering the economic worth of defaulted firms' assets. Similarly, a recession can lead to widespread industry distress, lowering the liquidation value of assets further below their revised economic worth. Indeed, in the original model by Shleifer and Vishny (1992), the shock is allowed to be economy-wide, not simply industry-wide, so that some firms are hit harder by a recession. The important point is that shocks not be specific to the asset seller (i.e., not be idiosyncratic in nature).[3] To date, however, empirical studies have found that while recovery rates appear to covary with the macroeconomy, the relation becomes weak or insignificant once other contract-, firm-, corporate finance structure-, bond market-, and industry-specific factors are employed as explanatory variables. These studies are reviewed in the next section and include contributions by Altman, Brady, Resti, and Sironi (2005); Acharya, Bharath, and Srinivasan (2007); James and Kizilaslan (2012); Jankowitsch, Nagler and Subrahmanyam (2013); among others.

This paper revisits this debate by reconciling industry downturns with the macroeconomic state. The literature does not allow for the possibility that industries vary in the extent of their sensitivity to the business cycle, whether for fundamental or liquidity reasons. For example, business prospects may be more sensitive to economic downturns in some industries such as apparel and accessories than in others such as tobacco. Or from an illiquidity angle, for example, industries in the nontradable sector (such as legal services) may have a greater likelihood of falling into distress during recessions than the tradable sector (such as oil or mining).

The results of this paper show that macroeconomic effects do operate differentially via industry conditions. The analysis draws on about 40 years of recovery data on defaulted debt instruments and controls for a range of contract-, firm-, and industry-level characteristics. Specifically, I find that industries whose sales growth is more correlated with GDP growth recover less during recessions. For example, when there is a recession, the industry at the 75th percentile recovers roughly 7 cents less on the dollar compared with the industry at the 25th percentile. This is an economically significant effect as it is comparable to the effect of a proxy for industry distress of between 7-10 cents (and I confirm that the industry distress effect closely

[3] See page 1355 in Shleifer and Vishny (1992) for a clear exposition.

matches that in the study by Acharya, Bharath, and Srinivasan, 2007). Similarly, recoveries in industries highly dependent on external finance increase with positive movements in the stock market. Moreover, the effects of direct proxies for industry distress and economic worth become weaker or insignificant once different industries are allowed to respond differently to the macroeconomy. Note that it is reasonable that in many cases industry conditions may be independent of the state of the economy such as episodes of accounting fraud or regulatory and technological changes. But the results indicate that economy-triggered industry conditions are also important drivers (so far overlooked).[4] Finally, the macro-sensitive industry channel is robust to the inclusion of bond market conditions as well as macroeconomic conditions at the time of debt origination that have been respectively emphasized in previous studies (e.g., Altman, Brady, Resti, and Sironi, 2005; Zhang, 2010). I also show that, in addition to the commonly examined factors of GDP growth and stock market returns, other macroeconomic factors are associated with hypothesized movements in industry conditions. These include house prices, interest rates, and credit spreads.

That asset liquidation values and recovery rates significantly depend on the business cycle has important implications for risk management at banks and other financial intermediaries. The aim of risk management is to reduce the risk of large losses and the intermediary's vulnerability to such losses. When only idiosyncratic or industry factors are considered and not economy-wide shocks, key measures of credit risk can appear misleadingly

[4] And therefore also overlooked is the extent to which asset liquidation values have common dependence. For example, the study by Acharya, Bharath, and Srinivasan (2007) considers separately the effect of macroeconomic factors and the effect of industry distress showing that macroeconomic factors are insignificant in the presence of industry controls. Note also that in practice, it is difficult to perfectly separate out the two potential channels through which macroeconomic factors influence recovery rates (whether fundamental value or illiquidity). But both of these channels are operative as their direct proxies (industry distress indicator and industry Q) become weaker in significance. Moreover, to the extent that the deadweight cost of default is greater due to inefficient fire-sale liquidations, there is evidence that macroeconomic effects are nonlinear supportive of fire sales. That is, recessions and periods of stock market crashes depress recoveries *more* than a symmetric effect would imply. Additional evidence of fire-sale effects is evident during recessions in industries with greater asset specificity.

low. The financial crisis revealed shortcomings in financial intermediaries' ability to assess ex ante the potential losses on their investments. To help protect the economy from future financial instability, one change policymakers have introduced is stress testing financial intermediaries whereby the likelihood of a large loss is explicitly conditioned on adverse macroeconomic outcomes. Therefore, policymakers' confidence about how well an intermediary passes the stress test depends on how robustly modeled the link is between bad economic outcomes and credit losses. [5] This study provides a framework for conducting macro-based stress testing of recovery risk.

It is also interesting to pause on the parallels of this research with a different research topic examining the determinants of cyclical fluctuations in the unemployment rate – whether these are due to aggregate demand shocks or to industry shifts. Abraham and Katz (1986) observe that aggregate demand fluctuations can be primarily responsible *even if* the unemployment rate is found to be positively related to cross-industry dispersion of employment growth. The idea also is that sectors differ in their sensitivity to the common aggregate demand shock.

The rest of this paper is organized as follows: Section II reviews descriptive statistics of creditor recoveries together with the related literature. Section III describes the empirical methodology employed in this paper, which has an analogy to Rajan and Zingales (1998). Section IV examines the macroeconomic determinants of recovery rates, considering the role of industry distress and their interrelationships. Section V follows with additional results and robustness checks. Section VI concludes.

[5] For example, a typical loss on a loan portfolio is projected by multiplying the exposure at default by the probability of default and by the loss given default, where different models are developed for these loss components (Appendix B in Board of Governors of the Federal Reserve System, 2012).

II. The Determinants of Recovery Rates

II.1. Variation across Instrument

Much of credit risk analysis has been devoted to likelihood of default with less attention paid to recovery or loss given default (see, for example, Bluhm, Overbeck, and Wagner, 2003, and the review in Altman, Resti, and Sironi, 2004). A common assumption made is that recovery is a fixed recovery based on historical averages, such as between 40%-50% on debt issued by U.S. corporate borrowers and 25% on debt issued by sovereign borrowers (Das and Hanouna, 2009). For example, Giesecke, Longstaff, Schaefer, and Strebulaev (2011) apply a long-run average loss rate of 50% and devote their analysis to the determinants of corporate bond defaults over a 150-year period. They find that macroeconomic factors such as GDP growth, stock returns, and stock return volatility are strong predictors of default rates.

Figure 1 shows the distribution of recoveries for debt instruments issued by U.S. firms based on trading-price recovery on defaulted securities over roughly 40 years (Moody's Default Risk Service).[6] Recovery is measured by the market value of defaulted debt as a percentage of par, one month after default, and averaged 39.3% (standard deviation 29.1%). Also shown in the figure is the estimated probability density of recovery rates, which is somewhat bimodal, as also discussed by Schuermann (2005). As a result, imposing a 40%-50% average recovery assumption can produce a misleading analysis of credit risk.

Therefore, another common approach is to apply a stochastic recovery rate. For example, a typical stochastic recovery is drawn from a beta distribution calibrated on the empirical mean

[6] Trading price recovery measured soon after default is meant to proxy for eventual recovery on the defaulted debt when the issuer emerges from default. Moreover, this measure represents actual recovery for the many investors that sell their positions immediately following default. Note also that recoveries can be somewhat greater than 100% when the coupon on the debt is large relative to the prevailing term structure of interest rates.

and variance as done by Pesaran, Schuermann, Treutler, and Weiner (2006).[7] While the recovery rate is allowed to be stochastic, it is commonly assumed to be nonsystematic, and therefore unrelated to factors like the default rate or the business cycle. This independence assumption considerably simplifies the portfolio loss analysis because the correlation between defaults and recoveries does not have to be modeled. Moreover, researchers disagree about the need to model a systematic recovery in practice. For example, some have argued that since the recovery rate represents the outcome of a bargaining process between the debtor and the creditor, it is reasonable to assume that it is unsystematic (Longstaff and Schwartz, 1995).

Seniority, collateral, and industry type are also important in explaining the variation in recoveries (Table 1). For example, bank loans have significantly greater recoveries (67.1%) than the next debt class of senior secured bonds (47.3%) (see also Khieu, Mullineaux, and Yi, 2012). Relative seniority, in addition to absolute seniority, is also an important determinant of recovery rates (Panel C of Table 1; see also Dwyer and Korablev, 2009). For example, a subordinated bond may still occupy the top place in the seniority structure of debt claims on the borrower (compare the unconditional mean recovery on senior subordinated debt (30.5%) to the mean recovery conditional on top seniority (47.4%)). Whether the instrument is secured and whether a third-party guarantor provides a credit guarantee is also important. The empirical analysis controls for all these factors.

II.2. Variation through Time

[7] Applying a beta distribution to recovery rates has become a common industry practice because of a number of advantages, including it is 1) parsimonious as only two parameters (mean and variance) are needed; 2) bounded between 0 and 1; and 3) can be asymmetric and fat-tailed. However, the beta distribution cannot be bimodal and does not allow for concentrations at specific recoveries, such as zero or 100 percent. Note, however, that even though the instrument-level distribution is bimodal, the firm-level recovery distribution may be unimodal because each firm has several seniority classes of debt with different recoveries (Carey and Gordy, 2009).

Recovery rates are also characterized by considerable time variation. A stylized fact is that the recovery rate is inversely related to the aggregate default rate (Figure 2). The time series shown in this figure are aggregate default rates and recovery rates, weighted by the debt amount, following the methodology in Altman and Kuehne (2011).[8] The average default rate over 1978-2010 was 3.8%, and the average recovery rate was 45.7% (comparable to the figures compiled by Altman with various coauthors from the NYU Salomon Center database: 3.6% and 44.8%, respectively). Defaults were clustered during 1982, the early 1990s, the early 2000s, and 2008-09 – periods of low recovery rates.[9] Indeed, Giesecke, Longstaff, Schaefer, and Strebulaev (2011) highlight the clustered nature of corporate bond default events at various times over the longer historical period they examine, including the railroad crisis of 1873-75, the banking panics of the late 1800s, and the Great Depression.

One reason for the inverse relation between the recovery rate and the default rate comes from common dependence on a systematic factor such as the business cycle. For example, the same adverse economic conditions that depress recoveries as discussed in the introduction also cause defaults to rise. Evidence that the recovery rate is procyclical is shown in Figure 3. The shaded areas are the periods of recessions as dated by the National Bureau of Economic Research. As is evident, the aggregate recovery rate closely tracks the business cycle. For

[8] Specifically, the default rate is the weighted average default rate on securities in the high-yield market in the United States (underlying data are instrument-level data from the Moody's DRS database). Weights are based on the face value of all high-yield (sub-investment grade) securities outstanding each year (measured at midyear) and the size of each defaulting issue within a particular year. The recovery rate is the aggregate annual weighted average recovery on all defaulted U.S. corporate securities. The weights are based on the defaulted debt amounts.

[9] The 1982 peak in the default rate is less reliable because there was less outstanding high-yield debt in the 1970s and early 1980s. In addition, while 2008-09 saw a marked increase in the default rate from preceding years, the default rate peaked at a lower rate than observers expected at the onset of the financial crisis. The default cycle was also short-lived, falling from a 10.8% default rate in 2009 to an average 1.3% in 2010-11 (Altman and Kuehne, 2011; Moody's and Fitch Ratings recent reports). One reason that defaults were fewer than expected is that the corporate sector was not at the center of the financial crisis (*The Economist,* 2010). Another reason may be that creditors such as banks wanted to avoid uncoordinated defaults and associated depressed recoveries. For example, there is evidence of reduced corporate restructurings and a practice of "extend and amend", or more pessimistically, "extend and pretend" (*Financial Times*, 2012). The choice of calling for default depends on creditors' incentives, in addition to those of borrowers.

example, the recovery rate is positively correlated with real GDP growth (correlation coefficient equal to 0.32 over 1978-2010). Previous studies also document a similar macroeconomic dependence, whereby recessions depress bond recoveries by up to one-third from normal-year averages (Frye, 2000; Schuermann, 2005; Figure 3).

Nonetheless, a common thread in recent papers is that macroeconomic conditions do *not* matter in explaining recovery rates on defaulted securities once other conditions are considered. There are several competing alternatives.

One view is that illiquidity in the financial market for the sale of defaulted securities is mainly responsible for the time-series variation. Altman, Brady, Resti, and Sironi (2005) therefore examine the relation of recoveries to conditions in the distressed bond market, motivated by the previously discussed Figure 2.[10] They argue that the recovery rate is a function of the supply and demand for defaulted securities, so that when the supply of defaulted bonds goes up, secondary market prices are driven down. This result relies on a somewhat inelastic demand in the distressed bond market. Such a condition may arise when investor capacity to absorb defaulted securities is limited. For example, only specialized investors such as vulture funds and hedge funds may be willing to buy distressed debt and other investors do not arbitrage away price differences in this segmented market. Therefore, in high default years when distressed debt is in excess supply relative to typical investor capacity, secondary market prices fall to equilibrate the market. For example, during the 1990-91 and 2000-01 periods, the ratio of

[10] Even ruling out common dependence on a credit cycle, the first generation structural model of credit risk developed by Merton (1974) (and extended by others) leads to a simple negative relationship between the likelihood of default and recovery (as discussed by Altman, Resti, and Sironi, 2004). In Merton's model, default occurs when the market value of the firm's assets falls below its liabilities. Therefore, to the extent that the likelihood of default goes up when the market value of the firm's assets goes down (or when leverage goes up), recovery will decline too. Further, increased asset volatility will mean a greater chance that realized asset values fall below the debt level, triggering default (and in later extensions of the structural model, a jump into default). In these cases, it is plausible that the recovery rate will also be low. Therefore, the main innovation in Altman et al (2005) was to model the inverse relation as a function of a common state variable, not isolated to a firm's structural characteristics.

the supply to the demand for distressed and defaulted securities reached 10-to-1 (Altman, Brady, Resti, and Sironi, 2005). See also a more recent discussion of dislocations in the European distressed debt market as banks are expected to shift their troubled assets to hedge funds (*Financial Times*, 2013).

The recent review by Shleifer and Vishny (2011) also discusses evidence of fire sales of financial assets that are triggered by a sudden stop of funding. If the stop of funding is systemic such as the recent financial crisis, arbitrageurs are forced into widespread liquidations bought by non-specialists at a steep discount (absent the Federal Reserve assuming the role of "high-valuation holder" of risky securities). Even in more isolated examples of funding stops such as experienced by poorly performing equity mutual funds, there is evidence of an impact on the pricing of securities they hold. For example, Coval and Stafford (2007) show evidence of negative future returns on the stocks held by weak funds that were forced to sell these stocks in response to investor withdrawals. Individual bond liquidity also matters (Jankowitsch, Nagler, and Subrahmanyam, 2013). They find that less liquid bonds (as measured by price dispersion of their trades) recover less, controlling for a range of other factors.

II.3. Industry Conditions and Fire-Sales

An alternative view is that illiquidity in the market for the sale of real assets and not illiquidity in the market for the sale of financial assets primarily determines liquidation values. Following from Shleifer and Vishny (1992) introduced earlier, a number of studies have directly examined asset sales. A classic example is the sale of used airplanes by distressed airlines, where the asset is highly specific to the airline industry. This forces distressed airlines to sell used aircraft at discounts to fundamental values when financial conditions of the airline industry-cohort are also poor (Pulvino, 1998). Campbell, Giglio, and Pathak (2011) and Gerardi, Rosenblatt, Willen, and Yao (2012) find similar evidence of a discount on forced home sales. Benmelech and Bergman (2011) take the argument one step further, showing that the bankruptcy of an airline reduces collateral values for all other airlines with similar airplanes. In other words, the condition of industry peers can itself be endogenous to the default of one of the firms. Firms also try very hard to avoid fire sales in illiquid markets so that debt workouts are more likely than liquidations (Asquith, Gertner, and Scharfstein, 1994).

Data on realized asset sales can be limited. Thus, valuable insight can be gained about anticipated liquidation values by examining prices of defaulted debt instruments. For example, equityholders can bargain down creditor claims if low prices from asset sales are expected. Acharya, Bharath, and Srinivasan (2007) take this approach and find that the relation between creditor recoveries and industry-wide distress is consistent with the anticipation of fire-sale prices. This effect is on top of the lower expected profitability of a defaulted firm's assets coming from the industry downturn (proxied by industry median Q).

While Acharya et al find that macroeconomic conditions (and bond market illiquidity conditions) are no longer significant in the presence of industry-specific conditions, Dieckmann, Spencer and Strickland (2007) and Thorburn (2000) find somewhat different results. For example, Dieckmann et al examine recoveries from the 1920s and find that the aggregate business failure rate remains significant in the presence of industry distress. Thorburn (2000) examines the downturn in Sweden in 1991. She finds a significant effect from the downturn, whereas the measure for industry distress is not. In all of these papers, however, industry distress is treated separately from the macroeconomic state.[11] One reason why Thorburn may have found a strong macroeconomic effect is because Scandinavia was hit by an acute recession and a credit

[11] See also a recent paper by James and Kizilaslan (2012) in which a firm's exposure to industry risk is modeled via a CAPM-model relating a firm's equity returns to market returns and industry-specific returns, separately.

crunch at the time, with the end result being a costly government rescue of the banking system. This extreme economic state may have swamped differential industry effects, as all industries were materially affected (her sample runs from 1988 to 1991). Differential dependence becomes visible with greater time series and industry variation, which this paper provides.

II.4. Other Conditions

Briefly, more recent papers have each placed emphasis on a different firm-specific hypothesis. For example, Carey and Gordy (2009) show that the recovery rate on a firm's assets will depend on the debt structure of the firm entering bankruptcy. The choice of bank debtholders' to call for liquidation depends on the size of their claim relative to firm value. If bank loans are most of the firm's debt, banks can force bankruptcy filing sooner and take control when firm value is not far below the insolvency point (since banks bear most of the losses as insolvency worsens). Banks have greater access to information by monitoring borrower deposits, cash flows, and covenant compliance. In contrast, if the bank-debt share is small, the firm is more likely to be deeply insolvent at the time of filing, and thus its recovery will be low.

Also emphasizing the special role of loan covenants in protecting creditors is Zhang (2010). He shows that loan covenants are set more strictly during downturns. This implies a negative relation between recoveries and macroeconomic conditions prevalent at the time of debt *origination*, controlling for macroeconomics conditions at the time of default. Donovan, Frankel, and Martin (2013) tie creditor recoveries to the extent of a firm's accounting conservatism.

Covitz and Han (2004) focus instead on a Merton structural form explanation of recoveries (see footnote 10). They find that firms that "jump into default" such as those experiencing large negative shocks from accounting fraud, tort or regulatory changes are also associated with significantly depressed recovery rates. One example is health-care providers that were hit by a reduction in cash flows from changes to Medicare reimbursements caused by the Balanced Budget Act of 1997.

To summarize, while recent papers have expanded what we know about asset liquidations and recoveries, each offers a different conclusion. In almost none of these views does the aggregate state of the economy play a leading role.

III. The Empirical Framework and Data

The recovery rate is related to the macroeconomic state and the dependence of the defaulted borrower's industry on the macroeconomy. The basic multivariate empirical specification takes the form:

$$\begin{aligned} Recovery_i = \alpha + \beta X_i + \gamma Y_j + \delta Macro + \theta Macro \times Industry\ Dependence_j \\ + Seniority\ Dummies + Backing\ Dummies + Industry\ Dummies + \epsilon_i, \end{aligned}$$

where *Recovery* is the recovery rate on debt instrument *i* issued by borrower *j*. The coefficient vector θ captures the economic effect of the borrower's industry sensitivity to the macroeconomy and is of special interest. The general hypothesis in this paper encompasses *both* possible channels (fundamental value or illiquidity) that might be operative and explain industry sensitivity to the macroeconomy (*hypothesis 1*). Also, to the extent that the deadweight cost of default is amplified by inefficient fire-sale liquidations, tests are conducted to determine whether a significant part of industry sensitivity to the macroeconomy can be isolated to the illiquidity channel (*hypothesis 2*).

The empirical method employed in this paper is closest in spirit to Rajan and Zingales (1998). They find that industries more dependent on external finance grow more in countries with developed financial markets. By a similar analogy, recovery rates on firms in industries that are more dependent on external finance are expected to be more sensitive to movements in the stock market for example. The two main macroeconomic variables are the standard ones employed in this literature, GDP growth and stock market returns. Additional factors such as house price are also evaluated.

I control for contract characteristics, X_i, for borrower characteristics one year prior to default, Y_j, and for seniority, backing, and industry dummies. I also augment this basic specification with industry distress and industry Q to evaluate the robustness and relative contribution of the industry macro-channel. I also employ the aggregate bond default rate and other factors to test alternative hypotheses in the literature. The industry variables and contract- and firm-specific controls follow closely those in Acharya, Bharath, and Srinivasan (2007), Zhang (2010), and other recent papers. Similar to these papers, the data structure can be described as pooled cross-sections over time to which ordinary least squares estimation can be applied. Robustness checks are conducted on alternative nonlinear models such as quasi-maximum likelihood estimation following Papke and Wooldridge (1996). Finally, standard errors are robust to heteroscedasticity, where the individual error terms are allowed to be correlated for all debt instruments of the same borrower.

The primary data source is Moody's Default Risk Service Database. As mentioned in the previous section, the measure of recovery is market recovery based on the trading prices of defaulted securities soon after the default event occurs (roughly 30 days).[12] While this measure

[12] The 30-day after default is a market convention that has been shown to be a reasonable one. Metz and Sorensen (2012) show that the 30-day price is a better predictor of workout (ultimate) recoveries than prices closer to default. Interestingly, they also show that there are more observations available 30 days after default than directly after default. They attribute this feature to a change in the type of debtholders from institutional investors to investors specialized in distressed debt. Note also that Acharya, Bharath, and Srinivasan (2007) show that trading prices at default are unbiased predictors of discounted workout recoveries, which they obtain from the S&P Credit Pro database. Other studies find that trading prices may not be unbiased predictors of discounted ultimate recovery rates (Metz and Sorensen; Khieu, Mullineaux, and Yi, 2012). Although, reassuringly, the trading price recovery explains the level of ultimate recovery and much of its variation. Moreover, a complication with using workout recovery instead of market recovery is the need to properly discount the future cash flows. Acharya et al discount with the high yield index; Metz and Sorensen discount using the bond's coupon rate; Schuermann (2005) points out however

may be an imperfect proxy of recovery, it has the advantage of being observed soon after default and, therefore, represents investors' anticipated recovery. Moreover, since many investors sell (or mark-to-market) debt instruments once default occurs, market price recovery represents actual recovery for many investors (Covitz and Han, 2004). Recovery and default data are for borrowers domiciled in the United States in order to match with firm characteristics from Compustat. Defaulted borrowers were carefully matched by hand with Compustat identifiers.[13]

Summary statistics on recovery rates were discussed previously in Section II.1. Summary statistics on contract, firm, industry, and the macroeconomic variables of interest are shown in Table 2. Contract characteristics include the coupon rate and the issue size in addition to various seniority and security dummies discussed previously.[14] Following the literature, firm-level characteristics are measured one fiscal year before default and are mostly from Compustat. These include the profit margin, leverage, asset tangibility (property, plant and equipment), and total asset size. Intuitively, the greater a firm's profitability and asset tangibility the higher the recovery expected on its claims because the firm is more valuable to would-be buyers. Higher leverage is typically associated with greater financial distress costs and therefore can be expected to reduce recoveries. Total assets proxy for firm size whose effect is ambiguous ex ante (e.g., a more complex firm has greater bankruptcy costs but may be characterized by smaller

---

that the debt restructuring may have resulted in the issuance of two or more debt instruments – one a risky equity and one a less risky note or even cash, making the choice of discount rate unclear.

[13] Specifically, of the 1,307 defaulting U.S. issuers in Moody's DRS over the sample 1970-2008 (and associated with the 4,422 instruments in Table 1) I was able to hand-match 1,146 of these issuers to Compustat identifiers (gvkey). I also confirmed through online searches on a random sample that the unidentifiable issuers were privately-held companies. Also note that the baseline sample in the regressions is further constrained by the availability of recorded recovery prices on the instruments (and non-missing covariates). This implies that the baseline sample in the regression tables is composed of 623 borrowers associated with 1,849 instruments.

[14] The effects of issue size and coupon rate are ex ante ambiguous. For example, a larger issue might be held by a larger stakeholder that has greater bargaining power. On the other hand, a larger issue might be associated with more creditors and coordination problems. Similarly, a higher coupon might be associated with higher recovery because it may be valuable to bondholders under certain default events (Jankowitsch et al, 2013). Alternatively, the recovery rate might be decreasing in the coupon because by increasing the cash flow it affects the marginal continuation value of the debt (Carey and Gordy, 2009).

information asymmetry problems). Finally, the number of a firm's issues and its debt concentration (Herfindahl measure) proxy for creditor coordination problems and are calculated from the underlying Moody's data.

The next group of explanatory variables is industry characteristics based on the median values for firms in the 2-digit SIC industry of the defaulted firm (robustness checks were also conducted on 3-digit SIC industries). Industry variables are constructed from Compustat data. Industry Q and the industry distress indicator are time varying and are measured in the year of default. Industry Q is the median of the ratio of the market value to book value of assets for all firms in the defaulted firm's industry. Higher values of this variable are meant to reflect favorable growth opportunities for a particular industry. Industry Q is therefore employed to control for movements in the fundamental worth of a firm's assets in a particular industry. Doing so (in addition to controlling for the firm's profit margin) partials out the effect of fundamental value on recoveries to isolate the effect of industry distress and fire sales.

Following Acharya et al (2007) and common practice, industry distress is an indicator meant to capture adverse financial conditions in the firm's industry as a whole in a particular year (without attaching a cause). This variable is set equal to 1 if the median industry stock return is less than -30% and zero otherwise. To the extent that fire sales only occur when industry peers are also experiencing financial distress, this variable is introduced as a nonlinear term.[15] Roughly, 12% of the industry-year sample is in distress. Moreover, the variable "industry asset specificity" is meant to measure the acute impact of industry distress in industries whose assets are specific to that industry. Specific assets are measured by machinery and equipment over the sample period (e.g., the airline industry is in the top 90th percentile).

[15] Acharya et al show that the impact of median industry equity returns is weak, meaning that positive shocks to industry returns do not increase recoveries to the same extent that negative shocks cause recoveries to fall. This asymmetry implies that the industry distress variable proxies for a fire-sales discount.

Of particular interest to the hypotheses in this paper are the next two industry variables, "sales growth correlation" and "external finance dependence". The latter variable is familiar in corporate finance research and was introduced in Rajan and Zingales (1998), broadly defined as capital expenditures minus cash flow from operations divided by capital expenditures (also evaluated at the industry median to minimize the effect of firm outliers). To also mitigate the effect of time outliers, Rajan and Zingales smooth temporal variation by summing each firm's capital expenditures and cash flows over the 1980s before computing the ratio. I construct similar measures over the full Compustat sample from 1980. Ranking industries by their external finance dependence means that higher values are industries whose investment is funded externally more than internally through funds from operations. Industries with low dependence include tobacco, food and kindred products, and forestry. Industries with high dependence include chemicals and allied products, and business services, for example.[16]

"Sales Growth Correlation" is the second industry measure of interest. As motivated in the introduction, it is the sensitivity of different industries to the business cycle measured by the industry median correlation of a firm's sales growth with GDP growth (similarly, temporal fluctuations are mitigated by first computing correlations over the Compustat sample from 1980). To the extent that an industry's sales are more synchronized with the business cycle, its recovery rate should be procyclical. Examples of industries with high GDP correlations are furniture and fixtures, apparel and accessory stores, auto dealers, building contractors, hotels, and durable goods wholesale trade; examples of industries with low GDP correlations are tobacco, local passenger transit, mining, utilities, health services, and food stores.

[16] Rajan and Zingales are only interested in the manufacturing sector. I find broadly similar results when comparing my measure to theirs conditional on manufacturing. For example, tobacco (SIC 21) has the lowest external finance dependence and chemicals & allied products (SIC 28) have the highest dependence. While manufacturing industries are grouped by ISIC codes in their study, tobacco also ranks lowest and plastic products and drugs rank highest.

Two additional variables measure an industry's sensitivity to the business cycle: "Industry Cash Flow Growth Correlation" and "Industry GDP Growth Correlation". The cash flow measure is computed in a similar manner to the sales measure from Compustat data on cash flows from operations (following the Rajan and Zingales method; results are similar when cash flows are proxied by EBITDA). The cash-flow measure is motivated by the observation that an industry falls into distress when its cash flows are sufficiently depleted. Results in the next section are also similar when allowing the growth of cash flows or sales to be affected by lag GDP growth in addition to contemporaneous economic activity. The second industry GDP growth correlation measure is computed directly from the Bureau of Economic Analysis' GDP-by-Industry data (chain-type indexes for value added in different industries).[17] All three business-cycle dependence measures are highly positively correlated.

The remaining industry-specific variables are introduced Section V when describing additional results. Finally, the last group of variables in Table 2 is macroeconomic-related. Following the literature, the two main aggregate factors are annual real GDP growth and S&P 500 stock return.

IV. The Macroeconomic Sensitivity of Recovery Rates

IV.1. Evaluating Separately Industry Conditions and the Macroeconomy

The direct impact of industry distress and industry Q on recovery rates is shown in the first two columns of Table 3. Widespread financial distress in a particular industry is found to depress the recovery rate by 10.62 percentage points in column (1), supporting an industry illiquidity view, controlling for industry Q and industry dummies in addition to other contract-

[17] The industries in the BEA are classified according to the 2002 North American Industry Classification Codes (NAICS). The NAICS-industry measure is linked to the recovery rate data using the firm's NAICs code, which is reported together with the SIC code in Compustat and Moody's DRS.

and firm-level variables.[18] The specification in the first column is comparable to the baseline model in Acharya et al (2007). The main difference is that the data in the latter study are from S&P's (discounted) ultimate recoveries for a narrower time period ending in 1999, while the data in this paper are from Moody's and includes a wider cross-sectional and time-series sample. Regardless of these differences, the relation between recoveries and distress is robust and stable; those authors find a similar impact of distress (about 11.1 cents less on the dollar). The specification in column (2) is identical to column (1) but replaces the 12 Moody's industry classification dummies with 2-digit SIC industry dummies (corresponding to 74 industries). The impact from industry distress is somewhat smaller (7.28) but still statistically significant at the 5% level. Interestingly, the greater number of controls for industry unique factors in column (2) also isolates a significant impact from variation in industry economic growth prospects. For example, a one standard deviation increase in industry Q is associated with a 6.79 percentage-point increase in the recovery rate.

Briefly, the other controls have the hypothesized effects for the most part. For example, contract characteristics such as seniority and security are among the most important determinants of recovery rates.[19] A firm's characteristics also shape the recovery outcome. For example, a one-standard-deviation increase in a firm's profit margin significantly increases recovery by over 4 percentage points. The greater number of issues that a firm has outstanding at the time of its

[18] Note also that the effect of industry median equity return is significant in an alternative specification replacing industry distress with returns, although it has a lower implied economic effect (roughly one-half) compared with its nonlinear distress representation (i.e., when computing its impact in the region of distress where the median and mean equity return is -40%).

[19] Relatedly, there might be a possible selection issue, e.g., if some industries issue more of particular debt seniority such as subordinated debt than senior debt and this issuance varies so that inference about industry distress is affected. To address this question, I first checked whether the fraction of any particular debt seniority in each industry-year is significantly related to industry distress. No supportive selection effect is identified. I also estimated the regression model including industry-seniority interaction dummies. The main results are robust to their inclusion. More importantly, the results of the next section on the macro-driven industry effects are robust to the inclusion of industry-seniority dummies as well as dummies for the year of default and the year of origination.

default the greater the potential for coordination problems and thus lower recovery. Firm leverage and asset tangibility have expected effects but are not statistically significant in these specifications (leverage is significant in alternative models controlling for 3-digit SIC industry dummies; Table A1).[20]

The next four columns of Table 3 consider separately the effect of industry conditions and the macroeconomy. These models continue to include the 12 Moody's industry dummies simply for comparability purposes with the previous literature. The models in subsequent tables control for 2-digit industry dummies particularly because I am interested in the interaction terms between conditions at this industry-level and economy-wide shocks. The main point in columns (3) and (4) for GDP growth (and columns (5) and (6) for stock returns) is that industry distress retains its significance in the presence of macroeconomic conditions. Moreover, these macroeconomic conditions (and also aggregate bond market conditions) are often significant in the absence of industry conditions but not when the latter are controlled for. For example, a one-standard-deviation increase in market stock returns increases recovery by 2.96 percentage points but has no effect on recovery in the presence of industry shocks.

IV.2. Variation in Industry Dependence on the Business Cycle and the Stock Market

The models in Table 4 instead consider the possibility that industry conditions depend on the aggregate state of the economy, which is where this paper contributes. Thus, the models in columns (3)-(7) allow for the possibility that industries vary in their sensitivity to the business cycle and some may be prone to fall into financial distress during recessions as previously motivated.

[20] In other results I also confirm the finding in Acharya et al that industry distress (measured in various ways including lower industry coverage ratios, current ratio, and leverage) adversely impacts recoveries the most in industries with high asset specificity. Similar results are found for industries with fewer potential buyers of assets (i.e., industries with smaller number of peers). These results are available upon request.

First, I show that recessions adversely affect recoveries more than the linear symmetric effect of GDP growth would imply – in a similar manner to the relation between industry distress and median equity returns. The model in column (1) estimates the average relation between recovery rates and a recession indicator. For example, recoveries in years characterized by an economy-wide recession are close to 5 percentage points lower than otherwise, while the effect exerted by GDP growth during recessions is insignificant.[21] Therefore, this hints at possible fire sales induced during recessions (*hypothesis 2*).

Column (3) estimates the sensitivity of different industries to the business cycle, controlling for 2-digit industry dummies. The key variable of interest is the interaction of the recession indicator with the correlation of industry sales and GDP growth, which is hypothesized to be negative. The results support this hypothesis. For example, if industries are ranked by the correlation of their sales growth with GDP growth from highest to lowest, durable goods trade and hotels are at the 75th percentile (correlation of 0.204) while food stores and mining are at the 25th percentile (correlation of 0.079) (see Table 2). Based on the model in column (3), the recovery rate is therefore 7.10 percentage points lower in durable goods trade than in food stores during a recession. This economic magnitude is comparable to the effect of a proxy for industry distress shown previously (Table 3(2)).

The models in columns (4) and (5) sequentially include median industry Q and industry distress to directly control for industry shifts in fundamental asset values and illiquidity, respectively. The coefficient on the interaction term of the recession and industry sales correlation remains statistically significant at the 5% level and with a similar economic effect. While the estimated effect is somewhat lower (from 7.10 in column (3) to 5.69 percentage points

[21] Even allowing for greater variation in GDP growth at the quarterly frequency – which has a statistically significantly effect in a model similar to Table 3(4) – implies only about a 0.4 percentage-point lower recovery based on median GDP growth during recessions.

in column (5) when both industry Q and distress are included), the results indicate that a meaningful part of both industry illiquidity and fundamental values is arguably induced by poor macroeconomic conditions. Note also that the statistical and economic significance of industry Q and distress are reduced (e.g., distress is significant at the 10% level and its magnitude is 12% smaller). One caveat is that while industry distress may be driven by the business cycle, the distress indicator may still perform better in a predictive sense because it is a more precisely measured summary indicator. For example, the term *recession x industry sales growth correlation* is positively correlated with industry distress (0.56 correlation coefficient) and to a lesser extent with industry Q (-0.33 correlation coefficient).[22]

The last two models in Table 4 employ alternative measures of business cycle dependence, cash flow growth correlation in column (6) and industry GDP growth correlation in column (7). The estimated coefficient on the interaction term of recessions and industry cash flow correlation is -69.295 (p-value 0.11), implying a 4.78 percentage-point lower recovery when moving from the 25- to the 75-percentile sector. The estimated impact is statistically significant at the 5% level and economically larger (6.84 percentage point) when also controlling for stock market and external finance dependence measures. Similarly, the coefficient on the interaction term in column (7) implies a 6.42 percentage point lower recovery during recessions in industries whose output is more synchronized with aggregate output.

There is also evidence that those industries that are relatively more dependent on external finance recover more when the stock market return increases (Table 5). For example, the 75-percentile sector (business services) recovers 2.54 percentage points more compared with the 25-

[22] Note also that, as motivated, industry distress is driven by the business cycle, but some economy-wide recessions may be triggered by industry shocks such as the tech industry bust of the early 2000s. Whatever the multicollinearity between the regressors, what matters is that the ensuing downturn is manifested in a systematic manner across all industries according to their ex ante sensitivity to the business cycle.

percentile sector (food & kindred products; forestry) when the S&P 500 annual return increases from -1.5% to 20.3% (from its 25 percentile to 75 percentile) based on the interaction term in column (4). Note also that stock market shocks have a similar positive impact on recoveries in industries with higher external equity dependence but the effect is not statistically significant. This latter measure was also introduced by Rajan and Zingales (1998) and ranks industries by the ratio of the net amount of equity issued to capital expenditures. While it correlates positively with the broader measure of external finance dependence, the latter variable appears to better capture an industry's vulnerability to equity market shocks.

The last two columns of Table 5 illustrate that the impact of equity market shocks is also nonlinear so that adverse shocks to the equity market put more downward pressure on recoveries than the effect from the continuous measure. Unlike recessions, there is no commonly agreed measure for bad times. Nonetheless, stock market "crashes" can be proxied by periods in which the stock return was in the bottom 10 percentile. This has parallels to the industry distress measure because the industry distress indicator is set to 1 when the industry equity return is less than -30%, which is roughly the bottom 10 percentile of industry-year observations. In this case, the coefficient on the interaction term of the stock crash with industry external finance dependence implies that the 75-percentile sector has a 5.52 percentage-point lower recovery than the 25-percentile sector when the market crashes. Similarly, the proxy for adverse equity market shocks applied in the model in column (5) is based on the upper 10 percentile of stock market return volatility, measured as in Giesecke, Longstaff, Schaefer, and Strebulaev (2011).

Therefore, a plausible case can be made for the view that the state of the business cycle exerts an important influence on recoveries (*hypothesis 1*) and at least part of this economy-wide shock shows up indirectly through industry distress and resulting fire sales of real assets (*hypothesis 2*). Liquidated asset values and recovery prices are therefore likely to be dislocated in industries less immune to recessions and stock market shocks when these shocks do occur. Table 6 combines both the industry dependence on the business cycle and on the stock market in one model and the results are similar.[23] Even with the equity market variables and direct controls for industry conditions in column (2), procyclical industries recover 7.26 cents less on the dollar than weakly procyclical industries during recessions (repeating the interquartile industry comparison). Similarly, meaningful differences characterize financially dependent industries. Figure 4 illustrates the time series of these differences over the past 25 years. For example, the sharp drop in market returns in 2008 (roughly -38.5%) depressed recoveries in high-dependence industries more than 5 cents on the dollar below low-dependence industries.

Therefore, the results are robust to proxies for industry conditions considered in Acharya, Bharath, and Srinivasan (2007). The next three columns of Table 6 show that the results are robust to other alternative hypotheses. The models in columns (3) and (4) control for credit-origination year effects. For example, Zhang (2010) hypothesizes that credit origination standards are more conservative in bad times. Both origination year and default year dummies are controlled for in column (3). Column (4) directly controls for macroeconomic conditions at the time of origination of the debt instrument. This model and variations on it are supportive of Zhang who also finds a negative dependence between lagged macroeconomic conditions and subsequent recoveries. The model in column (5) controls for the aggregate bond default rate as a measure of illiquid bond markets, following Altman, Brady, Resti, and Sironi (2005). There is

[23] Note that the results are also similar when the stock return shock is replaced by its nonlinear representation. For example, the coefficient on the interaction term of a stock crash with an industry's dependence on external finance is -9.94, also significant at the 1% level in a model similar to column (1). Similarly, replacing the recession indicator with GDP growth in column (1) produces a positive but statistically insignificant effect (6.61) on the interaction term. Employing instead greater variation in GDP growth (annualized quarterly rates of growth in the quarter of default) is associated with a larger effect (8.48 significant at the 10% level).

evidence that a greater supply of defaulted financial securities for a limited investor capacity lowers recoveries somewhat (e.g., a 10% default rate lowers recoveries by about 10 cents on the dollar but the effect is not significant at standard confidence levels).[24] In contrast, this variable (and other measures employed in Altman et al such as the total defaulted amount) is statistically significant in the absence of industry and macro-sensitive industry conditions.[25]

Finally, column (6) of Table 6 shows that the adverse impact of recessions on cyclical industries is especially pronounced in industries with high asset specificity. These are industries whose assets are less easily redeployed to other industries (proxied by a high concentration of assets in machinery and equipment). For example, the coefficient on the triple interaction term, *Asset Specificity x Recession x Sales Growth Correlation*, implies a 4.35 percentage point lower recovery during recessions in procyclical industries than in less cyclical industries for a one standard deviation increase in asset specificity. This effect is comparable to the direct effect from *Asset Specificity x Industry Distress,* in a model without the macro-related terms (4.09 percentage point lower recovery).[26]

Therefore, industry equilibrium conditions are sensitive to the macroeconomy (*hypothesis 1*). Results in the next section show that significant improvement to out-of-sample model performance comes from including macroeconomic-related factors to the baseline industry

[24] Results are similar when the author-computed aggregate default rate is replaced directly with the measure reported in Altman and Kuehne (2011).
[25] In other results on the type of default and the choice of creditors to call for default, I confirm that recoveries are higher for distressed exchanges (out-of-court restructuring). I also find that the time remaining to maturity at default is negatively related to recoveries as in Carey and Gordy (2009). And that a higher share of bank debt in a bank's total debt outstanding at the time of default is associated with lower recovery. This last finding differs from Carey and Gordy. It may be because the data on market price recoveries does not capture well this dimension of ultimate recoveries. Or it may be because the recovery data are instrument-level, not firm-level, so that even though banks may force bankruptcy when firm value is not far below the insolvency point, a higher bank share may imply lower recoveries for the lower priority bondholders. This question is outside the scope of this paper but may be interesting to explore in the future. In all these tests, the main results on macroeconomic dependence retain their economic and statistical significance.
[26] For example, when the recession- and equity-related terms are omitted, the coefficient on *Asset Specificity x Industry Distress* is -26.2, statistically significant at the 10% level (compared to an insignificant 9.7 in column (6)). Note also that as shown asset specificity does not appear to be important in the case of stock market shocks.

model in Table 3. Results are also supportive of inefficient asset liquidations triggered by macro-induced industry illiquidity (*hypothesis 2*). First, the macro-channel variables are significant in the presence of direct proxies for fundamental industry values (industry Q and profit margins). Second, the macro-channel effects are stronger when represented in a nonlinear manner, supportive of fire sales, because under the alternative, future growth prospects in an industry should respond symmetrically to macro shocks. Third, as shown in the last column of Table 6, asset specificity affects recoveries during macro-induced industry distress, as predicted by the Shleifer and Vishny industry illiquidity view.

V. Additional Results, Robustness Tests and Model Performance

Other macroeconomic factors such as house prices, interest rates and credit spreads are associated with hypothesized movements in industry conditions. The results are presented in Table 7 (in which all the contract- and firm-level controls are also included in the regressions but not shown in the interest of space). Care should be taken not to overinterpret these results, especially as these factors are less commonly examined in this literature than are growth and stock returns. Nonetheless, there are some interesting findings. For example, positive shocks to house prices are associated with higher recoveries in industries that depend on property.[27] The effect is statistically insignificant for nation-wide house price variation (column (1)) but significant at the 1% level for more local house price movements (state-level in column (2)). This is an intuitive result because property markets are more locally segmented than financial markets such as the stock market. For example, taking the average change in house price growth

[27] This is measured by the industry median of the sum of buildings, land, and construction-in-progress to total assets of firms in the industry of the defaulted firm (also based on Compustat data). Industries with high dependence include real-estate and petroleum and coal products. Industries with low dependence include miscellaneous retail and finance and insurance. Summary statistics are reported in Table 2.

between 2006 and 2008 implies about a 4 percentage-point lower recovery in the 75th percentile property-dependent industry vis-à-vis the 25th percentile.

I also construct a measure of industry external debt finance dependence (based on the ratio of net debt issuance to capital expenditures) to test whether these industries are more sensitive to interest rate and credit spread shocks. The findings are indicative, especially for credit spread shocks that are robust to the inclusion of other macroeconomic factors unlike shocks to risk-free rates such as the Treasury bill rate and other Treasury yields (columns (3) to (7)). This adds further weight to the importance of illiquidity shocks in the economy. For example, a 100 basis-point shock to commercial spreads (similar to that in the recent financial crisis) reduces recoveries by about 2 percentage points in the 75th percentile debt-dependent sector (real-estate) compared with the 25th percentile sector (eating and drinking places). This and the other main effects are robust to the inclusion of default year and origination year dummies as shown in column (6). Similarly, an increase in the corporate bond Baa-Aaa spread has a significantly negative impact on more debt-dependent sectors (column (7)). Similar findings characterize other proxies for discount rates such as average (and industry-year average) syndicated loan all-in-spread (based on Dealscan data).

Appendix Tables A1-A5 show the results of additional robustness tests. The models in Table A1 are evaluated for 3-digit SIC industries. Table A2 applies lagged measures of the industry dependence variables, *Sales Growth Correlation* and *External Finance Dependence*. For example, the model in column (2) of Table A2 computes industry medians over the period 1960-79 in Compustat and then estimates the recovery models post 1980. The estimated effects are similar to the main results.

The models in Table A3 present alternative models to the ordinary least squares models, such as the nonlinear quasi-maximum likelihood (MLE) model. The estimated effects and their significance are similar when applying Tobit estimation, logit or beta transform of the recovery rate, or when estimating a quasi-MLE model. One advantage of quasi-MLE for a fractional dependent variable discussed in Papke and Wooldridge (1996) is that no ad hoc transformation is needed to address observations at the extreme values of 0 or 1 because the conditional expectation of the dependent variable is estimated directly and ensures that the predicted values are bounded between 0 and 1.[28] In any case, the marginal effects produced by this model are similar to least squares. For example, the marginal effect evaluated at the sample means of the regressors is -62.5 for the business cycle interaction term and 0.24 for the stock return interaction term, similar to the effects in the baseline model Table 6(2). Also reported in the lower panel of Table A3 are out-of-sample root mean square prediction errors (RMSE) for each of the models and compared with the OLS models.[29] The quasi-MLE model has the best performance. But its RMSE is still very similar to the OLS model (26.9 compared with 27.8), while the main improvement in model performance comes from augmenting the industry-conditions model in Table 3(2) with the macroeconomic factors in Table 6(2) (RMSE falls from 35.4 to 27.8).

[28] Papke and Wooldridge apply a quasi-MLE model to estimate a model of employee participation rates in a pension program where many of their observations are clustered at 1 or 0. Therefore, the dependent variable must be adjusted before computing the log-odds ratio for a logit-type linear model, $E[log(y/(1-y)) \mid x] = x\beta$. In contrast, Papke and Wooldridge circumvent this problem by directly stating the functional form as $E[y \mid x] = G(x\beta)$, where $G(\bullet)$ is commonly the logistic function, $exp(\bullet)/(1+exp(\bullet))$, and the quasi-MLE estimator of β is obtained from maximizing $\sum_{i=1}^{n} l_i\,(b)$, where the Bernoulli log-likelihood function, $l_i(b) = y_i log((G(x_i b)) + (1-y_i) log(1-G(x_i b))$ is well-defined. Also see Khieu, Mullineaux, and Yi (2012) for a quasi-MLE application to recovery rates. For the other models, see Zhang (2010) for a similar two-sided Tobit regression model with upper and lower boundaries set at 1 and 0, respectively. See Chava, Stefanescu, and Turnball (2011) for a logit transform. See Gupton and Stein (2005) (Moody's LossCalc V.2) for a beta transformation of the dependent in order to create an approximately normally distributed dependent variable. The two shape parameters for the beta distribution are based on the mean and standard deviation of the sample recovery rates. Interestingly, Moody's LossCalc V.3 (Dwyer and Korablev, 2009) replace the beta transform with the recovery rate directly in a linear model in the interest of transparency and lack of evidence of a nonlinear relation between predicted and actual recoveries.

[29] I follow Chava, Stefanescu, and Turnball's (2011) method of forecasting out-of-sample RMSE for the sample over 1996-2008 based on rolling one-year-ahead regressions for each of the models. The RMSE is a standard statistical choice of penalty.

Finally, alternative specifications aggregated to the industry-level are presented in Table A4. In these models, the dependent variable is the industry (2-digit) annual weighted recovery rate, constructed in a similar way to the aggregate recovery rate shown in Figures 2 and 3. Also employed in the last column is the unweighted average recovery rate. The recovery rate in the previous tables was at the instrument-level and therefore various contract- and firm-level variables were employed as controls. There are advantages and disadvantages to each representation.[30] Interestingly, in this more balanced sample, the interaction term of GDP growth with industry sales growth correlation is statistically significant (coefficient of 10.84 in column (2)). But its impact is still smaller than the nonlinear recession shock implies (e.g., the interquartile industry difference is smaller than 3 percentage points even for adverse GDP growth of -2%). In contrast, just as in the previous models, an adverse business cycle shock represented by the interaction term of recessions with industry cyclicality retains its strong impact in the presence of industry distress (column (3)). Similarly, significantly adverse stock market shocks depress recoveries.

The estimated effects are stronger for the weighted average than for the simple average, indicating that the paper's main results cannot be attributed to only a few small obligors. Similar evidence is found when the main regression sample is partitioned along the size dimension (firm asset size or security issue size) (Table A5).

VI. Conclusion

The hypothesis motivating this paper is that the state of the macroeconomy at the time of default should be an economically important determinant of asset liquidation values – including

[30] For example, aggregating to the level of industry reduces the impact of particular firm outliers and provides a more balanced industry-year sample. However, the industry-year sample may be less suitable than the firm instrument-sample for testing causality from distress (including macro-driven distress) to asset liquidation values. For example, reduced collateral values (reflected in industry-level recovery rates) in turn increase the likelihood of industry distress (Benmelech and Bergman, 2011).

anticipated values – and therefore of creditor recoveries. But there is no reason to expect that its effect should be uniform across firms in different industries. Empirical evidence to date on recoveries, therefore, masks its importance. It is to this end that this paper contributes, pinpointing how industries that are most susceptible to a macroeconomic downturn yield depressed creditor recoveries.

One implication of this paper that was touched on in the introduction is the need to consider the aggregate state and its interactions with industry conditions when modeling credit risk and conducting stress tests. How well financial institutions cope with the possibility of large losses depends on the robustness of their risk management process, including a proper assessment of recovery risk and its common dependence.[31] See Mora (2012) for a simplified discrete credit loss problem that illustrates how unexpected loss can be magnified when the recovery rate is positively related to the state of the business cycle. In related work, Altman, Brady, Resti and Sironi (2005) and Bruche and Gonzalez-Aguado (2010) simulate losses on a representative credit portfolio comparing the case when default probabilities and recoveries are assumed to be uncorrelated with the case where they are correlated (assumed to commonly depend on a latent credit cycle in Bruche and Gonzalez). They find that potential large losses are understated in the uncorrelated case by 30%-40%. See also Jokivuolle and Viren (2013) and Caselli et al (2008) for evidence of the importance of a cyclical loss given default in bank loan stress testing. Therefore, failing to adequately consider common dependence and specifically the dependence on the economy (for both fundamental value and illiquidity reasons) can lead to the

[31] There is evidence of wide discrepancy on loss estimates across banks for an *identical* loan portfolio, especially for their loss given default estimates. For example, Firestone and Rezende (2013) find that the capital requirement for a bank that is the most conservative, i.e., that sets the highest LGD, is twice as large as that of a bank that sets the lowest LGD.

underestimation of the capital buffer required to cover unexpected losses, which in turn results in adverse feedback to the wider economy as seen in the recent global financial crisis.

References

Abraham, Katharine G., and Lawrence F. Katz. 1986. "Cyclical Unemployment: Sectoral Shifts or Aggregate Disturbances?" *Journal of Political Economy*, 94, 507-522.

Acharya, Viral V., Sreedhar T. Bharath, and Anand Srinivasan. 2007. "Does Industry-wide Distress Affect Defaulted Firms? Evidence from Credit Recoveries," *Journal of Financial Economics,* 85, 787-821.

Almeida, Heitor, and Thomas Philippon. 2007. "The Risk-Adjusted Cost of Financial Distress," *Journal of Finance*, 62, 2557-2586.

Altman, Edward I., Brooks Brady, Andrea Resti, and Andrea Sironi. 2005. "The Link between Default and Recovery Rates: Theory, Empirical Evidence, and Implications," *Journal of Business,* 78, 2203-2227.

Altman, Edward I., and Brenda J. Kuehne. 2011. "Special Report on Defaults and Returns in the High-Yield Bond and Distressed Debt Market: The Year 2010 in Review and Outlook," New York University Salomon Center, manuscript, February.

Altman, Edward I., Andrea Resti, and Andrea Sironi. 2004. "Default Recovery Rates in Credit Risk Modeling: A Review of the Literature and Empirical Evidence," *Economic Notes*, 33, 183-208.

Asquith, Paul, Robert Gertner, and David S. Scharfstein. 1994. "Anatomy of Financial Distress: An Examination of Junk Bond Issuers," *Quarterly Journal of Economics*, 109, 625-658.

Benmelech, Efraim, and Nittai K. Bergman. 2011. "Bankruptcy and the Collateral Channel," *Journal of Finance,* 66, 337-378.

Bluhm, Christian, Ludger Overbeck and Christoph Wagner. 2003. *An Introduction to Credit Risk Modeling*. Chapman and Hall.

Board of Governors of the Federal Reserve System. 2012. "Comprehensive Capital Analysis and Review 2012: Methodology and Results for Stress Scenario Projects," Mar. 13.

Bruche, Max, and Carlos Gonzalez-Aguado. 2010. "Recovery Rates, Default Probabilities, and the Credit Cycle," *Journal of Banking and Finance*, 34, 754-764.

Campbell, John Y., Stefano Giglio, and Parag Pathak. 2011. "Forced Sales and House Prices," *American Economic Review*, 101, 2108-2131.

Carey, Mark, and Michael B. Gordy. 2009. "The Bank as Grim Reaper: Debt Composition and Bankruptcy Thresholds," Board of Governors of the Federal Reserve System, manuscript.

Caselli, Stefano, Stefano Gatti, and Francesca Querci. 2008. "The Sensitivity of the Loss Given Default Rate to Systematic Risk: New Empirical Evidence on Bank Loans," *Journal of Financial Services Research*, 34, 1-34.

Chava, Sudheer, Catalina Stefanescu, and Stuart Turnball. 2011. "Modeling the Loss Distribution", *Management Science*, 57, 1267-1287.

Coval, Joshua D., and Erik Stafford. 2007. "Asset Fire Sales (and Purchases) in Equity Markets," *Journal of Financial Economics*, 86, 479-512.

Covitz, Daniel, and Song Han. 2004. "An Empirical Analysis of Bond Recovery Rates: Exploring a Structural View of Default," Board of Governors of the Federal Reserve System, Finance and Economics Discussion Series no. 2005-10.

Das, Sanjiv R., and Paul Hanouna. 2009. "Implied Recovery," *Journal of Economic Dynamics and Control*, 33, 1837-1857.

Dieckmann, Stephen, J. Spencer Martin and Deon Strickland. 2007. "Liquidation and Corporate Rehabilitation: Bondholder Recovery in the Roaring Twenties", Mimeo.

Donovan, John, Richard Frankel, and Xiumin Martin. 2013. "Accounting Conservatism and Creditor Recovery Rate," Washington University in St. Louis, Mimeo.

Duffie, Darrell, and Kenneth J. Singleton. 2003. *Credit Risk*. Princeton University Press.

Dwyer, Douglas, and Irina Korablev. 2009. "Moody's KMV LossCalc V3.0," Moody's Analytics, manuscript.

The Economist. 2010. "Dodging Defaults," August 5.

Financial Times. 2012. "Low Failure Rates Mask Tough Times," September 20. Special Report on Business Turnarounds.

Financial Times. 2013. "Distressed Debt Investors Focus on Europe," May 29.

Firestone, Simon, and Marcelo Rezende. 2013. "Are Banks' Internal Risk Parameters Consistent? Evidence from Syndicated Loans," Board of Governors of the Federal Reserve System, working paper 2013-84.

Fitch Ratings. 2012. "Fitch U.S. High Yield Default Insight – 2011 Review," Credit Market Research Special Report, Jan. 20.

Fitch Ratings. 2012. "Fitch U.S. High Yield Default Insight – January 2012," Credit Market Research Special Report, Feb. 17.

Frye, Jon. 2000. "Collateral Damage Detected." Federal Reserve Bank of Chicago, Emerging Issues Series, October.

Frye, Jon. 2000. "Depressing Recoveries" *Risk*, November.

Gerardi, Kristopher S., Eric Rosenblatt, Paul S. Willen, and Vincent W. Yao. 2012. "Foreclosure Externalities: Some New Evidence," Federal Reserve Bank of Atlanta Working Paper 2012-11.

Giesecke, Kay, Francis A. Longstaff, Stephen Schaefer, and Ilya Strebulaev. 2011. "Corporate Bond Default Risk: A 150-Year Perspective," *Journal of Financial Economics*, 102, 233-250.

Gupton, Greg M., and Roger M. Stein. 2005. "LossCalc V2: Dynamic Prediction of LGD," Moody's KMV, manuscript.

James, Christopher, and Atay Kizilaslan. 2012. "Asset Specificity, Industry Driven Recovery Risk and Loan Pricing," *Journal of Financial and Quantitative Analysis*, forthcoming.

Jankowitsch, Rainer, Florian Nagler, and Marti G. Subrahmanyam. 2013. "The Determinants of Recovery Rates in the US Corporate Bond Market," New York University, Mimeo.

Jokivuolle, Esa, and Matti Viren. 2013. "Cyclical Default and Recovery in Stress Testing Loan Losses," *Journal of Financial Stability*, 9, 139-149.

Khieu, Hinh D., Donald J. Mullineaux, and Ha-Chin Yi. 2012. "The Determinants of Bank Loan Recovery Rates," *Journal of Banking and Finance*, 36, 923-933.

Longstaff, Francis A., and Eduardo S. Schwartz. 1995. "A Simple Approach to Valuing Risky Fixed and Floating Rate Debt," *Journal of Finance*, 50, 789-819.

Merton, Robert C. 1974. "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates," *Journal of Finance*, 29, 449-470.

Metz, Albert, and Steffen Sorensen. 2012. "Trading Prices as Predictors of Ultimate Corporate Recovery Rates," Moody's Investor Service, Special Comment, March 20.

Moody's Investors Services. 2011. "Moody's Ultimate Recovery Database: Lessons from 1,000 Corporate Defaults," Special Comment, Nov. 30.

Mora, Nada. 2012. "What Determines Creditor Recovery Rates?" *Federal Reserve Bank of Kansas City Economic Review*, 97, 79-109.

Papke, Leslie E., and Jeffrey M. Wooldridge. 1996. "Econometric Methods for Fractional Response Variables with an Application to 401(K) Plan Participation Rates," *Journal of Applied Econometrics*, 11, 619-632.

Pesaran, M. Hashem, Til Schuermann, Bjorn-Jakob Treutler, and Scott M. Weiner. 2006. "Macroeconomic Dynamics and Credit Risk: A Global Perspective," *Journal of Money, Credit and Banking*, 38, 1211-1261.

Pulvino, Todd C. 1998. "Do Asset Fire Sales Exist? An Empirical Investigation of Commercial Aircraft Sale Transactions," *Journal of Finance*, 53, 939-978.

Rajan, Raghuram G. and Luigi Zingales. 1998. "Financial Dependence and Growth", *American Economic Review*, 88, 559-586.

Schuermann, Til. 2005. "What Do We Know about Loss Given Default?" In Altman, E., Resti, A., Sironi, A. (Eds.), *Recovery Risk: The Next Challenge in Credit Risk Management*. Risk Books, London.

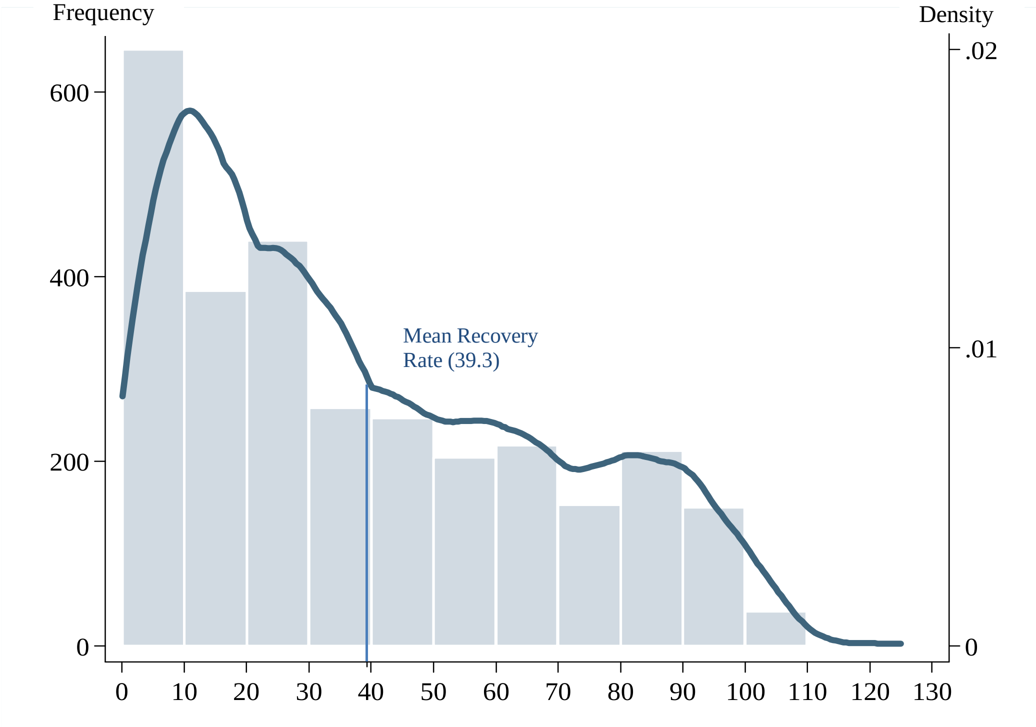
Shleifer, Andrei, and Robert Vishny. 1992. "Liquidation Values and Debt Capacity: A Market Equilibrium Approach." *Journal of Finance*, 47, 1343-1366.

Shleifer, Andrei, and Robert Vishny. 2011. "Fire Sales in Finance and Macroeconomics," *Journal of Economic Perspectives*, 25, 29-48.

Thorburn, Karin S. 2000. "Bankruptcy auctions: costs, debt recovery, and firm survival". *Journal of Financial Economics*, 58, 337-368.

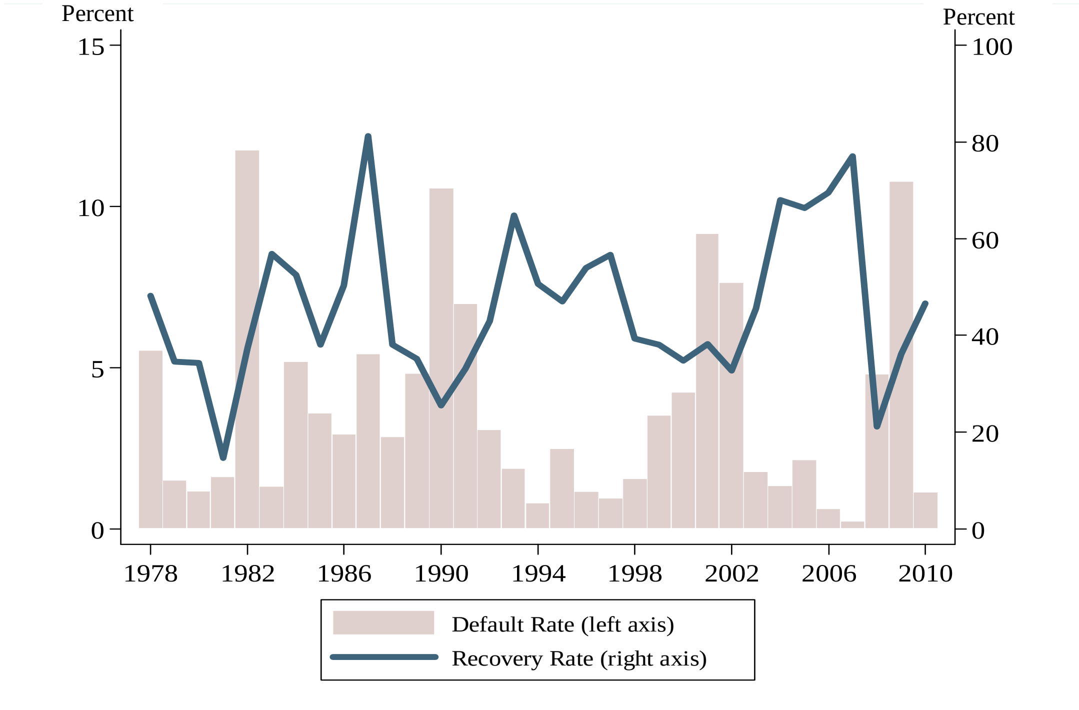
Zhang, Zhipeng, 2010. "Recovery Rates and Macroeconomic Conditions", Mimeo.

Figure 1. The Distribution of Recovery Rates



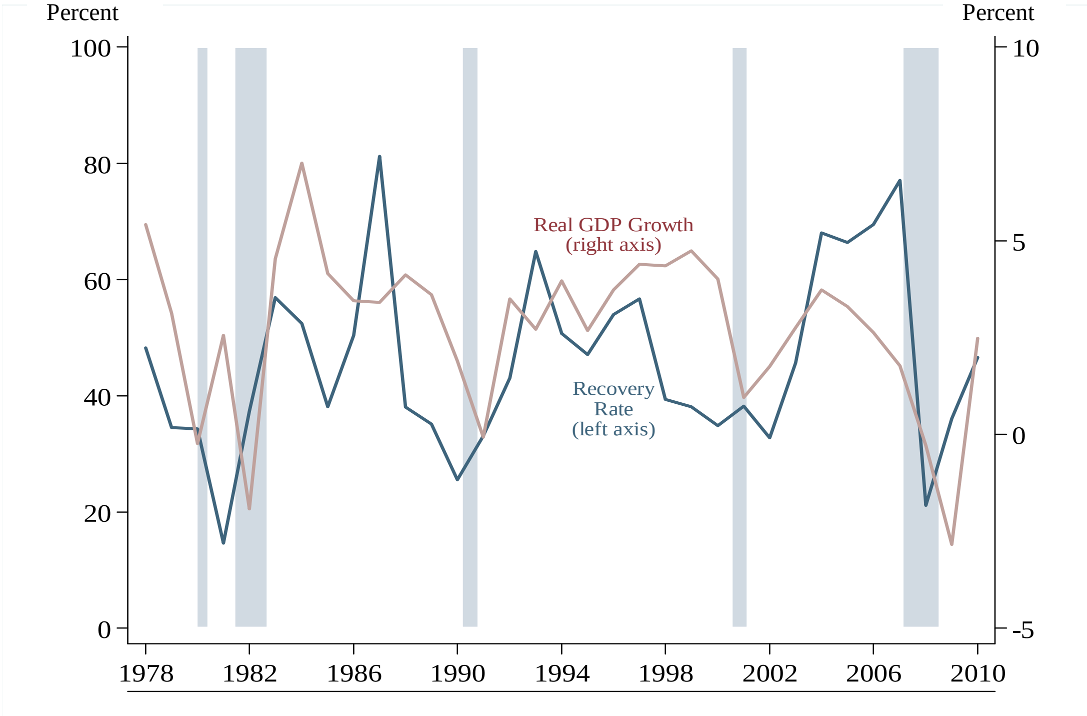
Source: Author's calculations based on Moody's DRS 1970-2008. The recovery rate is measured by the market value of defaulted debt as a percentage of par, one month after default.
Note: The bars represent the histogram of recovery rates scaled to frequencies of debt observations. The distribution is estimated using the Epanechnikov kernel function.

Figure 2. The Default Rate and the Recovery Rate on Defaulted Securities



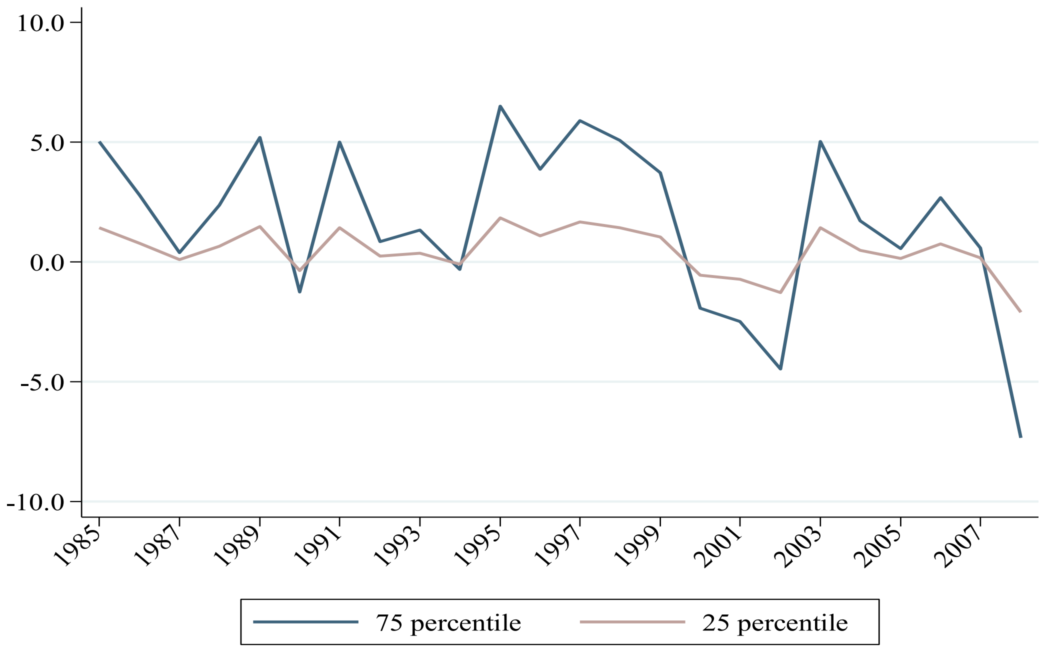
Source: Author's calculations based on Moody's DRS 1970-2008 and Altman and Kuehne (2011) for 2009-10.

Figure 3. The Recovery Rate and the Business Cycle



Source: Author's calculations based on Moody's DRS 1970-2008 and Altman and Kuehne (2011) for 2009-10. Real GDP figures are from the St. Louis FRED database (Bureau of Economic Analysis, U.S. Department of Commerce). Recessions (shaded areas) are from the National Bureau of Economic Research (NBER).

Figure 4. The Total Effect of Stock Returns on Recovery Rates:
A Comparison of Different Industry Sensitivities



Note: The "75th percentile" is the effect computed for an industry at the 75th percentile of dependence (high external finance dependence), which corresponds to Business Services (SIC 73), for example. And the "25th percentile" is the effect computed for an industry at the 25th percentile of dependence (low external finance dependence), which corresponds to Food & Kindred Products (SIC 20); Forestry (SIC 8). The industry percentiles are reported in Table 2 and the baseline model is reported in Table 6(2).

Table 1. Descriptive Statistics of Recovery Rates

Panel A. Industry Characteristics

Industry	Defaults	Firm Defaults	Mean	Median	Std. Dev.
Overall	4422	1307	39.3	30.5	29.1
A. Agriculture, Forestry and Fishing	18	6	39.9	46.5	25.6
B. Mining	81	38	50.8	48.6	26.0
C. Construction	36	14	28.7	20.0	31.4
D. Manufacturing	726	293	43.7	41.4	29.1
E1. Transportation	475	33	32.7	28.3	16.3
E2. Communications	331	87	39.6	30.0	31.0
E3. Utilities	164	22	57.5	62.9	31.8
F. Wholesale Trade	87	37	43.2	48.5	33.2
G. Retail Trade	235	91	43.3	41.0	29.8
H. Finance, Insurance and Real Estate	1020	64	24.6	10.0	27.7
I. Services	339	115	49.3	56.8	31.2

Panel B. Seniority and Security Characteristics

Absolute Seniority	Defaults	Firm Defaults	Mean	Median	Std. Dev.
Overall	4422	1307	39.3	30.5	29.1
Bank Loans	655	84	67.1	70.0	25.7
Senior Secured	649	143	47.3	36.0	26.5
Senior Unsecured	1891	426	36.3	26.0	29.0
Senior Subordinated	364	216	30.5	23.0	25.8
Subordinated	723	408	32.2	29.0	22.7
Junior Subordinated	32	11	23.4	13.9	24.2
Preferred Stock	99	16	10.1	4.2	21.1

Panel C. Relative Seniority: Most Senior Debt

Relative Seniority (Top)	Defaults	Firm Defaults	Mean	Median	Std. Dev.
Bank Loans	527	63	67.8	71.2	25.5
Senior Secured	620	121	48.0	36.0	26.7
Senior Unsecured	1476	268	36.8	25.0	30.2
Senior Subordinated	74	56	47.4	45.0	26.6
Subordinated	416	291	34.8	32.0	22.2
Junior Subordinated	4	4	32.3	32.3	20.9

Panel D. Backing Indicator

If a credit guarantee is provided by a third-party issuer	Defaults	Firm Defaults	Mean	Median	Std. Dev.
Yes	550	228	53.7	55.0	32.2
No	3872	1079	37.1	28.3	28.0

Source: Author's calculations based on Moody's DRS 1970-2008. The industry divisions are based on 1-digit SIC codes (except for division E, which is further divided by 2-digit SIC codes: Transportation SIC 40-47, Communications SIC 48, and Utilities SIC 49). Relative Seniority statistics are computed for the securities that are at the top of the firm issuer's capital structure at the time of default. Note that some securities are missing an industry SIC code or a seniority type in Moody's DRS. And that not all defaulted securities are reported with a recovery rate (only 2,952 of the 4,422 total defaulted securities in the sample).

Table 2. Summary Statistics of Contract, Firm, Industry and Macroeconomic Variables

	Mean	Std. Dev.	25th Perc.	Median	75th Perc.	Obs.
Contract and Firm Characteristics						
Coupon Rate	10.423	3.079	9.000	10.750	12.500	979
Log (issue size)	4.470	1.137	3.912	4.605	5.165	1052
Log (assets)	6.264	1.579	5.277	6.113	7.148	804
Profit Margin	-0.007	0.564	0.001	0.064	0.132	779
Leverage	0.443	0.266	0.224	0.486	0.722	793
Tangibility	0.378	0.241	0.179	0.349	0.565	792
Number of Issues	5.770	28.444	1.000	3.000	5.000	1023
Debt Concentration	0.629	0.330	0.336	0.556	1.000	1023
Industry Characteristics						
Industry Q	1.284	0.490	1.018	1.183	1.429	2736
Industry Distress Indicator	0.124	0.330	0.000	0.000	0.000	2725
Industry Asset Specificity	0.193	0.156	0.115	0.149	0.227	72
Industry Sales Growth Correlation	0.142	0.134	0.079	0.143	0.204	74
Industry Cash Flow Growth Correlation	0.073	0.143	0.031	0.058	0.100	74
Industry GDP Growth Correlation	0.323	0.315	0.088	0.388	0.539	104
Industry External Finance Dependence	0.015	3.745	-0.479	-0.245	0.141	74
Industry External Debt Finance Dependence	0.238	0.458	0.080	0.139	0.209	74
Industry Property Dependence	0.128	0.167	0.018	0.071	0.167	74
Macroeconomic Variables						
GDP Growth	2.943	1.988	1.774	3.403	4.354	39
Stock Return	7.589	17.593	-1.539	10.787	20.264	39
House Price Growth	5.217	3.887	3.072	4.942	6.840	33
House Price Growth (state-level)	5.123	6.888	2.130	4.569	7.833	1683
Treasury Bill Rate (3 month)	5.806	2.829	4.247	5.375	7.479	39
Commercial Paper Spread	0.616	0.425	0.318	0.503	0.877	38
Corporate Bond Baa-Aaa Spread	1.092	0.401	0.800	0.945	1.313	39

Notes: The summary statistics reported are computed for the sample of defaulted debt securities in Moody's DRS 1970-2008. *Contract Characteristics* are from Moody's. *Firm Characteristics* are from Compustat and are measured as of the last fiscal year before the default. The number of observations are for unique firm-year observations in the defaulted sample. *Industry Characteristics* are mostly from Compustat and are based on the medians for each industry (74 industries according to 2-digit SIC codes). Industry variables are measured in the year of default for time-varying industry variables (Industry Q and Industry Distress where the number of observations are for unique industry-year observations). The other industry variables are not time-varying but are aggregated over the sample period to smooth temporal fluctuations, following the methodology in Rajan and Zingales (1998). For particular contract and firm variable definitions, see Acharya, Bharath, and Srinivasan (2007). For example, *Log (assets)* is the natural log of total assets; *Profit Margin* is the ratio of EBITDA to sales; *Leverage* is the ratio of long-term debt to total assets; *Tangibility* is the ratio of property, plant, and equipment (PPE) to total assets; *Number of Issues* is the total number of debt issues outstanding at the time of a firm's default; *Debt Concentration* is the Herfindahl index measure by amount of the debt issues outstanding at the time of a firm's default. *Industry Q* is the median of the ratio of market value to book value of all firms in the industry of the defaulting firm (where market value is measured as book value of total assets - book value of equity + market value of equity). The *Industry Distress Indicator* equals one if the median stock return of all firms in the industry of the defaulting firm in the year of default is less than -30%, and zero otherwise. *Industry Asset Specificity* is the industry median of the ratio machinery and equipment to total assets. *Industry Sales Growth Correlation* is the median of the correlation of sales growth and real GDP growth in the industry of the defaulting firm. *Industry Cash Flow Growth Correlation* is the median of the correlation of cash flow growth (Rajan-Zingales method) and real GDP growth in the industry of the defaulting firm. *Industry GDP Growth Correlation* is calculated directly from the industry-level chain-type quantity indexes for value added reported by the Bureau of Economic Analysis (the industry classification for these is based on the 2002 NAICS classification). *Industry External Finance Dependence* is the median of capital expenditures minus total funds from operations scaled by capital expenditures in the industry of the defaulting firm. The method and codes are described in detail in Rajan and Zingales (1998). *Industry External Debt Finance Dependence* is the median of long-term debt issuance minus long-term debt reduction scaled by capital expenditures in the industry of the defaulting firm. *Industry Property Dependence* is the median of the sum of buildings, land, and construction-in-progress to total assets of firms in the industry of the defaulting firm. Finally, *GDP Growth* is real gross domestic product annual growth from the Bureau of Economic Analysis via FRED. *Stock Return* is the annual return on the S&P 500 composite stock index from CRSP or from the Chicago Board Options Exchange. *House Price Growth* measures are, respectively, nationwide and state-level annual growth of house prices from the FHFA using all transactions indexes. Finally, the *Treasury Bill Rate,* the *Commercial Paper Spread,* and the *Corporate Bond Baa-Aaa Spread* are from the Federal Reserve H.15 Release, where the commercial paper spread is the 3 month commercial paper rate for high grade nonfinancial borrowers minus the 3 month Treasury bill rate and the corporate bond spread is the yield difference between Moody's Baa- and Aaa-rated corporate bonds.

Table 3. Evaluating Separately Industry Conditions and the Macroeconomy

The dependent variable is the security-level recovery rate

	(1)	(2)	(3)	(4)	(5)	(6)
Coupon Rate	0.516*	0.482*	0.515*	0.519*	0.476*	0.447
	(0.269)	(0.264)	(0.269)	(0.276)	(0.266)	(0.275)
Log (issue size)	0.723	0.251	0.733	0.713	0.834	0.883
	(0.629)	(0.594)	(0.631)	(0.634)	(0.625)	(0.616)
Log (assets)	-0.030	-0.545	-0.012	-0.399	0.112	-0.056
	(1.281)	(1.139)	(1.284)	(1.307)	(1.282)	(1.303)
Profit Margin	7.347***	7.386***	7.297***	6.222***	7.092***	6.162***
	(1.279)	(1.678)	(1.263)	(1.289)	(1.271)	(1.319)
Leverage	-1.976	-4.114	-2.029	-2.776	-2.089	-2.720
	(4.864)	(4.999)	(4.880)	(4.914)	(4.949)	(5.062)
Tangibility	3.555	5.109	3.543	3.037	3.573	3.272
	(6.321)	(6.890)	(6.342)	(6.489)	(6.463)	(6.661)
Number of Issues	-0.054***	-0.046***	-0.054***	-0.062***	-0.052***	-0.057***
	(0.013)	(0.011)	(0.014)	(0.015)	(0.014)	(0.016)
Debt Concentration	-6.853	-6.796	-6.902	-8.410*	-6.869	-7.927*
	(4.503)	(4.222)	(4.478)	(4.709)	(4.522)	(4.741)
Bank Loan	41.226***	45.311***	40.762***	30.045***	41.186***	33.770***
	(9.183)	(8.476)	(9.340)	(8.865)	(9.203)	(9.069)
Senior Secured	19.246**	20.679***	19.113**	18.212**	19.814**	19.774**
	(7.835)	(6.493)	(7.837)	(7.896)	(7.906)	(8.030)
Senior Unsecured	14.341**	13.684**	14.322**	13.393*	14.539**	14.033*
	(7.134)	(5.574)	(7.128)	(7.160)	(7.147)	(7.227)
Senior Subordinated	8.521	8.221	8.508	7.728	8.942	8.700
	(7.019)	(5.554)	(7.012)	(7.039)	(7.037)	(7.116)
Subordinated	5.742	7.011	5.745	4.922	5.407	4.518
	(6.786)	(5.314)	(6.770)	(6.823)	(6.841)	(6.912)
Most Senior	14.857***	14.711***	14.936***	15.896***	14.833***	15.411***
	(2.935)	(2.902)	(2.901)	(2.960)	(2.927)	(2.984)
Backing	7.976***	6.856*	7.894***	8.422***	7.750***	8.032***
	(2.992)	(3.666)	(2.982)	(3.097)	(2.986)	(3.074)
Industry Q	1.336	13.861**	1.261		0.758	
	(2.997)	(6.357)	(2.957)		(2.894)	
Industry Distress	-10.615***	-7.276**	-10.514***		-9.045***	
	(3.004)	(3.219)	(3.059)		(3.484)	
GDP Growth			0.206	0.566		
			(0.710)	(0.710)		
Stock Return					0.090	0.168**
					(0.081)	(0.074)
Industry Dummies	Moodys IC	2-digit SIC	Moodys IC	Moodys IC	Moodys IC	Moodys IC
Observations	1849	1849	1849	1849	1849	1849
R^2	0.373	0.432	0.373	0.356	0.375	0.365

The models are estimated using OLS. The ommitted seniority category is junior subordinated. The Moody's 12 industry classification dummies are similar to the S&P 12 industry dummies included in the regressions in Acharya, Bharath, and Srinivasan (2007). Note that ***, **, *, indicate 1, 5, and 10 percent statistical significance, respectively. The standard errors used in calculating significance levels are robust to heteroscedasticity, clustered at the firm level (Compustat gvkey), and are shown in parentheses.

Table 4. The Variation in Industry Dependence on the Business Cycle

The dependent variable is the security-level recovery rate

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Coupon Rate	0.542**	0.506*	0.460*	0.447*	0.452*	0.452*	0.491*
	(0.276)	(0.268)	(0.266)	(0.264)	(0.261)	(0.261)	(0.263)
Log (issue size)	0.659	0.423	0.389	0.164	0.242	0.373	0.200
	(0.638)	(0.585)	(0.560)	(0.592)	(0.584)	(0.583)	(0.603)
Log (assets)	-0.278	-0.978	-0.928	-0.692	-0.491	-0.419	-0.621
	(1.299)	(1.276)	(1.254)	(1.214)	(1.158)	(1.163)	(1.167)
Profit Margin	5.673***	5.826***	6.066***	6.635***	7.168***	7.209***	7.590***
	(1.234)	(1.549)	(1.553)	(1.690)	(1.655)	(1.646)	(1.670)
Leverage	-2.539	-3.025	-1.949	-3.471	-3.097	-3.396	-3.893
	(4.816)	(5.010)	(4.922)	(4.893)	(4.875)	(4.898)	(5.084)
Tangibility	2.555	3.741	5.378	6.419	6.391	6.261	7.235
	(6.414)	(7.153)	(7.066)	(7.075)	(6.896)	(6.936)	(7.166)
Number of Issues	-0.061***	-0.048***	-0.042***	-0.044***	-0.040***	-0.045***	-0.047***
	(0.015)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Debt Concentration	-8.381*	-8.225*	-6.621	-6.433	-5.640	-5.799	-7.732*
	(4.829)	(4.529)	(4.454)	(4.355)	(4.229)	(4.230)	(4.261)
Industry Q				17.291***	12.368**	13.000**	11.431*
				(6.270)	(6.249)	(6.248)	(6.372)
Industry Distress					-6.385*	-6.213*	-7.012**
					(3.347)	(3.359)	(3.383)
Recession	-4.933*	-3.888	3.523	3.854	3.851	2.130	2.926
	(2.736)	(2.503)	(4.083)	(4.047)	(4.115)	(3.859)	(4.307)
Recession × Industry Sales Growth Correlation			-56.787***	-49.729**	-45.553**		
			(21.832)	(21.787)	(22.517)		
Recession × Industry Cash Flow Growth Correlation						-69.295	
						(43.507)	
Recession × Industry GDP Growth Correlation							-14.228*
							(8.177)
Seniority Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Backing Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummies	Moodys IC	2-digit SIC	2-digit SIC	2-digit SIC	2-digit SIC	2-digit SIC	2-digit SIC
Observations	1849	1849	1849	1849	1849	1849	1839
R^2	0.360	0.417	0.424	0.433	0.438	0.436	0.438

The models are estimated using OLS. The Moody's 12 industry classification dummies are similar to the S&P 12 industry dummies included in the regressions in Acharya, Bharath, and Srinivasan (2007). Note that ***, **, *, indicate 1, 5, and 10 percent statistical significance, respectively. The standard errors used in calculating significance levels are robust to heteroscedasticity, clustered at the firm level (Compustat gvkey), and are shown in parentheses. All the seniority and backing dummies shown in Table 3 are included in these regressions but are not shown in the interest of space. Also note that the "Industry Sales Growth Correlation" and the "Industry Cash Flow Growth Correlation" variables are 2-digit SIC variables and are, therefore, subsumed in the 2-digit industry dummies. The variable "Industry GDP Growth Correlation" is computed using BEA industry-level value-added GDP data, which are divided according to North American Industry Classification Codes. Therefore, this variable is also controlled for in the regression in column (7) (insignificant). The Recession indicator is one in recession years and zero otherwise.

Table 5. The Variation in Industry Dependence on the Stock Market

The dependent variable is the security-level recovery rate

	(1)	(2)	(3)	(4)	(5)	(6)
Coupon Rate	0.434	0.509*	0.510*	0.530**	0.492*	0.511**
	(0.269)	(0.270)	(0.268)	(0.263)	(0.261)	(0.261)
Log (issue size)	0.634	0.548	0.333	0.354	0.645	0.305
	(0.550)	(0.549)	(0.570)	(0.567)	(0.550)	(0.615)
Log (assets)	-0.534	-1.192	-1.092	-0.997	-0.921	-0.668
	(1.217)	(1.235)	(1.225)	(1.170)	(1.130)	(1.155)
Profit Margin	6.082***	6.018***	6.399***	7.000***	6.301***	6.735***
	(1.602)	(1.584)	(1.673)	(1.605)	(1.501)	(1.585)
Leverage	-3.702	-5.363	-6.177	-5.769	-6.716	-5.165
	(5.202)	(5.373)	(5.336)	(5.249)	(5.235)	(5.157)
Tangibility	5.043	5.094	5.715	5.635	5.529	6.012
	(7.255)	(7.599)	(7.556)	(7.347)	(7.776)	(7.339)
Number of Issues	-0.035***	-0.064***	-0.067***	-0.068***	-0.056***	-0.056***
	(0.010)	(0.015)	(0.015)	(0.014)	(0.014)	(0.015)
Debt Concentration	-7.385*	-10.247**	-10.058**	-9.435**	-8.865**	7.954*
	(4.295)	(4.449)	(4.412)	(4.289)	(4.142)	(4.277)
Industry Q			12.772**	8.401	5.765	9.672
			(6.132)	(6.233)	(5.833)	(5.981)
Industry Distress				-7.045**	-7.713**	-6.422*
				(3.485)	(3.172)	(3.306)
Stock Return	0.213***	0.263***	0.213**	0.175*		
	(0.074)	(0.088)	(0.089)	(0.090)		
Stock Return × Industry External Finance Dependence		0.179***	0.173***	0.188***		
		(0.060)	(0.060)	(0.057)		
Stock Crash					-10.445**	
					(4.452)	
Stock Crash × Industry External Finance Dependence					-8.911***	
					(3.333)	
High Volatility						-5.558
						(3.421)
High Volatility × Industry External Finance Dependence						-5.264*
						(2.938)
Seniority Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Backing Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummies	2-digit SIC	2-digit SIC	2-digit SIC	2-digit SIC	2-digit SIC	2-digit SIC
Observations	1849	1849	1849	1849	1849	1849
R^2	0.428	0.441	0.445	0.450	0.459	0.442

The models are estimated using OLS. Note that ***, **, *, indicate 1, 5, and 10 percent statistical significance, respectively. The standard errors used in calculating significance levels are robust to heteroscedasticity, clustered at the firm level (Compustat gvkey), and are shown in parentheses. All the seniority and backing dummies shown in Table 3 are included in these regressions but are not shown in the interest of space. Also note that the "Industry External Finance Dependence" variable is a 2-digit SIC variable and is therefore subsumed in the 2-digit industry dummies. The "Stock Crash" indicator is one in years where the stock market return is in the lower 10th percentile, and the "High Volatility" indicator is one in years where the stock market return volatility is in the upper 10th percentile (measured by the volatility of the 12 monthly stock market returns for each year following Giesecke, Longstaff, Schaefer, and Strebulaev, 2011).

Table 6. The Variation in Industry Dependence on the Business Cycle and the Stock Market
The dependent variable is the security-level recovery rate

	(1)	(2)	(3)	(4)	(5)	(6)
Coupon Rate	0.495*	0.514**	0.553**	0.597**	0.549**	0.589**
	(0.264)	(0.259)	(0.257)	(0.280)	(0.255)	(0.253)
Log (issue size)	0.451	0.305	-0.128	0.571	0.158	0.635
	(0.540)	(0.560)	(0.582)	(0.568)	(0.627)	(0.582)
Log (assets)	-1.237	-1.066	-2.080*	-1.397	-1.001	-1.109
	(1.240)	(1.178)	(1.108)	(1.163)	(1.160)	(1.158)
Profit Margin	5.783***	6.697***	4.632***	6.601***	6.447***	6.619***
	(1.571)	(1.614)	(1.341)	(1.553)	(1.517)	(1.567)
Leverage	-4.289	-4.683	-6.812*	-4.759	-6.013	-3.404
	(5.233)	(5.129)	(3.895)	(4.941)	(4.836)	(4.715)
Tangibility	6.930	7.187	2.340	6.380	7.843	7.844
	(7.518)	(7.303)	(6.602)	(7.258)	(7.305)	(6.826)
Number of Issues	-0.064***	-0.067***	-0.061***	-0.066***	-0.071***	-0.056***
	(0.015)	(0.014)	(0.017)	(0.014)	(0.017)	(0.021)
Debt Concentration	-9.125**	-8.489**	-11.182***	-8.463**	-8.483**	-7.535*
	(4.441)	(4.283)	(4.253)	(4.308)	(4.249)	(4.249)
Industry Q		6.456	2.766	7.528	3.074	4.997
		(6.149)	(6.692)	(6.150)	(6.047)	(6.150)
Industry Distress		-6.435*	-6.877	-6.239*	-7.028**	-8.591*
		(3.487)	(4.391)	(3.415)	(3.468)	(4.837)
Recession	4.412	4.243		4.546	8.694	1.627
	(3.668)	(3.787)		(3.764)	(4.889)	(3.560)
Recession × Industry Sales Growth Correlation	-64.086***	-58.118***	-58.792***	-59.231***	-55.938***	-1.026
	(20.599)	(21.446)	(21.014)	(21.391)	(21.361)	(31.033)
Stock Return	0.231***	0.160*		0.132	0.083	0.190***
	(0.086)	(0.086)		(0.084)	(0.076)	(0.065)
Stock Return × Industry External Finance Dependence	0.216***	0.220***	0.165***	0.216***	0.193***	0.251***
	(0.061)	(0.058)	(0.063)	(0.057)	(0.058)	(0.058)
GDP growth at Origination				-0.624		
				(0.425)		
Stock Return at Origination				-0.115**		
				(0.046)		
Aggregate Bond Default Rate					-1.045	
					(0.696)	
Asset Specificity × Industry Distress						9.692
						(19.455)
Asset Specificity × Recession × Industry Sales Growth Correlation						-222.966**
						(113.550)
Asset Specificity × Stock Return × Industry External Finance Dependence						-0.896
						(0.793)
Default- and Origination-Year Dummies	No	No	Yes	No	No	No
Seniority Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Backing Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummies	2-digit SIC	2-digit SIC	2-digit SIC	2-digit SIC	2-digit SIC	2-digit SIC
Observations	1849	1849	1849	1796	1849	1849
R^2	0.452	0.459	0.534	0.468	0.463	0.468

The models are estimated using OLS. Note that ***, **, *, indicate 1, 5, and 10 percent statistical significance, respectively. The standard errors used in calculating significance levels are robust to heteroscedasticity, clustered at the firm level (Compustat gvkey), and are shown in parentheses. All the seniority and backing dummies shown in Table 3 are included in these regressions but are not shown in the interest of space.

Table 7. Additional Factors: The Variation in Industry Dependence on House Prices and Interest Rates

The dependent variable is the security-level recovery rate

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
House Price Growth	-0.706* (0.423)						
House Price Growth × Industry Property Dependence	1.878 (2.119)						
House Price Growth (state-level)		-0.375 (0.253)			-0.505 (0.318)	-0.091 (0.292)	-0.023 (0.293)
House Price Growth (state-level) × Industry Property Dependence		2.105*** (0.814)			1.659* (0.954)	1.936** (0.764)	1.593** (0.785)
Treasury Bill Rate (3 month)			0.390 (0.619)		-0.477 (0.951)		
T-Bill × Industry External Debt Finance Dependence			-1.331** (0.635)		-0.091 (0.579)	-0.121 (0.724)	-0.911 (0.798)
Commercial Paper Spread				7.619 (5.275)	11.584 (7.504)		
CP Spread × Industry External Debt Finance Dependence				-15.077** (5.993)	-17.340*** (5.412)	-21.479*** (6.004)	
Corporate Bond Spread × Industry External Debt Finance Dependence							-9.097* (4.895)
Industry Q					8.664 (6.926)	4.260 (6.846)	3.707 (6.888)
Industry Distress					-6.386* (3.947)	-6.690 (4.585)	-6.416 (4.633)
Recession					3.823 (4.057)		
Recession × Industry Sales Growth Correlation					-67.545*** (22.117)	-64.100*** (21.460)	-62.753*** (21.261)
Stock Return					0.147 (0.093)		
Stock Return × Industry External Finance Dependence					0.172*** (0.066)	0.101* (0.064)	0.148** (0.065)
Default Year and Origination Year Dummies	No	No	No	No	No	Yes	Yes
Contract and Firm Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Seniority Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Backing Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummies	2-digit SIC	2-digit SIC	2-digit SIC	2-digit SIC	2-digit SIC	2-digit SIC	2-digit SIC
Observations	1839	1820	1849	1848	1820	1820	1820
R^2	0.418	0.419	0.419	0.421	0.474	0.546	0.540

The models are estimated using OLS. Note that ***, **, *, indicate 1, 5, and 10 percent statistical significance, respectively. The standard errors used in calculating significance levels are robust to heteroscedasticity, clustered at the firm level (Compustat gvkey), and are shown in parentheses. All the seniority and backing dummies in addition to all the other contract and firm characteristics shown in Table 3 are included in these regressions but are not shown in the interest of space.

Table A1. Robustness Check: 3-digit SIC Industries

The dependent variable is the security-level recovery rate

	(1)	(2)	(3)	(4)
Coupon Rate	0.523**	0.605**	0.465*	0.588**
	(0.263)	(0.273)	(0.262)	(0.269)
Log (issue size)	0.426	0.086	0.455	0.184
	(0.575)	(0.604)	(0.550)	(0.577)
Log (assets)	-0.675	-0.034	-0.701	0.037
	(1.187)	(1.355)	(1.228)	(1.354)
Profit Margin	5.696***	5.574***	5.736***	5.308***
	(1.568)	(1.871)	(1.657)	(1.816)
Leverage	-4.882	-9.550*	-4.665	-9.111*
	(5.102)	(5.063)	(5.164)	(4.969)
Tangibility	5.812	4.848	8.252	7.011
	(7.273)	(9.296)	(7.394)	(9.315)
Number of Issues	-0.041***	-0.047***	-0.052***	-0.053***
	(0.010)	(0.011)	(0.013)	(0.016)
Debt Concentration	-7.219*	-6.099	-7.824*	-4.722
	(4.253)	(4.490)	(4.188)	(4.561)
Industry Q	2.797	11.829*	5.139	8.614
	(4.014)	(6.162)	(4.449)	(6.172)
Industry Distress	-9.078**	-6.878	-4.909	-3.446
	(3.646)	(4.644)	(3.843)	(4.549)
Recession			2.182	0.554
			(3.610)	(4.238)
Recession × Industry Sales Growth Correlation			-32.567*	-44.313**
			(18.230)	(22.182)
Stock Return			0.144**	0.103
			(0.073)	(0.076)
Stock Return × Industry External Finance Dependence			0.126***	0.104
			(0.048)	(0.072)
Seniority Dummies	Yes	Yes	Yes	Yes
Backing Dummies	Yes	Yes	Yes	Yes
Industry Dummies	2-digit SIC	3-digit SIC	2-digit SIC	3-digit SIC
Observations	1849	1849	1849	1849
R^2	0.432	0.545	0.453	0.556

The models are estimated using OLS. Note that ***, **, *, indicate 1, 5, and 10 percent statistical significance, respectively. The standard errors used in calculating significance levels are robust to heteroscedasticity, clustered at the firm level (Compustat gvkey), and are shown in parentheses. All the seniority and backing dummies shown in Table 3 are included in these regressions but are not shown in the interest of space. Note that the industry variables in these regressions are measured at the 3-digit SIC industry-level (Industry Q, Industry Distress, Industry Sales Growth Correlation, and Industry External Finance Dependence).

Table A2. Robustness Check: Industry Dependence Variables Measured Pre-Sample

The dependent variable is the security-level recovery rate

	(1)	(2)	(3)	(4)
	Regression sample post 1980		Regression sample post 1990	
		1960-79 measures		1960-89 measures
Coupon Rate	0.519**	0.466*	0.466	0.416
	(0.262)	(0.259)	(0.296)	(0.295)
Log (issue size)	0.335	0.337	0.602	0.563
	(0.563)	(0.555)	(0.479)	(0.483)
Log (assets)	-1.116	-0.839	-1.107	-0.884
	(1.187)	(1.198)	(1.409)	(1.394)
Profit Margin	6.728***	6.490***	7.572***	7.633***
	(1.632)	(1.626)	(1.740)	(1.745)
Leverage	-4.998	-4.352	-3.937	-4.392
	(5.174)	(5.215)	(5.617)	(5.642)
Tangibility	6.714	5.611	3.985	3.532
	(7.363)	(7.397)	(8.698)	(8.777)
Number of Issues	-0.067***	-0.073***	-0.037*	-0.043*
	(0.014)	(0.016)	(0.019)	(0.024)
Debt Concentration	-8.707**	-7.541*	-9.707*	-9.545*
	(4.322)	(4.207)	(5.131)	(5.089)
Industry Q	8.020	10.150	12.081	15.315*
	(6.866)	(7.058)	(8.216)	(8.181)
Industry Distress	-6.195*	-6.136*	-4.895	-4.908
	(3.536)	(3.552)	(4.042)	(4.010)
Recession	4.527	-0.511	4.412	-0.876
	(3.783)	(2.633)	(4.028)	(3.008)
Recession × Industry Sales Growth Correlation	-60.658***	-36.482***	-56.495**	-32.655*
	(21.511)	(13.454)	(23.444)	(18.157)
Stock Return	0.157*	0.153*	0.136	0.117
	(0.088)	(0.092)	(0.094)	(0.097)
Stock Return × Industry External Finance Dependence	0.224***	0.242***	0.172***	0.240
	(0.059)	(0.088)	(0.065)	(0.160)
Seniority Dummies	Yes	Yes	Yes	Yes
Backing Dummies	Yes	Yes	Yes	Yes
Industry Dummies	2-digit SIC	2-digit SIC	2-digit SIC	2-digit SIC
Observations	1833	1833	1551	1551
R^2	0.460	0.458	0.484	0.480

The models are estimated using OLS. Note that ***, **, *, indicate 1, 5, and 10 percent statistical significance, respectively. The standard errors used in calculating significance levels are robust to heteroscedasticity, clustered at the firm level (Compustat gvkey), and are shown in parentheses. All the seniority and backing dummies shown in Table 3 are included in these regressions but are not shown in the interest of space. Note the models in columns (2) and (4) compute the industry measures ("Industry Sales Growth Correlation" and "Industry External Finance Dependence") over the pre-estimation sample (1960-79 in column (2) and 1960-89 in column (4)). These industry measures are highly correlated with the standard measures reported in Table 2 and serve to confirm that the main results are not sensitive to possible reverse causality (albeit remote since the regressions are conducted at the firm instrument-level not at the industry-level). Note that the interquartile range for "industry sales growth correlation" over the lagged period is somewhat higher (0.210 compared to 0.125 in Table 2) so that the implied economic effects are very similar (e.g., procyclical industries recover 7.66 percentage points lower than weakly cyclical industries in column (2), similar to 7.58 from column (1)).

Table A3. Robustness Check: Alternative Regression Models
The dependent variable is the security-level recovery rate

	(1)	(2)	(3)	(4)
	Tobit Model Two-Sided	Logit Transform	Beta Transform	Quasi MLE Logistic function
Coupon Rate	0.522**	0.039**	0.019**	0.022*
	(0.254)	(0.017)	(0.009)	(0.012)
Log (issue size)	0.316	-0.048	-0.014	-0.015
	(0.548)	(0.042)	(0.019)	(0.031)
Log (assets)	-1.078	-0.048	-0.031	-0.050
	(1.153)	(0.065)	(0.036)	(0.054)
Profit Margin	6.726***	0.362***	0.202***	0.313***
	(1.580)	(0.105)	(0.055)	(0.079)
Leverage	-4.655	-0.220	-0.127	-0.225
	(5.032)	(0.280)	(0.157)	(0.225)
Tangibility	7.270	0.482	0.263	0.346
	(7.176)	(0.401)	(0.225)	(0.312)
Number of Issues	-0.067***	-0.004***	-0.002***	-0.004***
	(0.014)	(0.001)	(0.000)	(0.001)
Debt Concentration	-8.513**	-0.649***	-0.351***	-0.474***
	(4.199)	(0.239)	(0.132)	(0.184)
Industry Q	6.352	0.426	0.218	0.240
	(6.029)	(0.355)	(0.196)	(0.274)
Industry Distress	-6.469*	-0.298	-0.177*	-0.306*
	(3.412)	(0.191)	(0.107)	(0.162)
Recession	4.251	0.071	0.071	0.158
	(3.717)	(0.213)	(0.119)	(0.175)
Recession × Industry Sales Growth Correlation	-58.032***	-2.885**	-1.701**	-2.717***
	(21.049)	(1.200)	(0.671)	(0.993)
Stock Return	0.160*	0.010**	0.005**	0.007*
	(0.085)	(0.004)	(0.003)	(0.004)
Stock Return × Industry External Finance Dependence	0.221***	0.012***	0.007***	0.010***
	(0.057)	(0.003)	(0.002)	(0.003)
Seniority Dummies	Yes	Yes	Yes	Yes
Backing Dummies	Yes	Yes	Yes	Yes
Industry Dummies	2-digit SIC	2-digit SIC	2-digit SIC	2-digit SIC
Observations	1849	1831	1831	1831
R^2 (or pseudo R^2)	0.065	0.442	0.456	0.473
RMSE	29.747	28.517	27.958	26.969
RMSE from OLS model 6(2)	27.817	27.817	27.817	27.817
RMSE from OLS model 3(2)	35.434	35.434	35.434	35.434

This table presents alternative estimation methods to the benchmark OLS model in Table 6(2). Note that ***, **, *, indicate 1, 5, and 10 percent statistical significance, respectively. The standard errors used in calculating significance levels are robust to heteroscedasticity, clustered at the firm level (Compustat gvkey), and are shown in parentheses. All the seniority and backing dummies shown in Table 3 are included in these regressions but are not shown in the interest of space. The reported RMSE is the root mean square error from out-of-sample testing on 1996-2008. The initial sample period is 1970-1995 and rolling one-year ahead predicted recovery rates and RMSE are calculated for each subsequent year. The average RMSE over the forecast horizon is shown. Also shown is the out-of-sample RMSE for the comparable OLS model 6(2) and the OLS model 3(2) without macroeconomic factors.

Table A4. Robustness Check: The Variation in Industry Dependence on the Business Cycle and the Stock Market

The dependent variable is the industry-level recovery rate

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Weighted Average Recovery Rate						Simple Average Recovery Rate
Industry Q	9.468**	9.515**	8.782**	8.145*	7.073*	13.759	5.624
	(4.370)	(4.310)	(4.215)	(4.360)	(4.021)	(9.629)	(3.979)
Industry Distress	-6.498**	-6.851**	-4.768*	-3.826	-2.333	0.425	-0.865
	(2.835)	(3.035)	(2.919)	(3.268)	(3.101)	(3.695)	(3.156)
GDP Growth		-2.197**					
		(1.058)					
GDP Growth × Industry Sales Growth Correlation		10.839*					
		(6.132)					
Recession			1.981	2.607	5.299	3.628	2.465
			(2.728)	(3.078)	(3.168)	(3.771)	(3.075)
Recession × Industry Sales Growth Correlation			-43.843***	-43.682***	-44.204***	-32.103*	-31.163**
			(14.383)	(14.819)	(15.843)	(17.085)	(14.604)
Stock Return				0.068			
				(0.071)			
Stock Return × Industry External Finance Dependence				0.031			
				(0.031)			
Stock Crash					-10.670***	-9.060***	-9.252***
					(2.887)	(3.302)	(2.972)
Stock Crash × Industry External Finance Dependence					-2.277**	-1.631*	-1.944*
					(1.067)	(0.945)	(1.055)
Industry Dummies	1-digit SIC	1-digit SIC	1-digit SIC	1-digit SIC	1-digit SIC	2-digit SIC	1-digit SIC
Observations	375	375	375	375	375	375	376
R^2	0.094	0.100	0.108	0.113	0.143	0.274	0.117

This table presents OLS regressions in which the dependent variable in columns (1)-(6) is the industry (2-digit SIC) annual weighted average recovery, 1978-2008. These are constructed at the industry-level in a similar way to the aggregate weighted recovery rate shown in Figures 2 and 3, following Altman et al (2005). Weights are based on the defaulted debt amounts within an industry in a particular year. As a robustness check, the simple average recovery rate is employed in column (7). Also note that the "Industry Sales Growth Correlation" variable and the "Industry External Finance Dependence" variable are included in these regressions (with the exception of column (6) where they are redundant). Note that ***, **, *, indicate 1, 5, and 10 percent statistical significance, respectively. The standard errors used in calculating significance levels are robust to heteroscedasticity, clustered at the 2-digit SIC industry level, and are shown in parentheses.

Table A5. Robustness Check: By Asset Size of Obligor or by Issue Size
The dependent variable is the security-level recovery rate

	(1)	(2)	(3)	(4)	(5)
	Asset Size			Issue Size	
	Below Median	Above Median	Above Median	Below Median	Above Median
Coupon Rate	1.317***	0.085	0.143	0.788**	0.591*
	(0.324)	(0.344)	(0.342)	(0.349)	(0.349)
Log (issue size)	-0.736	1.338**	1.147**	0.136	2.333
	(0.865)	(0.599)	(0.539)	(0.666)	(1.766)
Log (assets)	-0.386	1.138	1.401	-0.899	-2.094
	(1.398)	(3.039)	(2.746)	(1.354)	(1.580)
Profit Margin	5.521***	5.768*	8.794*	1.322	7.898***
	(1.258)	(3.524)	(4.749)	(3.945)	(1.642)
Leverage	-3.664	0.039	-4.930	-12.840*	2.150
	(3.896)	(11.288)	(11.096)	(6.960)	(5.593)
Tangibility	1.402	2.397	4.874	23.183**	-7.529
	(5.910)	(13.385)	(13.346)	(9.179)	(8.010)
Number of Issues	-0.153***	-0.071***	-0.074***	-0.071***	-0.055***
	(0.037)	(0.015)	(0.014)	(0.026)	(0.012)
Debt Concentration	-5.233	-21.769*	-22.187*	-3.296	-16.466***
	(4.567)	(11.454)	(11.507)	(5.237)	(5.987)
Industry Q			16.585	1.653	11.710
			(14.493)	(7.791)	(9.349)
Industry Distress			-8.005	-6.533	-4.231
			(6.374)	(4.123)	(4.377)
Recession	-4.398	11.865**	12.845**	5.736	5.891
	(4.261)	(5.319)	(5.707)	(4.540)	(4.577)
Recession × Industry Sales Growth Correlation	-3.707	-106.615***	-97.307***	-64.303**	-74.691***
	(23.256)	(32.589)	(31.697)	(28.234)	(25.517)
Stock Return	0.194***	0.543***	0.395**	0.065	0.183**
	(0.064)	(0.143)	(0.163)	(0.125)	(0.077)
Stock Return × Industry External Finance Dependence	0.054	0.282***	0.265***	0.164*	0.232***
	(0.064)	(0.083)	(0.088)	(0.099)	(0.060)
Default- and Origination-Year Dummies	No	No	Yes	No	No
Seniority Dummies	Yes	Yes	Yes	Yes	Yes
Backing Dummies	Yes	Yes	Yes	Yes	Yes
Industry Dummies	2-digit SIC	2-digit SIC	2-digit SIC	2-digit SIC	2-digit SIC
Observations	902	947	947	795	1054
R^2	0.308	0.700	0.707	0.617	0.445

The models are estimated using OLS. Note that ***, **, *, indicate 1, 5, and 10 percent statistical significance, respectively. The standard errors used in calculating significance levels are robust to heteroscedasticity, clustered at the firm level (Compustat gvkey), and are shown in parentheses. All the seniority and backing dummies shown in Table 3 are included in these regressions but are not shown in the interest of space. The median asset size is 1,628 ($ million) and the median issue size is 100 ($ million).