Does Industry-wide Distress Affect Defaulted Firms? - Evidence from Creditor Recoveries[1]

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This Draft: August 2006[2]

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[2]This is a revised version of the earlier draft titled "Understanding the Recovery Rates on Defaulted Securities." We thank Bo Becker (WFA discussant), Mark Chen, Sergei Davydenko, Amy Dittmar, Darrell Duffie, Denis Gromb, Rohit Guha, Julian Franks, Gautam Kaul, Tom Nohel, Herbert Rijken, Roger Stein, Ilya Strebulaev, Per Stromberg, and Stuart Turnbull for useful discussions, the seminar participants at Bank of England, Copenhagen Business School, EFA Meetings (2003), European Central Bank, Federal Reserve Board at Atlanta, HEC – Paris, INSEAD, Lehman Brothers, London Business School, New York University, University of Michigan Business School, Anderson School of Business – UCLA, Wharton School of Business, the 14th Annual Financial Economics and Accounting Conference (2003), the Joint Inquire UK, Europe and Q–Group Conference (2004), the Financial Intermediation Research Society Meeting at Capri (2004), the Moody's–Stern Workshop on Credit Risk (2004), the CEPR workshop at Credit Suisse First Boston and the Western Finance Association Meetings (2005) for comments, and Deepak Bhandari, Karthik Balakrishnan, Harish Haridas, Jugal Parekh, and Anupam Sharma for excellent research assistance. The authors acknowledge the help of Edward Altman, Brooks Brady, and Standard and Poors for the provision of data employed. The authors are grateful to the Institute for Quantitative Investment Research (INQUIRE), UK, for its financial support for the project. Acharya is grateful to the Research and Materials Development (RMD) grant from London Business School. The views expressed and errors that remain in the paper are our own and should not be attributed to these supporting institutions.

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Abstract

Using data on defaulted firms in the United States over the period 1982 to 1999, we show that creditors of defaulted firms recover significantly lower amounts in present-value terms when the industry of defaulted firms is in distress. We investigate whether this is purely an economic-downturn effect or also a fire-sales effect along the lines of Shleifer and Vishny (1992). We find the fire-sales effect to be also at work: Creditors recover less if the industry is in distress and non-defaulted firms in the industry are illiquid, particularly if the industry is characterized by assets that are specific, that is, not easily redeployable by other industries, and if the debt is collateralized by such specific assets. The interaction effect of industry-level distress and asset-specificity is strongest for senior unsecured creditors, is economically significant, and robust to contract-specific, firm-specific, macroeconomic, and bond-market supply effects. We also document that defaulted firms in distressed industries are more likely to emerge as restructured firms than to be acquired or liquidated, and spend longer in bankruptcy.

Keywords: Bankruptcy, Illiquidity, Asset specificity, Loss given default, Credit risk.

J.E.L. Classification Code: G33, G34, G12.

1 Introduction

The magnitude of the deadweight costs of corporate defaults is an important determinant of capital structure in several corporate finance theories. The empirical literature has, however, found that the direct – administrative and legal – costs of formal bankruptcy are rather small (see, for example, Altman, 1984, and Weiss, 1990). Hence, the literature has shifted its attention to indirect costs arising from the loss of intangibles and growth opportunities, bargaining inefficiencies, and fire-sale liquidations during industry-wide distress. This paper is concerned with the last of these effects. Industry-wide distress can affect a defaulted firm along two dimensions: First, industry distress is invariably associated with a downturn in economic prospects which lowers the economic worth of the defaulted firm's assets. Second, the fire-sales or the industry-equilibrium notion developed by Shleifer and Vishny (1992) suggests that the prices at which assets of the defaulted firm can be sold depends on the financial condition of the peer firms. Both of these effects lower the amount recovered by firm's creditors and thereby affect the ex-ante debt capacity of firms.

In this paper, we shed light on the issue of whether defaulted firms, and, in turn, their creditors, are affected by industry distress purely through the economic-downturn channel or (also) through the fire-sales channel. We do so by studying comprehensively the empirical determinants of creditor recoveries using the data on observed prices of defaulted securities in the United States over the period 1982–1999. Our analysis of creditor recoveries complements the existing literature on asset sales that also has attempted to test the fire-sales channel (see the discussion of related literature below).

From an econometric standpoint, the issue of disentangling the economic-downturn effect from the fire-sales effect is inherently a tricky one. However, the industry-equilibrium theory has precise implications in terms of where the industry distress effect should be stronger in terms of other industry conditions and characteristics. In particular, Shleifer and Vishny argue that fire sales are more likely under the following conditions: if the industry has more specialized assets along the lines of Williamson (1988), that is, assets that have few alternative uses outside the industry, and if the industry is concentrated resulting in a less than perfect market for active bidding in cash auctions of assets. Furthermore, these effects should be stronger if the firm's competitors in the same industry are experiencing distress, liquidity problems, and/or are highly levered restricting their ability to raise additional financing. In contrast, it is not clear that the economic-downturn effect would affect industries and firms differentially in this manner.

In summary, under the fire-sales hypothesis, the researcher should find a strong interaction effect of industry-level asset-specificity and concentration with industry-level distress on firm-level debt recoveries. We employ several variants of these interactions in our empirical tests. Furthermore, this interaction effect should be stronger for those creditors who have weaker bargaining power and whose priority and security make them vulnerable to fluctuations in the liquidation price of firm's assets.[1]

Results: We measure creditor recoveries using the prices of defaulted securities at the time of emergence from default or bankruptcy, suitably discounted up to the time of default.[2] We identify the industry of the defaulted firm using the 3-digit SIC code of the company. First, in the spirit of Gilson, John, and Lang (1990) and Opler and Titman (1994), we define an industry to be "distressed" if the median stock return for this industry in the year of default is less than or equal to -30%.[3] We find that when the defaulting firm's industry is in "distress," its instruments recover about 10–15 cents less on a dollar compared to the case when the industry is healthy. This magnitude is about half the relative effect of seniority of the instrument (Bank Loans vs. Senior Debt vs. Subordinated Debt). Importantly, this effect of industry return is always non-linear, suggesting that it is indeed a "distress" effect as we call it: Continuous industry return variable, that is, the industry return without any truncation, has no explanatory power for recoveries.

In order to distinguish between the economic-downturn and fire-sales channels, we test the interaction effect of industry-level asset-specificity and concentration with industry-level distress. We measure an industry's asset-specificity as the median book value of the industry's machinery and equipment divided by the book value of total assets (a measure of Specific Assets also employed by Berger, Ofek, and Swary, 1996, and Stromberg, 2001).[4] We find that an industry's asset-specificity lowers creditor recoveries more if the industry is in distress and if the non-defaulted firms in the industry are more illiquid (measured by the inverse of the median coverage ratio of surviving firms in the industry). Furthermore, the industry's concentration (measured inversely by the number of non-defaulted peer firms)

[1]It is important to note that asset sales or liquidations are endogenously less likely to be seen when the industry is in distress and assets are specific. However, the anticipation of low prices for asset sales can confer greater bargaining power to equityholders in writing down creditor claims. Also, the lack of a sufficiently liquid market for asset sales can render the firm's distress a long-drawn process, and creditors may recover less in present-value terms.

[2]We verify in the unabridged version of the paper that these discounted emergence prices are unbiased predictors of prices at time of default (for the smaller sample of firms for which we have both default and emergence prices).

[3]We also measure industry distress in the year centered at the mid-point between the time of default and the time of emergence. In addition, we also employ measures of distress that incorporate sales-based past performance of the industry and credit rating of firms in the industry. We document that the effects of industry distress are robust across these measures.

[4]This measure is different from tangibility, generally measured as the book value of property, plant, and equipment divided by the book value of assets, since property (non-industrial real estate) is easily redeployable across industries and, hence, not considered a specific asset.

decreases creditor recoveries more when the industry is in distress.

These effects are economically significant. For example, a positive standard-deviation shock to industry-level asset-specificity lowers creditor recoveries in times of industry distress by around ten cents on a dollar. The effects are also robust to inclusion of controls for industry-fixed effects, contract-specific effects (seniority and security of instruments), firm-specific effects (profitability, leverage, size, tangibility, number of creditors, and creditor dispersion), and Median Q of the industry. Finally, non-parametric evidence confirms the findings in a striking fashion. For industry-year pairs where the industry is not in distress, there is no correlation between recoveries and asset-specificity; however, for industry-year pairs where the industry is in distress, this correlation is -0.76.

We also exploit the priority and collateral structure of the firm's debt in triple interactions of industry-level distress, asset-specificity, and debt-level seniority or security. We find that the adverse interaction effect of asset-specificity and distress is strongest for senior unsecured debt relative to that for bank debt and junior debt, and that debt collateralized by industry-specific equipment does experience lower recoveries during industry distress. This suggests that during an industry-wide distress, bank debt and collateralized debt lose little except when backed by industry-specific collateral. It is un-collateralized senior debt that appears to bear the brunt of asset-value fluctuations the most. Finally, junior debt is relatively unaffected between industry distress and otherwise. We provide some evidence that the stronger effect for senior unsecured debt is likely due to over-collateralization of secured bank debt which exposes the next-in-line creditors to collateral-value fluctuations.

Investigation of the outcome of default reveals important additional insights. Illiquidity in the market for real assets during industry distress implies that more bankrupt firms, including inefficient going concerns, are likely to emerge as restructured firms than to be sold to alternative users or to be liquidated. This should lower creditor recoveries in cash-flow terms relative to selling assets at full value. Furthermore, if the fire-sales effect is at work, then during times of industry distress, bankruptcy of defaulted firms should take longer to resolve (see, for example, Bris, Welch, and Zhu, 2003, discussed below). This delay should lower recoveries in present-value terms. We find evidence consistent with these hypotheses. In contrast to times when there is no industry distress, we find that when the industry is in distress, there are virtually no cases of liquidation or acquisition over our entire sample period: Most distressed firms emerge as restructured entities during industry distress, a finding that is consistent with the literature on asset sales. Furthermore, firms spend more time in bankruptcy during periods of industry distress: 2.16 years versus 1.37 years in times of no industry distress.

Finally, we check whether the industry-distress effect on recoveries is robust to macroeconomic and bond-market conditions at the time of default. We employ data from Altman, Brady, Resti, and Sironi (2003) who find that aggregate recovery rates are negatively related to aggregate default rates and to aggregate supply of defaulted bonds. We find that the aggregate default rate in the default year and the aggregate supply of defaulted bonds measured mid-year in the default year (Altman et al. variables BDR and BDA, respectively) significantly lower recovery rates when employed in the *absence* of industry conditions. However, once industry conditions are employed, the effects of aggregate default rates and supply become weak or insignificant. In contrast, the industry distress effect retains its economic magnitude and statistical significance. The linkage between bond market aggregate variables and aggregate recoveries is stressed by Altman et al. as arising from supply-side effects in segmented bond markets. We conclude that in addition to (and possibly instead of) the illiquidity in the financial market for trading defaulted instruments, illiquidity in the market for the sale of real assets is important in understanding creditor recoveries.

To summarize, we provide evidence that in times of industry-wide distress, creditor recoveries are significantly depressed, and in a manner that is consistent with anticipation of fire-sale prices in such times. This constitutes an indirect cost of corporate default that may have important consequences for capital-structure choices of firms. Viewed in another light, our results demonstrate that recovery risk – unpredictable variation in creditor recoveries over time – exists and its magnitude is economically significant. Our corporate-finance investigation of creditor recoveries thus has important implications for credit-risk models in the asset-pricing literature. In particular, we document that the determinants of risk of default and the risk of recovery are positively, but not perfectly, correlated. In particular, the effect of industry distress on recovery risk remains unaffected by the presence of default-risk proxies. This provides preliminary evidence that credit-risk models incorporating recovery risk would likely also need to model industry conditions as a separate state variable.

The remainder of the paper is structured as follows. Section 2 presents the related literature and our hypotheses. Section 3 discusses the data. Section 4 presents summary statistics. Section 5 presents the regression results as well as non-parametric results. Section 6 compares the determinants of recovery risk with the determinants of default risk. Section 7 concludes.

2 Hypotheses Development

Before stating the hypotheses we test, it is useful to briefly review the literature that is related to our investigation of fire-sales effects in creditor recoveries.

Related literature: Prior work that has tested implications of the Shleifer and Vishny model using data on asset sales in the United States is as follows: Asquith, Gertner, and Scharfstein (1994) find in their study of “junk” bonds during the 1970s and 1980s that the use of asset sales in restructuring of distressed firms is limited by industry conditions such as poor performance and high leverage. Pulvino (1998) examines data on asset sales in the airline industry. He finds that companies that sell aircraft when they are financially constrained, or companies that sell aircraft when the industry is doing poorly, receive a lower price for these aircraft than companies that sell aircraft at other times. Our study complements this literature in that it also provides evidence in line with the Shleifer and Vishny model, but instead of examining limited data available on asset sales, it examines how industry distress affects creditor recoveries using comprehensive data on defaults in the United States (from 1982 to 1999 and spanning all industries). However, using a sample of 31 highly levered transactions, Andrade and Kaplan (1998) find evidence that high leverage is the primary cause of distress. They also find that poor firm performance, and then poor industry performance, play a role, albeit a smaller one.

In addition to these papers, Franks and Torous (1994) examine the recovery rates of different classes of creditors in the event of a distressed exchange of securities or a bankruptcy. The recovery rates in their sample are largely based on book values of securities received in a reorganization or bankruptcy. Hotchkiss (1995) documents an important result that firms that emerge from Chapter 11 tend to default again subsequently. Therefore, recovery rates based on book values are likely to overstate true recoveries. We use the market prices of debt and thereby circumvent this problem.[5] Izvorski (1997) examines the recovery ratios for a sample of 153 bonds that defaulted in the United States over the period 1983–1993 but does not examine effects related to industry distress. In a recent paper, Bris, Welch, and Zhu (2003) examine recoveries for defaults in Arizona and New York over the sample period 1995 to 2001. They find that firms that emerge as restructured firms in Chapter 11 recover more than firms that are liquidated (Chapter 7). Although this is true in our data as well, note that our focus is on whether firms in either category, emergence or liquidation, recover less during times of industry distress and, if so, whether this is due to the fire-sales effect.

In evidence outside the United States, Thorburn (2000) looks at the recovery rates for debt in a set of bankruptcy auctions in Sweden and documents a significant effect on recoveries of a binary variable signifying if bankruptcy occurred during an economic downturn (year 1991) or not. In contrast, the focal point of our study is the effect of *industry-specific* characteristics on debt recoveries during times of distress. Finally, there is less than a perfect consensus on evidence for fire sales in the Swedish bankruptcy auctions: Stromberg (2001)

[5] Franks and Torous (1994) do report recovery rates for a sub-sample of 10 cases of distressed exchanges and 12 cases of bankruptcy based on market values for all securities received by the given creditor class. The median recovery for this sub-sample was significantly lower than their overall sample, providing a further justification for using market-based recovery measures.

finds evidence consistent with the fire-sales hypothesis, whereas Eckbo and Thorburn (2002) conclude that evidence is consistent with overbidding in auctions rather than with fire sales.

In a recent paper, Brown, Ciochetti, and Riddiough (2006) study sales of commercial real estate assets by financially distressed firms over the period 1974–1990. In findings that are resonant with those of this paper, they show that asset sales are delayed in the absence of well-capitalized and deep-pocket investors: In the worst years of real estate downturn, only about 12% of the foreclosed asset inventory was sold per year, whereas during the extended recovery of 1993 and 1994, between 30% and 40% of assets were sold and at lower discounts to fundamental value compared to those in downturn. Finally, in another recent contribution, Dieckmann, Martin, and Strickland (2006) also show using the set of corporate bond defaults during 1918–1929 that creditor recovery is negatively related to time in default and the total amount of defaulted debt in the same industry group.

Hypotheses: The principal question we wish to address is whether industry-wide distress affects creditor recoveries and, if yes, whether this is due to the economic-downturn effect or (also) due to the anticipation or realization of asset fire sales.

In times of industry distress, the economic worth of assets generally falls. Indeed, this fall may have been the cause for distress in the first place. However, in times of industry distress, the liquidation value of assets could fall below the revised economic worth of assets due to the fire-sales effect proposed by Shleifer and Vishny (1992). Shleifer and Vishny's model provides the theoretical insight that financial distress is more costly for firms if they default when their competitors are experiencing cash flow problems. This renders difficult for an empiricist the identification problem as to whether industry-wide distress affects firm values and creditor recoveries through the economic-worth channel and/or through the fire-sales channel. To circumvent this identification problem, the econometric strategy we employ is to test for the effects of industry-wide distress (i) after controlling for the determinants of the economic worth of firm assets and crucially (ii) by studying interaction effects. In particular, we test the effect of industry-wide distress differentially across industries (based on asset-specificity) and also across industry conditions at the time of default (based on the number of peer firms and their liquidity). These interactions generate varying severities of the fire-sales problem, and, in turn, lend statistical power to our tests for isolating the effect of fire sales on creditor recoveries from that of a decline in economic worth of assets.

In fact, the Shleifer and Vishny model has precise implications regarding such interaction effects. To elaborate, they consider the scenario where a firm responds to financial distress by asset sales. Whether the assets are sold to an industry insider or an outside buyer depends on the valuations and abilities to pay of both parties. If the assets are specific to an industry, that is, not easily redeployable outside the industry, then inside buyers are likely to place a higher value than outsiders due to their ability to be a more productive user. In contrast, if the assets are generic, both inside and outside buyers are likely to place a similar value. During industry recessions, even if the industry insider is a more productive user, he will be unable to offer the best value for the assets. If the insider's financial constraints are much more severe than those of the outsider, the outsider will outbid and the assets will be redeployed to a lower value use. We examine the implications of the model for valuation and recoveries of one class of firms' financial assets – the debt instruments. Our focus thus complements the earlier studies that consider actual asset sales. Note, however, that using the Shleifer and Vishny model as a motivation for testing the effects of industry distress on creditor recoveries requires an extra logical step. This step is to recognize that valuable information about *anticipated* liquidation values can be embedded in bond prices due to the effect of these values on the bargaining outcomes between equityholders and creditors. In other words, looking at debt recoveries can enable the empiricist to understand the magnitude of losses expected from distressed asset sales, even if such asset sales do not actually occur in times of industry-wide distress.

Specifically, if the distress of the firm entails asset sales to pay creditors, or if the firm is likely to be liquidated, then the liquidation value of assets would affect creditor recoveries. However, even if asset sales or liquidation do not actually take place (as is the case for many defaults), the anticipation of low prices for asset sales could give greater bargaining power to equityholders in writing down creditor claims. This is because in Chapter 11 in the U.S., debtors have the first-mover advantage in filing a reorganization plan.

For sake of argument, suppose the debtors can make a take-it-or-leave-it offer to creditors (Anderson and Sundaresan, 1996, and Mella-Barral and Perraudin, 1997). If the take-it-or-leave-it offer is rejected by creditors, the firm would be liquidated. Then, the first-mover advantage enables the debtors to strategically offer to creditors only the value that the creditors would receive if the firm's assets were liquidated. The firm may eventually get reorganized, acquired, or merged, but the creditors receive simply their expected value from the scenario where the firm is liquidated.[6] In reality, the bargaining powers may not be distributed so unequally. Nevertheless, the presence of a first-mover advantage to equityholders in the U.S. bankruptcy code opens up the possibility that creditor recoveries are affected by the liquidation value of assets, even if the firm is not eventually liquidated.

[6]The recent example of the bankruptcy of United Airlines illustrates this point well: "Some of the US's leading companies, including Ford and Philip Morris, are facing billions of dollars of losses on United Airlines leases... The US airline believes it can slash its costs by renegotiating its $8bn of aircraft leases that are spread among 300 companies, ranging from Walt Disney to Pitney Bowes and DaimlerChrysler. It plans to send revised terms to leaseholders over the next three days... United's advisers argue it is in a strong negotiating position because of the weak market for used aircraft." (*US groups face UAL lease losses*, by Robert Clow in New York, *Financial Times*, December 13, 2002). Indeed, general creditors have even less bargaining power than lessors do, and such effects should magnify their losses.

An alternative possibility is that the illiquid market for sale of real assets could render the resolution of distress slower as the firm keeps soliciting alternative bids and the creditors await a change in business environment for at least some time before accepting any restructuring package.[7] This delay by itself may lead to lower creditor recoveries in present-value terms. It also should be noted that a likely delay in bankruptcy resolution also can strengthen the bargaining power of equityholders and management against the creditors.

In either of these possible cases, the implication is that the interaction of industry-level distress and asset-specificity should lead to more depressed recoveries for creditors with weaker bargaining power and whose priority and security make them vulnerable to asset-value fluctuations. To the extent that the fire-sales effect works on industry-specific assets, it is plausible that secured debt backed by such collateral may be the worst affected. In practice, however, secured debt is often over-collateralized, precisely to avoid such an outcome. If this is the case, then the worst effects would be experienced by the next set of creditors in priority, namely the senior unsecured debt. By this argument, the junior debt of the defaulted firm may not experience varying fortunes between industry distress and otherwise.

With this background, we state our primary empirical hypotheses: (1) Poor industry conditions when a company defaults should depress creditor recoveries; (2) Industries that have more specific assets and creditors backed by industry-specific collateral should have lower recoveries when industry conditions are poor; (3) The interaction effect of industry-level distress and asset-specificity may be stronger for next-in-priority creditors such as senior unsecured debt if the secured debt is over-collateralized; and (4) Firms operating in industries with fewer players should have lower recoveries in an industry-wide distress due to the lack of an active market of bidders in poor industry conditions. Although the first hypothesis arises under both candidate explanations – the economic-downturn channel and the fire-sales channel, the remaining hypotheses pertaining to the interaction effects are specific to the fire-sales channel.

[7] A case in point here is the resolution of failed financial institutions in the Great Depression in the 1930s, when the regulators awaited bids from alternative buyers for several years, before eventually throwing open the piecemeal auction of banks and financial institutions to all potential bidders. The resolution of the Savings and Loans crisis in the 1980s similarly took longer than individual bankruptcies. Finally, in the recent airline industry defaults of 2001 and 2002, workouts at both US Airways and United Airlines have taken over two years, at least partly due to the weak market for used aircraft and the inability (or lack of interest) of other players in the industry to buy these firms and their assets.

3 Data

Our data source is the Credit Pro database (version 4.0) developed by Standard and Poor's (S&P). The database contains recovery data developed by Portfolio Management Data (PMD, a part of S&P). The PMD data includes recovery information in the form of price emergence on bank loans, high-yield bonds, and other debt instruments, totaling over $100 billion. The information is derived from more than 300 non-financial, public and private U.S. companies that have defaulted until the end of 1999. The coverage becomes extensive after 1987. In addition, the database also provides information on collateral backing the instruments in default. For debtors that have emerged from bankruptcy, emergence dates also are furnished. The source data was obtained by S&P from bankruptcy documents: reorganization and disclosure statements, Securities and Exchange Commission filings, press articles, press releases, and their internal rating studies on the issuer.

The PMD database measures recoveries at emergence (henceforth denoted as Pe) using three separate methods: (1) Trading prices of pre-petition instruments at the time of emergence; (2) Earliest available trading prices of the instruments received in a settlement; (3) Value for illiquid settlement instruments at the time of a "liquidity event" – the first date at which a price can be determined, such as the subsequent acquisition of the company, significant ratings upgrade, refinancing, subsequent bankruptcy, or distressed exchange. There are 1,511 observations of Pe in this data. The sample of prices at emergence from PMD database is close to being exhaustive and captures well the set of defaults in the United States over the period 1982 to 1999. Our data does not contain trade credit or project finance instruments, recovery rates for which likely behave differently from those for bank loans and public bonds.

It should be noted that the measure of recovery, Pe, is given in nominal terms and should be interpreted as Recovery of Face Value or Recovery of Par. This way of measuring recovery is often used in practice and is justified by the fact that when a firm defaults on any one of its obligations, cross-acceleration clauses typically cause all its other claims to also file for default. Furthermore, interest ceases to accrue on unsecured claims once the firm is in bankruptcy. Collateralized instruments are the exception as they continue to accrue post-petition interest (after filing for bankruptcy) and thus the amount payable can exceed par.[8]

[8]Guha (2003) discusses the institutional underpinnings of Recovery of Face Value as the appropriate measure of recovery. In particular, Guha documents with examples (Enron Corp. and WorldCom Inc.) that prices of bonds of a corporation with different maturities and coupons but the same seniority differ substantially before bankruptcy; however, once the bankruptcy is announced, the prices of these bonds converge to identical or close to identical values, since bond covenants contain a provision that makes the principal amount immediately payable upon default. We have confirmed this finding by also examining

We obtain the firm and industry variables for our analysis by cross-matching the CUSIPs of these firms with the CRSP–COMPUSTAT merged database. Several of the defaulted companies were private at the time of default since they had undergone leveraged buy-outs prior to the default event. Therefore, we were unable to obtain accounting or stock market data for these firms around the time of default or even one year prior to default.

4 Creditor recoveries: Summary

We assume the price at default of each instrument is an unbiased estimate of its actual recovery at emergence. Our approach is consistent with Eberhart and Sweeney (1992) who have documented that bond prices at the time of bankruptcy are unbiased estimates of the bonds' payoff upon settlement of the bankruptcy. For investors who sell or mark to market their instruments once default occurs, the price at default is indeed the relevant measure of recovery. Thus, we need to adjust the recovery prices at emergence (which forms our data sample) in order to interpret them as recoveries upon default. Otherwise, the time value of when creditors actually recover their funds is not suitably accounted for: Each defaulted firm's private work-out or bankruptcy takes a different period of time so that the duration between default and emergence dates is not identical for different default instances.

Hence, we construct emergence prices discounted at high yield index, denoted as $Pehyld$:

$$Pehyld = Pe * \frac{I_d}{I_e} , \qquad (1)$$

where I_d and I_e are the level of a high-yield index at default date and at emergence date, respectively. We employed Lehman Brothers, Salomon Brothers, and Merrill Lynch high-yield indices since none of these indices were available for use over the entire sample period.[9]

We verify in the unabridged version of the paper that the discount rate employed is suitable. In particular, for a substantially smaller sub-sample of firms we also have data on actual prices at time of default, denoted as Pd. For this sub-sample, we show that $Pehyld$

prices on defaulted instruments provided by LoanX (now part of MarkIt Partners), a new data service started jointly by a group of the largest investment banks. Our private communication with "distress" hedge-fund managers also revealed that they often engage in convergence trades between bonds of the same firm with differing maturities in order to bet that the firm will default, an event that would make prices of these bonds identical.

[9] These indices are total return indices. For example, Merrill Lynch High Yield Master II index is a market value-weighted index comprised of 1,800 domestic and yankee high-yield bonds, including deferred interest bonds and payment-in-kind securities. Issues included in the index have maturities of one year or more and have a credit rating lower than BBB–/Baa3, but are not in default. The index is a fully invested index, which includes reinvestment of income.

divided by Pd is not related to risk factors such as Fama French factors and the high yield return. Hence, throughout the paper we employ $Pehyld$ as our unbiased, present-value measure of creditor recoveries.

Time-series behavior: In Table 1 Panel A, we describe the time-series behavior of recovery prices at emergence. The number of firm defaults is quite small during the period from 1982 to 1985 (under fifteen), picks up rapidly reaching its maximum during the recessionary phase between 1986 and 1992, and reduces somewhat in the mid-1990s. The mean (median) recovery rate at emergence is 51.11 (49.09) with a standard deviation of 36.58. There is a substantial variation in these recoveries through time. Figure 1 plots the time-series variation in the number of firm defaults and median recovery price at default ($Pehyld$) in each year. There is a negative relationship between $Pehyld$ and aggregate default intensity, the relationship being particularly strong for the period starting 1987. For this period, the mean and the median $Pehyld$ are lowest in 1990, with respective values of 41.24 and 34.14, with a standard deviation of 35.78 for the year. This coincides with a period of deep recession in the U.S. The number of firm defaults in 1990 and 1991 were respectively 69 and 81.[10]

Effect of Industry: In Panel B, we present the industry-based summary for recovery prices at emergence. Our data divides the defaulting firms into 12 industries using S&P's classification. Based on emergence date recovery data, the highest number of firm defaults have been for the Consumer and Service sector, Leisure Time and Media sector, and Aerospace, Auto and Capital Goods industries, the numbers being 126, 54, and 46, respectively.

Consistent with the evidence of Altman and Kishore (1996), who examine 696 defaulted bond issues over the period 1978 to 1995, we find recoveries are the highest for the Utility sector. The mean (median) recovery at emergence is 74.49 (76.94). These levels are statistically different from mean recoveries for other industries (at 5% level using the Scheffe, 1953, test). However, it should be noted that while the number of instrument defaults is large for the Utility sector, the number of firm defaults in this sector has been quite low (9 firms). The mean recoveries are not statistically different across the other 11 industries, though the Energy and Natural Resources sector does stand out with mean (median) recoveries at emergence of 60.41 (58.80). Thus, the Utility sector appears as being different from other

[10]Though we do not have complete data on recoveries after 1999, the recent evidence on recoveries is a point in case for the negative correlation between aggregate default intensity and recovery levels. In 2002, global defaults hit a record amount of $157.3 billion, and simultaneously bank loans achieved their lowest recovery rate of 72% (in terms of value of instruments received at emergence). This recovery is 8% to 10% below the 15–year mean for bank loan recoveries of 81.6%. Indeed, unsecured bondholders have recovered even less: 28% in 2002 and 22.1% in 2001 compared to the 15–year mean of 46%. See "Unsecured Bondholders Hit Hardest in 2002 Amidst Declining Recovery Rates," Standard and Poor's (www.risksolutions.standardandpoors.com).

industries (perhaps partly due to regulatory issues), but the simple industry classification by itself does not have much power in explaining the cross-sectional variation of defaults.

Effect of Seniority and Collateral: In Panel C, we classify defaulted instruments by seniority. The categories in decreasing seniority are: Bank Loans, Senior Secured, Senior Unsecured, Senior Subordinated, Subordinated, and Junior Subordinated. In level terms, median recoveries at emergence decline from 91.55 cents for Bank Loans, to 26.78 cents for Senior Subordinated instruments, and further down to 6.25 cents for Junior Subordinated instruments. Comparing the mean recoveries across these different seniority categories, we find that 11 out of 15 pair-wise means are different at the 5% level using Scheffe's test.

Panel D documents the behavior of *Pehyld* across these collateral categories. About two-thirds of our sample (1,005 of 1,511 defaulting instruments) has no collateral information. We have verified that most of these instruments are in fact un-collateralized bonds. The Unsecured category corresponds to un-collateralized loans.

Instruments backed by Current Assets have the highest mean (median) recovery of 94.19 (98.81) cents on a dollar, and those backed by All or Most Assets have the second-highest mean (median) recovery of 80.05 (89.16) cents. The other collateral categories (PPE, Real Estate, Other Assets, Unsecured, and Secured) have mean recoveries ranging from 63.0 to 72.0 cents. When no information is available on collateral, mean (median) recovery is the lowest at 38.64 (30.91). Although there is some cross-sectional variation in recoveries across these categories, only the mean recoveries for instruments backed by Current Assets and for instruments with no collateral information (un-collateralized bonds) are statistically different from other collateral categories at 5% statistical significance level using a Scheffe's test.

This descriptive summary of our data suggests that contract-specific characteristics such as seniority and security (collateral), industry of defaulting firm (utility sector or other sector), and macroeconomic condition (aggregate default intensity), are likely to play an important role in explaining variation in recoveries. Within all categories, there remains a substantial variation in recoveries around the means. In order to develop a more formal model of factors that determine the remaining time-series and cross-sectional variability in creditor recoveries (and the interaction of these two forms of variability), we proceed to a multi-variate regression analysis.

5 Effect of Industry Distress on Creditor Recoveries

Our primary tests relate the discounted prices at emergence of defaulted instruments to industry distress and its interaction with those industry characteristics that should produce a differential effect of industry distress through the fire-sales channel. We test variants of the specification:

$$\begin{aligned}\text{Recovery} &= \alpha_0 + \alpha_{\text{ industry}} + \beta * \text{Contract Characteristics} + \\ &\quad \gamma * \text{Firm Characteristics} + \delta * \text{Industry Q} + \\ &\quad \theta * \text{Industry Distress} + \omega * \text{Industry Characteristic} + \\ &\quad \mu * \text{Industry Distress} * \text{Industry Characteristic} + \epsilon \ . \qquad (2)\end{aligned}$$

We test this specification on pooled data that combines the entire time-series and the cross-section of recoveries on defaulted instruments, dropping the Industry Characteristic if it is time-invariant (and thus subsumed by the industry fixed-effect). In all our tests, we use ordinary least squares estimates, and standard errors of these estimates are adjusted for heteroscedasticity using the White (1980) estimator and also adjusted for the existence of firm-level clusters as described in Williams (2000) and Wooldridge (2002). That is, we consider each firm's debt instruments as a single cluster. This helps us address the issue that a single distressed firm may have multiple defaulted instruments, and all these instruments show up in our data as separate observations.[11] All our regressions include industry dummies using the classification employed by S&P.

We describe below the construction of various contract, firm, and industry characteristics employed in the tests.

Contract Characteristics: We consider seniority of the instrument (dummies for Bank Loans, Senior Secured, Senior Unsecured, Senior Subordinated, Subordinated) and collateral of the instrument (dummies for Current Assets and Unsecured). These factors were found to be relevant for recoveries in the summary statistics of Section 4. Larger issues may earn higher recoveries since a larger stakeholder may exert greater bargaining power in bankruptcy. Hence, we include Log (Issue Size) as an additional control in our tests.[12]

Firm Characteristics: Since accounting data is difficult to obtain in the year of default, we

[11] The average number of defaulted instruments per firm in our sample is about 4.5, and only eight firms in the whole sample have multiple firm default observations. Defaults on instruments of the same firm that are separated by more than one year are counted as being parts of separate firm default observations. The eight firms experiencing such multiple defaults are: Ballys, Caldor, Cherokee, Greyhound, Heileman, New Valley Corp, TWA, and Zale. The rest of the firms have defaults of different securities within a 3-month period of the first default and these are counted as being part of a single firm default observation. The difference of about 3-month period arises due to the fact that bank loans typically default first followed by bonds.

[12] Another candidate for bargaining power is Issue Size divided by Total Size which controls for the overall quantity of debt issuance by the firm. In unreported tables, we did not find this proxy to be significant. Hence, we include Log (Issue Size) in all the tables as it does show up as being significant in some of the specifications.

follow prior literature by using firm-level accounting data one year prior to default. The first three firm-specific characteristics considered in the specification are: Profit Margin, defined as EBITDA/Sales for the defaulting company; Leverage, measured as Long-Term Debt to Assets ratio - we report results only with book leverage as employing market leverage yielded similar results; Log (Assets), the natural log of total book assets, as a proxy for firm size. From Table 2, the median values of these characteristics for firms in our sample are: 7% profitability, 49% book leverage ratio (76% market leverage ratio), and 6.14 for log of asset size which corresponds to $464 million of assets (all in the year preceding default).

The profitability of a firm's assets should positively affect recoveries: The greater the profitability, the more a potential buyer would be willing to pay for it (all else being equal). Though we include the leverage of the firm, its effect on recoveries is somewhat difficult to anticipate ex ante. Bankruptcy proceedings of high-leverage firms may be more difficult to resolve: Higher leverage may be associated with greater dispersed ownership requiring greater coordination among bargaining parties. Conversely, high leverage may proxy for highly leveraged transactions (especially in 1990) that were easily restructured. Finally, high leverage may imply lower recoveries for junior class of creditors.

The next three firm-specific characteristics we consider are: Tangibility, proxied by the ratio of Property, Plant, and Equipment (PPE) to Assets; No. of Issues, measured as the total number of issues defaulting for the defaulted company; and Debt Concentration, the Herfindahl index measured using the amount of the debt issues of the defaulted company. The median values of these characteristics for firms in our sample are: 35% for tangibility of assets, 4.0 number of defaulted issues, and 0.34 Herfindahl index of debt concentration among defaulted firms. The tangibility of assets is generally expected to enhance recovery rates. Firms with greater number of issues and more dispersed creditor base, that is, lower debt concentration, may experience greater coordination problems and in turn lower recovery rates for creditors.

Industry Characteristics: Following the literature, the industry of a defaulted firm is identified as the set of firms with the same 3-digit SIC code as the defaulted firm. All industry variables are computed using data from CRSP and COMPUSTAT and are measured contemporaneous to default, that is, in the year of default. The defaulted firm is excluded from calculation of industry variables. If the 3-digit SIC code of a defaulted firm does not include at least five other firms, then we do not include the observation in the tests.[13]

Our primary measure of industry's poor conditions is based on how distressed the industry is as a whole. In the spirit of Gilson, John, and Lang (1990) and Opler and Titman (1994),

[13]We did not however find this exclusion to have any significant effect on our results: It switched only three observations from no industry-wide distress to industry-wide distress, all for SIC code 790 in the year 1994.

we define an industry to be "distressed" if the median stock return for the industry of the defaulting firm in the year of default is less than or equal to -30%. We call this dummy Distress1. In our data, this industry dummy takes on the value of 1 for about 9% of the sample based on the number of defaulted firms (and about 13% in terms of defaulting instruments). We consider several variants of this basic measure which we elaborate on while reporting the results.

In addition, we also employ measures of financial constraints – illiquidity and leverage – for firms in the industry to proxy for poor conditions. Industry illiquidity is proxied using (i) Illiq1, the inverse of the median Interest Coverage ratio, measured as EBITDA/Interest, as frequently employed in empirical corporate finance to proxy for industry liquidity conditions (for example, Asquith, Gertner, and Scharfstein, 1994, and Andrade and Kaplan, 1998);[14] and, (ii) Illiq2, the inverse of the median Quick ratio, measured as [Current Assets - Inventory] divided by Current Liabilities, as employed by Stromberg (2001). Median Industry Leverage is the median Long-Term Debt to Assets for all firms in the industry. Illiq1, Illiq2, and Median Industry Leverage have median values of 32%, 100%, and 20%, respectively in our sample (Table 2).

The asset-specificity of an industry is calculated as the median of Specific Assets of all firms in that industry and over the entire sample period. As in Berger, Ofek, and Swary (1996) and Stromberg (2001), we define Specific Assets of a firm as the book value of its machinery and equipment divided by the book value of total assets. Under their classification, Cash and Cash equivalents, and Property (non-industrial real estate) are Non-specific assets, and other assets such as Working Capital are Intermediate assets. It is in order to stress that Specific Assets is not identical to Tangible Assets, measured as the book value of property, plants and equipment divided by the book value of assets, since property is considered under the classification as being readily redeployable across industries. What is of interest in testing the fire-sales effect is the interaction of industry-level asset-specificity with proxies for poor conditions of the industry: Distress1, Illiq1, Illiq2, and Median Industry Leverage. Finally, Peer Firms for a defaulted firm is proxied by the number of firms in the industry. From Table 2, the median values of these variables for industry-year pairs in our sample are: 16.92% for asset specificity and 38 for the number of peer firms in the industry.

We include the Median Industry Q to proxy for the growth prospects of assets which also should affect recovery rates positively. Median Industry Q is the median of the ratio of market value of the firm (estimated as book value of total assets − book value of total equity + market value of equity) to the book value of the firm (estimated as book value of total assets). The median is taken over all other firms in the 3-digit SIC code of the defaulted

[14] When median interest coverage ratio for the industry is negative, we set it to zero, and calculate Illiq1 using the formula 1 / (0.001 + median interest coverage ratio).

firm. The median value of this variable for industry-year pairs in our sample is 0.94.

5.1 Direct effect of industry distress

In Table 3, we report results from estimation of equation (2) without employing industry characteristics or their interaction with industry distress. We find that when the defaulting firm's industry is in "distress," as defined by Distress1, its instruments recover about 11.11 cents less on a dollar compared to when the industry is healthy, an effect that is statistically significant at the 1% confidence level. This effect is economically large and statistically significant even after controlling for industry fixed effects. The magnitude of the effect is about half of the average relative effect of seniority of the instrument (Bank Loans vs. Senior Debt vs. Subordinated Debt). This provides strong support for the first hypothesis that poor industry conditions when a company defaults depress recovery rates on the defaulting company's instruments.

One interpretation of the result is that a very high negative median stock return for the industry arises when assets of this industry are not expected to be profitable in the future. That is, the median stock return for industry may in fact proxy for expected profitability of assets of the defaulting firm, a very high negative return generating lower recoveries simply because defaulting firm's assets are fundamentally not worth much. This argument would generate a negative coefficient on Industry Distress dummy without any role for fire sales that depend upon the conditions of peer firms in the industry.

In itself, it is somewhat difficult to use this evidence to disentangle which of the two effects – fall in the economic worth of assets or the fire-sales effect (or perhaps both) – is at work. However, some conclusions can be drawn based on the following observations. First, we have controlled for the Profit Margin of the defaulting firm one year prior to default. We have also included median industry Q in the specification. Our assumption is that median industry Q proxies for future growth prospects of the industry and in turn of the defaulting firm's assets. Thus, examining the coefficient of distress dummies in the presence of firm-level and industry-level measures of profitability helps us (at least in part) control for the economic-downturn effect. This assumption is strongly borne out in the estimates: In Table 3, in all specifications, the coefficient on Profit Margin is positive and significant at the 1% level, and the coefficient of Median Industry Q is also positive and significant at the 1% level.

Second, if industry conditions merely capture the expectation of future growth prospects and its effect on the economic worth of assets, then the positive linkage between industry conditions and recoveries should be symmetric: When the industry is doing well, debt recoveries should be higher; when the industry is not doing well, debt recoveries should be lower. In Column 2 of Table 3, we include the median stock return for the industry as a continuous, un-truncated variable. We find that the level of median industry return has no incremental explanatory power at all for debt recoveries. That is, the effect of industry return on recoveries is always non-linear and restricted to situations where the industry is in distress. Based on these arguments, we draw a preliminary conclusion that the Shleifer and Vishny fire-sales effect is likely also at work in explaining debt recoveries.

In Columns 3–5, we consider three alternative definitions of industry distress dummies, Distress1a, Distress2, and Distress3. Distress1a is a variant of Distress1 with the default year (in which median stock return for the industry is computed) being centered at the mid-point between default date and emergence date. The two measures have a positive correlation of 0.55, and thus not surprisingly, Distress1a also has a negative and significant effect on recoveries, the magnitude being -10.76 cents on a dollar. This confirms the robustness of the result to measuring industry distress during the period of negotiations between the defaulted firm and its creditors.

In addition to Distress1 being one, Distress2 requires that one-year or two-year median sales growth for the industry in the year of default or the preceding year (based on data availability) be negative. Distress2 is thus based on stock market performance of the industry as well as on the book measure of industry performance and, in turn, is less likely to embed only the expectations of future profitability. That is, Distress2 also reflects the proximity of firms in the industry to financial constraints. We find that the effect of Distress2 is stronger than that of Distress1 by about 40%, implying that even if one were to attribute the entire effect of Distress1 in Column 1 to the downward revision in expectation of future growth prospects, there is a residual effect of industry distress in the Distress2 dummy.

Distress3 is a dummy variable that takes on a value of one if the average (numerical) credit rating of other firms in the industry is below investment grade and zero otherwise. The average credit rating is equally weighted across firms where the numerical rating for each firm is calculated using an assignment of 2 corresponding to AAA rating and 24 to C, so that each unit increase in numerical rating corresponds to a fall in the credit rating by one notch.[15] Unlike Distress1 and Distress2, Distress3 captures purely the proximity of firms in the industry to default. The effect of Distress3 on recoveries is also negative and significant, and about 30% larger than that of Distress1.

Finally, Columns 6 and 7 verify that the effect of Distress1 and Distress1a survives in the sub-sample where we exclude all observations in Utilities and Financial Institutions sectors, which may contain regulatory effects in observed creditor recoveries. Given the similarity in results with different distress dummies, henceforth we chiefly employ Distress1 in our tests.

[15] For example, an increase in numerical rating from 4 to 5 implies a fall in credit rating from AA+ to AA, and an increase from 4 to 7 implies a fall in rating from AA class to A class. While calculating the average credit rating of firms in the industry, we removed all firms whose ratings were "unassigned."

5.2 Interaction of industry distress and asset-specificity

In our most importance piece of evidence, we examine in Table 4 the interaction effects between industry asset-specificity and poor industry conditions, also allowing for the direct effect of asset-specificity. Industry conditions are proxied in separate estimations by Distress1 and Distress1a (Columns 1 and 2), industry illiquidity measures Illiq1 and Illiq2 (Columns 3 and 4), and Median Industry Leverage (Column 5). Specific to the fire-sales effect, all of these interaction effects must be negative. Note that, given only 9% and 6% of the observations are in industry distress as per Distress1 and Distress1a, we have very little power to find the interaction effects even when present in the data. This lack of power notwithstanding, the interaction effects are negative and statistically significant with 1% confidence level, except for the interaction with Median Industry Leverage which has the correct sign but is insignificant.

These interaction effects are also economically significant. Based on Table 2, we find that a standard deviation increase in (i) industry's asset-specificity causes recoveries to fall by around 9 cents on a dollar during industry distress; (ii) industry illiquidity Illiq1 (Illiq2) increases the magnitude of negative marginal effect of asset-specificity on recoveries by around 6 (8.5) cents on a dollar. Furthermore, it is interesting to note that in Columns 1 and 2, the direct effects of Distress1 and Distress1a are rendered insignificant when the interaction effect with asset-specificity is introduced, making a compelling case for the hypothesized fire-sales effect during times of industry-wide distress. In fact their coefficient are positive. This implies that for firms with very low asset specificity, industry distress actually increases recoveries (with a low t-statistic).

The direct effect of asset-specificity on recoveries is generally negative (with the exception of Column 4) and significant (with the exception of Columns 4 and 5). We find that in Columns 1 and 2, this direct coefficient is roughly of the same magnitude as the interaction coefficient with Distress1 and Distress1a. This implies that the negative effect of asset-specificity on recoveries becomes twice as large during industry-wide distress. Under the Shleifer and Vishny hypothesis, asset-specificity should affect recoveries only during industry-wide distress. The fact that asset-specificity also has a direct negative effect on recoveries may thus be attributable to it being correlated with some other determinant of industry-level recoveries on average. This would however refute the hypothesis only if this other determinant is also expected to have a similar interaction effect with industry-wide distress.

Hence, in Columns 6 and 7, we provide additional evidence in support of the fire-sales effect by considering the interaction of Peer Firms with Distress1 and Distress1a, respectively. Consistent with priors, the interaction is positive and significant, with a standard deviation increase in the number of peer firms in the industry raising recovery in times of Distress1 by around 18 cents on a dollar. In this case, the direct effect of the number of peer firms is zero, consistent with the Shleifer and Vishny hypothesis.

Table 4 thus lends firm support to the industry-equilibrium channel for explaining the properties of creditor recoveries. We add to this evidence by examining whether the effect of industry distress and its interaction with asset-specificity is uniform across different creditor types, classified by seniority and security. Though interesting in its own right, this question is important for providing additional evidence on the channel through which creditor recoveries become lower. Specifically, if weak market for asset sales in industry distress strengthens the bargaining power of equity holders and management relative to a set of creditors, then we would expect the recoveries to be lower for that set of creditors.

First, we test in Column 1 of Table 5 how industry distress effect affects creditors with different security.[16] In particular, we interact Distress1 with dummies for whether debt is backed by current assets (first category in Table 1D), industry-specific collateral (second category in Table 1D), or no collateral (last category in Table 1D). Since the value of current assets is not affected by industry-wide distress, we expect the interaction to be insignificant in this case and that is indeed what we find. Also consistent with priors, the effect of industry distress is strong for debt backed by industry-specific collateral, the recovery being lower by around 24 cents on a dollar for this debt in times of distress. Interestingly, recoveries for unsecured debt are also lower by around 20 cents on a dollar during distress.

To investigate this last finding further, we need to examine how the effect of industry distress on collateral values itself gets transmitted across to different seniorities and securities of creditors. In Column 2, we interact Distress1 with seniority – Bank, Senior, and Junior, which correspond to codes 1, 2–4, and 5–6, respectively, in Table 1C. In Column 4, we interact Distress1 with security – Secured and Unsecured, which correspond to codes (1–5, 7) and (6, 8), respectively, in Table 1D. We find that the recoveries on bank debt and junior debt are not different between times of industry distress and otherwise. In contrast, senior debt has lower recoveries in industry distress by close to 21 cents on a dollar. Furthermore, average recoveries for secured debt is also unaffected by industry distress. In contrast, unsecured debt experiences a fall in recoveries by close to 14 cents on a dollar during industry distress.

In Columns 3 and 5, we investigate whether this effect of industry distress on senior unsecured debt is through asset-value fluctuations. To do this, we add to the specification triple-interaction terms between industry-level distress, asset-specificity, and seniority (Column 3) or security (Column 5) of debt. As in Table 4, we find that the effect of industry distress on senior unsecured debt operates entirely through the asset-specificity channel. The triple-interaction effects are significant for senior debt and unsecured debt (and marginally

[16]The control variables employed are the same as in Tables 3 and 4, but we do not report their coefficients to conserve space.

so for junior debt), whereas the double-interaction effect of Distress1 with seniority and security are all rendered insignificant.

This suggests that during an industry-wide distress, bank debt and collateralized debt loses little except when it is backed by industry-specific collateral; un-collateralized senior debt appears to bear the brunt of asset-value fluctuations; and junior debt is unaffected relatively between industry distress and otherwise. The stronger effect for senior unsecured debt is likely due to over-collateralization of secured bank debt which exposes the next-in-line creditors to collateral-value fluctuations. To confirm this, we examine in Columns 6 and 7 respectively the interaction of distress with seniority and the triple-interaction with asset-specificity for those firms where there is no secured debt, whereby any fire-sales effect on asset values would transmit directly to unsecured creditors. Consistent with the over-collateralization argument, we find that (i) the overall effect of Distress1 on unsecured creditors is more negative by about five cents on a dollar when there is no secured debt in the capital structure (Column 6 versus Column 4); and (ii) the triple-interaction coefficient is of almost identical magnitude regardless of the presence of secured debt (Column 7 versus Column 5), echoing the finding that secured bank debt is little affected on average by asset-specificity during times of industry distress (Columns 3 and 5).[17]

5.3 Non-parametric results

To examine the effects of industry distress on creditor recoveries closely, we identify in Table 6 Panel A the industries that experience distress based on Distress1 and the year in which they do so. The table shows the 23 industry-year distress pairs. In Panel B of Table 6, we examine non-parametrically the difference in recoveries between no industry distress years and industry distress years. The difference is 14.6 cents on a dollar and is statistically significant with p-value close to zero. The alternative z-statistic for Wilcoxon rank sum test for the median recoveries between no industry distress and distress samples also has a p-value close to zero. Interestingly, the magnitudes of the differences based on non-parametric tests are close to the ones implied by the coefficients on Distress1 in the parametric regressions of Table 3.

We also examine the difference in recoveries between no industry distress years and industry distress years where we exclude 1990, the NBER recession year, in which nine out of the twenty-three industry distress events occur. This is to confirm that our results are not driven by just one year of economy-wide distress in which recoveries were skewed toward

[17]It is also possible that unsecured debt has relatively weaker bargaining power compared to secured creditors who under the U.S. bankruptcy code are owed interest payments even during bankruptcy (unlike unsecured creditors).

zero. This year was also special in that a large number of defaults occurred in the aftermath of the leveraged buy-out (LBO) phenomenon. We find that the difference in recoveries between no industry distress years and industry distress years (excluding 1990) is of similar magnitude as for the sample which includes 1990, and the difference is also statistically significant with p-value close to zero. This illustrates that it is not per se the existence of an economy-wide recession year which depresses recoveries at emergence. What is crucial is whether the industry of the defaulting firm is itself in distress or not. If an industry is in distress, the recoveries for firms defaulting in this industry are significantly depressed even when the overall economy is not in distress or recession. Finally, we also show that this non-parametric result is robust to the exclusion of Utilities and Financial Institutions, the regulated industries, the difference in recoveries now being in fact larger (around 19 cents on a dollar).

Panel A of Table 7 lists the time-series mean and median of Specific Assets for the twelve industries. The four most asset-specific industries are Transportation (44% median Specific Assets), Telecommunications (30%), Energy and Natural Resources (25%), and Consumer and Service sector (24 %). Insurance and Real Estate and Financial Institutions have close to zero asset-specificity, whereas all other industries have moderate asset-specificity lying between 14% and 17%. Panel A of Table 7 also reports mean and median *Pehyld* for industry-year pairs with no distress and with distress. Panel B correlates industry-level recovery with industry-level asset-specificity for industry-year pairs when industry is in distress in a year and when it is not in distress. Panel B illustrates that there is no correlation between recovery and asset-specificity in industry-year pairs when the industry is not in distress. The correlation coefficients have unstable signs and are not statistically significant. The correlation is however significantly negative in industry-year pairs when the industry is in distress: -0.76 (-0.63) for mean (median) recovery and mean (median) asset-specificity. Industries with highly specific assets (e.g., Transportation and Energy and Natural Resources) experience a significant drop in debt recoveries (about 30 cents on a dollar) when they are in distress relative to their no-distress levels.[18]

It should be noted that for Financial Institutions and for High Technology, Computers, and Office Equipment, recoveries are actually higher when these industries are in distress compared to when they are not in distress. This is due to the small sample size of defaulted firms in distress years for these industries. The correlation patterns are qualitatively

[18]Unfortunately, there is no data in our sample period for Utilities and Telecommunications when these industries are in distress. It is striking to note though that 1999–2002 constituted years of industry distress for Telecommunications sector, and they also were characterized by extraordinarily low debt recoveries for defaulted telecom firms. In particular, many firms (e.g., Exodus and PSI–Net) were unable to sell most of their core telecom assets and their creditors recovered value only from the sale of office space and other such non-specific assets.

unaffected by the exclusion of these two industries. In particular, when these industries are excluded, the correlation between mean (median) *Pehyld* and mean (median) asset-specificity is -0.90 (-0.69) for industry distress years. The corresponding correlations for no industry distress years are insignificantly different from zero.

We believe that the combination of regression-based and non-parametric findings is difficult to reconcile with the alternative hypothesis that debt recoveries are low during periods of industry distress simply because the economic worth of assets has gone down: It is not clear why this effect should be sensitive to the asset-specificity of distressed industries. Overall, we conclude that the fire-sales hypothesis motivated by Shleifer and Vishny (1992) is also significant in explaining the time-series variation in recovery rates.

5.4 Effect of industry distress on outcome of default

We develop further evidence on the effects of industry distress on recoveries by examining the outcome of default in Table 8. Illiquidity in the market for real assets during industry distress implies that more bankrupt firms are likely to emerge as restructured firms than to be sold to (sub-optimal) alternative users or to be liquidated. In addition, the strong bargaining power that industry distress confers upon equityholders and management may imply that many inefficient going concerns continue to operate as restructured firms. This should lower creditor recoveries in cash-flow terms. Furthermore, if the fire-sales effect is at work, then during times of industry distress, bankruptcy of defaulted firms should take longer to resolve: Creditors and firmowners would optimally await the arrival of stronger bids before exercising the option to do a piece meal liquidation of assets that can lead to significant loss of value (see, for example, Bris, Welch, and Zhu, 2003, discussed below). This, in turn, should lower recoveries in present-value terms.

We find that in sharp contrast to times when industries are healthy, there are virtually no cases of liquidation (one) or acquisition (zero) when industries are in distress: Over our entire sample period, most defaulting firms from the sample of firms employed in the regression results emerge as restructured firms during periods of industry distress (top half of Panel A).[19] Similar to the the findings of Bris, Welch, and Zhu (2003), firms in our sample that emerge as restructured firms in Chapter 11 recover more than firms that are liquidated (Chapter 7). Crucially, Panel B of Table 8 suggests that firms spend more time in bankruptcy during periods of industry distress: 2.16 years as against 1.37 years in times of

[19]Unreported parametric tests based on logit regressions for the likelihood of emergence from bankruptcy as a restructured firm (as against being acquired or liquidated) confirm the importance of industry distress as a key determinant.

no industry distress. This difference is statistically significant at the 1% level. These results are strikingly similar between the regression sample and the overall sample, as evidenced by the bottom halves of Panel A and Panel B. Overall, this evidence is consistent with our starting hypotheses, and suggests that delayed resolution to avoid fire sales is an important reason why creditors recover less in present-value terms during industry distress.

5.5 Effect of macroeconomic and bond market conditions

We test whether the effect of industry distress on creditor recoveries is robust to macroeconomic and bond-market conditions at the time of default. Specifically, we examine the bond-market variables shown by Altman, Brady, Resti, and Sironi (2003) to be significant in explaining the time-series of *average annual recoveries*. These variables are: BDR, the aggregate weighted average default rate of bonds in the high yield market where weights are based on the face value of all high-yield bonds outstanding in the year; and BDA, the total face value amount of defaulted bonds in a year measured at mid-year and in trillions of dollars. From Table 2, we see that both BDA and BDR are highly skewed variables; median aggregate default rate is about 2% reaching a maximum value of 10%. Similarly, median face value of defaulted bonds in a year is about 4 billion dollars with a maximum of 23.5 billion dollars (in 1999).[20]

If we interpret high values of BDR and BDA as capturing adverse macroeconomic conditions, then the negative effects of these variables on creditor recoveries would be consistent with the hypothesis that poor macroeconomic conditions reduce the ability of potential buyers to pay high prices for these assets. Altman et al. in fact do find such an effect. They find that BDR and BDA (and their logarithms) affect average annual recoveries significantly and negatively. In particular, a 1% increase in BDR, the aggregate default rate, is associated with a reduction of 4% in aggregate recoveries. Similarly, a 10 bln. USD increase in BDA, the supply of defaulted bonds, is associated with a lowering in aggregate recoveries of 4.5%. However, in addition to the effect from a fall in the economic worth of assets, Altman et al. present the hypothesis that such a negative effect may capture supply conditions in the defaulted bond market: The set of investors participating in the defaulted bond market is segmented and limited mainly to vulture funds, hedge funds, high-yield desks, and a few high net-worth individuals. A greater supply of defaulted bonds for a limited demand could imply that the prices on defaulted bonds must fall in order to clear the markets.[21]

[20]The time–series variation in BDR and BDA is also quite large. For example, in the Altman et al. data, the aggregate default rate is 1.6% in 1998 and 9.6% in 2002. Similarly, the aggregate defaulted amount was $7.5bln in 1998 and $63.6bln in 2002, the latter being driven by large number of defaults in telecom, airlines, and steel sectors.

[21]This is also the perceived wisdom in some industry literature concerning the depressed prices of defaulted

We attempt to disentangle whether it is the illiquidity in market for real assets or illiquidity in financial market for defaulted securities that causes recoveries to be low during periods of industry distress. In addition to BDR and BDA, we capture the extent of macroeconomic risk in the year of default by examining the effect of SR, the S&P 500 stock return for the year, and GDP, the annual Gross Domestic Product growth rate. In Table 9, we report the estimates of specifications wherein we employ these four variables one at a time, in the presence as well as absence of Distress1. As the table reveals, the macroeconomic and bond market conditions are not significant determinants of recoveries, once industry dummies and industry conditions (Distress1 and Median Industry Q) are controlled for. The coefficients on SR, GDP, BDA, and BDR are either rendered insignificant or reduced in significance in the presence of controls for industry conditions. Since Altman et al. examine annual average recovery rates, such industry-level conditioning is not possible.[22] In contrast, in Table 9 the macroeconomic and bond-market conditions do not drive out the effect of industry distress on *Pehyld*. The effect of Distress1, even in the presence of these variables, is negative, significant always at 5% level, and of the order of 10–14 cents on a dollar as before.

We conclude that industry conditions are an essential ingredient of a specification that explains well the time-series variation in recoveries. Also, our results suggest that the linkage between bond market conditions and recoveries stressed by Altman et al. as arising due to supply-side effects in segmented bond markets may be a manifestation of omitted industry conditions. Indeed, it is difficult to be certain that illiquidity in the financial markets for trading defaulted instruments causes lower recoveries during industry distress: An equally (if not more) likely candidate is the change in the economic worth of assets and illiquidity in the market for real assets during industry downturns.

6 Recovery Risk and Default Risk

To summarize our results, we find that industry distress is an important determinant of creditor recoveries. Viewed in a different light, our results demonstrate that recovery risk – unpredictable variation in creditor recoveries over time – exists and its magnitude is economically significant. Our corporate-finance investigation of creditor recoveries thus has

securities in 2001–2002 period (an NBER recession period): "As the huge volume of defaulted debt floods the market, trading prices for distressed debt have become depressed, a response to increased supply meeting a generally shallow, illiquid market." (*Ultimate Recovery Remains High for Well-Structured Debt, Dropping for Poorly Structured Debt*, Standard & Poors, Risk Solutions, January 2002)

[22] One possibility we must entertain is the following. Altman et al. (2003) results are for *Pd*, recoveries at default, using the NYU Salomon Center data on the closing "bid" prices for about 1300 bonds (as close to the default as possible) over the period 1982–2002. Our sample is much smaller since we require firm-level characteristics, which are not available for many defaulted firms.

important implications for credit-risk models in the asset-pricing literature. In particular, we ask whether our results imply that a credit-risk model attempting to explain credit spread behavior must incorporate factors to explain recovery risk, over and above the ones that determine default risk.

We examine whether ex-ante measures of likelihood of default of a firm, found to be important by extant empirical literature, affect recoveries or not. In particular, we examine three predictors of default risk of a firm employed in the literature and in practice. First, we employ the Z–score employed in credit-scoring models by rating agencies. The Z–score we employ is as defined in Altman (1968, 2000) and as modified by Mackie-Mason (1990):

$$\mathrm{Z} = (3.3 * \mathrm{EBIT} + \mathrm{Sales} + 1.4 * \mathrm{Retained\ Earnings} + 1.2 * \mathrm{Working\ Capital})/\mathrm{Assets}. \quad (3)$$

Second, we consider another credit-scoring model from the accounting literature, the Zmijewski Score, as defined in Zmijewski (1984):

$$\begin{aligned} \text{Zmijewski Score} &= -4.3 - 4.5 * \text{Net Income/Total Assets} \\ &+ 5.7 * \text{Total Debt/Total Assets} \\ &- 0.004 * \text{Current Assets/Current Liabilities.} \end{aligned} \quad (4)$$

Finally, we also employ the Distance to Default as computed by KMV (www.kmv.com) using stock returns and volatility, based on the Merton (1974) model. We have employed (but do not report the results for) the Expected Default Frequency (EDF), a variant of the Distance to Default (DD) measure. The computation of these measures is available in the unabridged version of the paper. We also compute Asset Value and Asset Volatility, the inputs needed to calculate EDF and DD measures, using the iterative algorithm of Vassalou and Xing (2004).

Note that since the determinants of default risk are also based on firm-specific characteristics, we exclude profitability among these variables. This lets us capture cleanly whether determinants of likelihood of default are also determinants of recoveries or not. The estimates are reported in Table 10. The balance-sheet based determinants of default risk – Z–Score and Zmijewski Score – are in general also significant as determinants of recoveries. Most important, effects of Distress1 and Distress2 remain of the same economic magnitude as before. In contrast, the Distance to Default, Asset Value, and Asset Volatility are not significant in our tests. This might be an artifact of the low number of observations for which the Merton Model could be solved using the Vassalou and Xing (2004) method in our sample. The smaller sample (239 observations instead of 778 in previous tables) also renders Distress1 insignificant. However, the effect of Distress2 remains overall significant even in the smaller sample from the presence of these determinants of ex-ante default risk.

Implications for Credit Risk Models: Our results from Sections 5 and 6 together show that while determinants of default risk and recovery risk are correlated, they are not perfectly correlated. Seniority and collateral, firm and industry profitability, and industry distress are factors that seem to affect creditor recoveries over and above factors that affect default risk. How do these factors affect inputs of recovery rates in existing credit risk models? Though contract-specific and firm-specific characteristics could be captured by allowing a constant recovery rate but one that varies depending on the firm and the instrument, the state of the industry of the defaulted firm – distressed or healthy – is potentially a systematic risk factor: It constitutes a dimension of risk in creditor recoveries that may in fact carry a risk premium. Our results thus underscore the need for modeling recovery risk – the risk that the level of recovery in default may vary unpredictably – as stemming from firm-specific factors as well as systematic, industry-specific factors.

To the best of our knowledge, such an integrated credit risk model does not yet exist either in the structural class of credit risk models or in the reduced form variety.[23] Building a next generation of credit risk models that embed industry-specific factors thus appears to be a fruitful goal to pursue, and our empirical work should provide guidance in this pursuit. Finally, rating agencies that have recently indicated that future credit ratings will also separately reflect expected recovery on specific instruments also may need to take account of industry-distress effects.

7 Conclusions

We have employed comprehensive data on defaulted loans and bonds in the United States over the period 1982–1999 to analyze the effect of industry-wide distress on creditor recoveries. Our main finding is that industry conditions at the time of default are robust and economically important determinants of creditor recoveries. In particular, our evidence suggests that recoveries fall during industry distress not only due to a downward revision in the economic worth of firm's assets, but also because of the financial constraints that industry peers of the defaulted firms face, as proposed by the fire-sales or the industry-equilibrium theory of Shleifer and Vishny (1992). The indirect costs of corporate default arising from industry-equilibrium effects are thus substantial, and should have important implications for debt capacity and capital structure of firms, as proposed by Shleifer and Vishny.

[23]Das and Tufano (1996), Frye (2000a, 2000b), Jarrow (2001), and Guntay, Madan, and Unal (2003) consider variants of models where recovery risk is captured through its dependence on interest rates, state of the economy, and tangibility of assets. These models do not incorporate the effect of industry distress on recoveries. As our tests reveal, it is the risk of an industry recession rather than an economy-wide recession that is the primary driver of recovery risk.

These corporate-finance results also have important implications for the credit-risk models employed in the asset-pricing literature. Indeed, an interesting research agenda would be to analyze the asset-pricing counterpart of the Shleifer and Vishny model: a general equilibrium model which analyzes the risk premium arising from the industry distress effect, that is, from the risk of low recovery due to anticipation or realization of asset fire-sales when firms receive common sectoral shocks. Such an exercise would be valuable in understanding the implications of industry-driven recovery risk for credit spreads.

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Table 1 Panel A: Time-series Behavior of Recovery Prices at Emergence (Pehyld). This table documents the time series behavior of recovery prices in terms of cents per dollar. Pehyld is the price observed at emergence discounted by the high yield index for the period between default and emergence. Note that one firm could have defaulted in multiple years. There was only one default in 1981.

			Pehyld		
Year	**Defaults**	**Firm defaults**	**Average**	**Median**	**St.Dev.**
Overall	1511	465	51.11	49.09	36.58
1982	12	5	44.86	51.66	16.57
1983	5	4	46.17	35.94	34.95
1984	6	3	50.70	48.57	26.91
1985	12	8	21.71	10.82	30.13
1986	37	16	21.53	15.48	23.49
1987	56	11	55.59	58.80	36.11
1988	101	24	56.59	64.64	33.73
1989	110	29	43.76	36.02	37.49
1990	245	69	41.24	34.14	35.78
1991	326	81	48.97	47.62	35.06
1992	137	53	58.80	62.58	33.89
1993	103	36	55.84	49.09	38.18
1994	60	25	66.02	82.54	38.23
1995	97	35	63.22	68.30	36.96
1996	75	27	60.64	62.40	36.55
1997	38	11	61.18	73.71	40.27
1998	49	16	36.69	38.76	29.47
1999	42	12	67.18	80.00	37.19

Table 1 Panel B : Industry Behavior of Recovery Prices at Emergence. This table documents the industry behavior of recovery prices in terms of cents per dollar. Pehyld is the price observed at emergence discounted by the high yield index for the period between default and emergence. Note that one firm could be classified in multiple industries based on the division that defaulted. ∗∗ means significantly different from other group means at 5% level using a Scheffe's test.

				Pehyld		
S&P Code	**Industry Description**	**Def**	**Firm defaults**	**Avg**	**Mdn**	**St.Dev.**
	Overall	1511	424	51.11	49.09	36.58
1	Utility	82	9	74.49**	76.94	18.79
2	Insurance and Real Estate	77	23	37.13	27.92	30.96
3	Telecommunications	26	6	53.01	49.49	44.29
4	Transportation	99	20	38.92	18.69	40.76
5	Financial Institutions	76	24	58.79	51.94	42.13
6	Healthcare / Chemicals	111	35	55.67	49.41	38.13
7	High Technology/ Office Equipment	63	22	47.05	40.11	38.07
8	Aerospace / Auto / Capital Goods	138	46	52.08	48.43	37.18
9	Forest,Building Prod / Homebuilders	114	30	53.50	53.33	32.35
10	Consumer / Service Sector	472	126	47.22	41.09	35.57
11	Leisure Time / Media	167	54	51.82	48.50	36.05
12	Energy and Natural Resources	86	29	60.41	58.80	35.41

Table 1 Panel C : Seniority Behavior of Recovery Prices at Emergence. Pehyld is the price observed at emergence discounted by the high yield index for the period between default and emergence. All recovery prices are measured in cents per dollar. Note that one firm could be classified in multiple seniorities based on instruments that defaulted. 11 of the 15 pairwise means test for difference is significant at 5% level or lower using a Scheffe's test.

		Pehyld				
Seniority Code	**Seniority Description**	**Def**	**Firm defaults**	**Avg**	**Mdn**	**St.Dev.**
	Overall	1511	829	51.11	49.09	36.58
1	Bank Loans	358	219	81.12	91.55	26.26
2	Senior Secured	267	119	59.14	61.99	30.18
3	Senior Unsecured	236	98	55.92	54.63	34.58
4	Senior Subordinated	266	172	34.37	26.78	30.39
5	Subordinated	346	186	27.07	16.66	30.37
6	Junior Subordinated	38	35	18.28	6.25	27.11

Table 1 Panel D : Collateral Behavior of Recovery Prices at Emergence. Pehyld is the price observed at emergence discounted by the high yield index for the period between default and emergence. All recovery prices are measured in cents per dollar. Note that one firm could be classified in multiple collateral classes based on instruments that defaulted. ** means different from other group means is significant at 5% level using a Scheffe's test.

		Pehyld				
Collateral Code	**Collateral Description**	**Def**	**Firm defaults**	**Avg**	**Mdn**	**St.Dev.**
	Overall	1511	644	51.11	49.09	36.58
1	Current Assets	52	46	94.19**	98.81	15.96
2	PP and E	83	44	71.36	77.74	27.51
3	Real Estate	38	23	71.83	77.77	31.07
4	All or Most assets	228	126	80.05	89.16	26.35
5	Other	33	20	60.94	53.67	31.21
6	Unsecured	32	25	63.71	63.79	33.48
7	Secured	40	17	63.59	67.42	36.43
8	Information Not available	1005	343	38.64**	30.91	33.48

Table 2: Summary Statistics of Firm, Industry and Macro Variables. Note that the number of data observations are different for each variable due to data availability. All firm-specific variables are measured as of the last fiscal year before the default and data is obtained from COMPUSTAT. The variables include: Log (Assets) is the natural logarithm of the total assets. Profit Margin is the ratio of EBITDA to Sales. Leverage is the ratio of Long-Term Debt to Total Assets. No. of issues is the total number of debt issues of the firm that is currently under default. Debt concentration is the Herfindahl index measure by amount of the debt issues of the firm that are under default. Tangibility is the ratio of Property Plant and Equipment to Total Assets. Med.Ind.Q is the median, of the ratio of Market value of the firm (estimated as Book Value of total assets $-$ book value of equity $+$ market value of equity) to the book value of the firm (estimated as book value of total assets), of all the firms in the 3 digit SIC code of the defaulted firm. Distress1 is a dummy variable that takes a value 1 if the median stock return of all the firms in the 3-digit SIC code of the defaulted firm is less than -30% and 0 otherwise. Distress1a is a dummy variable that takes a value 1 if the median stock return (measured for the year at the midpoint between default and emergence for each firm) of all the firms in the 3-digit SIC code of the defaulted firm is less than -30% and 0 otherwise. Distress2 is a dummy variable that takes on a value 1 if distress1 is 1 and if the median sales growth of all the firms in the 3-digit SIC code of the defaulted firm is negative in any of the 2 years before the default date. Distress3 is a dummy variable that takes on a value 1 if the average credit rating of other firms in the 3 digit SIC code of the defaulted firm is below investment grade and 0 otherwise. Ind. Illiq1 and Ind. Illiq2 is the inverse of the median interest coverage ratio (EBITDA/Interest) and median quick ratio, Med. Ind. leverage is the median Long term debt to total assets, of all the firms in the 3 digit SIC code of the defaulted firm. Asset specificity is defined as the median ratio of machinery and equipment as percentage of total assets and follows Stromberg(2000) for all firms in COMPUSTAT over the sample period and using the S and P industry classification. Peer firms is the number of other firms in the 3 digit SIC code of the defaulted firm. All Industry variables are measured in the year of default. SR, GDP, BDA and BDR are the macro variables used by Altman et.al (2002). SR is the annual return on the SandP 500 stock index. GDP is the annual GDP growth rate. BDA is the total amount of high yield bonds defaulted amount for a particular year (measured at mid-year in trillions of and represents the potential supply of defaulted securities. BDR is the weighted average default rate on bonds in the high yield bond market. Weights are based on the face value of all high yield bonds outstanding each year.

Variable	n	Mean	S.D.	Min	25th Percentile	Median	75th Percentile	Max
Log(assets)	238	6.27	1.25	3.43	5.40	6.14	7.04	10.46
Profit Margin	231	0.07	0.32	-3.96	0.01	0.07	0.14	0.72
Leverage	234	0.50	0.34	0.00	0.28	0.49	0.69	1.93
Tangibility	232	0.39	0.25	0.00	0.17	0.35	0.58	0.93
No of issues	277	5.11	4.66	1.00	2.00	4.00	6.00	33.00
Debt Concentration	277	0.42	0.26	0.09	0.24	0.34	0.53	1.00
Med Ind Q	193	1.02	0.36	0.19	0.81	0.94	1.16	3.52
Distress1	194	0.09	0.28	0.00	0.00	0.00	0.00	1.00
Distress1a	194	0.06	0.23	0.00	0.00	0.00	0.00	1.00
Distress2	194	0.03	0.16	0.00	0.00	0.00	0.00	1.00
Distress3	194	0.01	0.07	0.00	0.00	0.00	0.00	1.00
Ind Illiq1	186	21.98	145.38	0.10	0.23	0.32	0.52	1000.00
Ind Illiq2	179	1.20	0.59	0.49	0.85	1.00	1.32	4.04
Med Ind Leverage	189	0.21	0.12	0.00	0.14	0.20	0.29	0.65
Med Asset Specificity	193	19.37	8.75	0.00	15.84	16.92	23.61	44.23
Peer Firms	193	65.79	90.74	1.00	20.00	38.00	58.00	592.00
SR	18	0.18	0.12	-0.03	0.08	0.17	0.29	0.38
GDP	18	3.22	1.99	-2.03	2.67	3.54	4.17	7.27
BDA	18	6.47	6.84	0.30	2.29	4.07	7.49	23.53
BDR	18	3.06	2.82	0.84	1.25	1.81	3.50	10.27

Table 3 - OLS Estimates of Regression of Recovery Prices at emergence - Pehyld

Pehyld is the price observed at emergence measured in cents per dollar for each debt instrument and discounted by the high yield index for the period between default and emergence. All firm-specific variables are measured as of the last fiscal year before the default and data is obtained from COMPUSTAT. Log (Assets) is the natural logarithm of the total assets. Profit Margin is the ratio of EBITDA to Sales. Leverage is the ratio of Long-Term Debt to Total Assets. Med.Ind.Q is the median, of the ratio of Market value of the firm (estimated as Book Value of total assets − book value of equity + market value of equity) to the book value of the firm (estimated as book value of total assets), of all the firms in the 3 digit SIC code of the defaulted firm. No. of issues is the total number of debt issues of the firm that is currently under default. Debt concentration is the Herfindahl index measure by amount of the debt issues of the firm that are under default. Tangibility is the ratio of Property Plant and Equipment to Total Assets. Distress1 is a dummy variable that takes a value 1 if the median stock return of all the firms in the 3-digit SIC code of the defaulted firm is less than −30% and 0 otherwise. Distress1a is a dummy variable that takes a value 1 if the median stock return (measured for the year at the midpoint between default and emergence for each firm) of all the firms in the 3-digit SIC code of the defaulted firm is less than −30% and 0 otherwise. Distress2 is a dummy variable that takes on a value 1 if distress1 is 1 and if the median sales growth of all the firms in the 3-digit SIC code of the defaulted firm is negative in any of the 2 years before the default date. Distress3 is a dummy variable that takes on a value 1 if the average credit rating of other firms in the 3 digit SIC code of the defaulted firm is below investment grade and 0 otherwise. All Industry variables are measured in the year of default. All regressions have seniority, collateral and industry dummies. Specifications 6 and 7 are versions of specifications 1 and 3 with utilities and financial institutions excluded. Cluster (based on each firm's debt instruments as a single cluster) and heteroscedasticity corrected standard errors are reported in parentheses. $***, **, *$ represent significance levels at 1%, 5%, and 10% respectively.

Table 3 - Determinants of Pehyld

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Const.	92.51***	90.41***	92.90***	91.97***	92.20***	48.88**	48.58**
	(24.67)	(26.44)	(25.28)	(25.15)	(25.35)	(22.01)	(22.24)
Coupon	0.19	0.11	0.13	0.13	0.12	-0.14	-0.21
	(0.44)	(0.45)	(0.45)	(0.45)	(0.45)	(0.51)	(0.50)
Log(issue Size)	2.29**	2.36**	2.23**	2.39**	2.35**	1.73	1.56
	(1.00)	(1.00)	(1.01)	(1.01)	(1.01)	(1.07)	(1.07)
Log(assets)	-1.04	-0.97	-0.95	-0.94	-1.03	0.35	0.60
	(2.12)	(2.13)	(2.13)	(2.12)	(2.13)	(2.24)	(2.25)
Profit Margin	15.57***	15.46***	15.58***	15.74***	15.43***	17.43*	16.70*
	(4.56)	(4.55)	(4.56)	(4.61)	(4.55)	(9.42)	(9.37)
Leverage	-4.64	-5.44	-5.76	-5.51	-5.42	-1.03	-1.73
	(5.55)	(5.70)	(5.69)	(5.68)	(5.69)	(5.49)	(5.58)
Med Ind Q	17.58***	20.09***	19.38***	19.03***	19.95***	19.73***	21.01***
	(6.67)	(6.82)	(6.80)	(6.84)	(6.81)	(6.69)	(6.71)
No. of Issues	-0.43	-0.52	-0.54	-0.54	-0.54	-1.52***	-1.68***
	(0.50)	(0.55)	(0.55)	(0.56)	(0.56)	(0.56)	(0.59)
Debt Concentration	3.77	3.57	3.59	3.96	3.41	-4.68	-5.30
	(11.08)	(11.57)	(11.39)	(11.40)	(11.46)	(11.79)	(12.02)
Tangibility	0.84	2.09	1.47	2.42	2.16	0.31	0.64
	(10.01)	(10.05)	(10.08)	(10.04)	(10.08)	(10.25)	(10.25)
Distress1	-11.11***					-8.34**	
	(4.39)					(3.82)	
Med Ind Ret		.76					
		(4.26)					
Distress1a			-10.76**				-10.67**
			(4.94)				(4.95)
Distress2				-15.26**			
				(7.21)			
Distress3					-14.32***		
					(5.23)		
Seniority Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Collateral Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	778	778	778	778	778	668	668
R^2	0.54	0.53	0.53	0.53	0.53	0.51	0.51

Table 4 - OLS Estimates of Regression of Recovery Prices at emergence - Pehyld (Interaction Effects)

Pehyld is the price observed at emergence measured in cents per dollar for each debt instrument and discounted by the high yield index for the period between default and emergence. All firm-specific variables are measured as of the last fiscal year before the default and data is obtained from COMPUSTAT. Log (Assets) is the natural logarithm of the total assets. Profit Margin is the ratio of EBITDA to Sales. Leverage is the ratio of Long-Term Debt to Total Assets. Med.Ind.Q is the median, of the ratio of Market value of the firm (estimated as Book Value of total assets − book value of equity + market value of equity) to the book value of the firm (estimated as book value of total assets), of all the firms in the 3 digit SIC code of the defaulted firm. No. of issues is the total number of debt issues of the firm that is currently under default. Debt concentration is the Herfindahl index measure by amount of the debt issues of the firm that are under default. Tangibility is the ratio of Property Plant and Equipment to Total Assets. Distress1 is a dummy variable that takes a value 1 if the median stock return of all the firms in the 3-digit SIC code of the defaulted firm is less than −30% and 0 otherwise. Distress1a is a dummy variable that takes a value 1 if the median stock return (measured for the year at the midpoint between default and emergence for each firm) of all the firms in the 3-digit SIC code of the defaulted firm is less than −30% and 0 otherwise. Peer firms is the number of firms in the 3-digit SIC code of the defaulted firm. Ind. Illiq 1 and 2 are the inverse of the median interest coverage ratio (EBITDA/Interest) and quick ratio, Med. Ind. leverage is the median Long term debt to total assets, of all the firms in the 3 digit SIC code of the defaulted firm. Asset specificity (AS) is defined as the ratio of machinery and equipment as percentage of total assets and follows Stromberg(2000) for all firms in COMPUSTAT over the sample period and using the S and P industry classification. All Industry variables are measured in the year of default. All regressions have seniority, collateral and industry dummies. Cluster (based on each firm's debt instruments as a single cluster) and heteroscedasticity corrected standard errors are reported in parentheses. The coefficients on the constant and coupon are not reported to conserve space eventhough they are included in all specifications as controls. $***$, $**$, $*$ represent significance levels at 1%, 5%, and 10% respectively.

Table 4 - Determinants of Pehyld (Interaction Effects)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log(issue Size)	2.22**	2.21**	2.25**	1.36	2.15**	2.35**	2.09**
	(.99)	(1.02)	(1.04)	(1.01)	(1.02)	(0.98)	(0.99)
Log(assets)	-0.98	-0.86	-0.72	0.46	-0.35	-1.23	-1.06
	(2.05)	(2.11)	(2.13)	(1.98)	(2.13)	(2.08)	(2.09)
Profit Margin	14.41***	15.53***	14.03	12.68	14.40	15.83***	15.92***
	(4.59)	(4.56)	(8.91)	(9.54)	(9.69)	(4.63)	(4.67)
Leverage	-3.83	-5.97	-6.85	-3.09	-5.83	-4.70	-6.24
	(5.54)	(5.73)	(5.54)	(5.58)	(5.84)	(5.29)	(5.44)
Med Ind Q	17.66***	19.58***	16.07**	16.20***	15.89**	19.72***	21.60***
	(6.63)	(6.83)	(6.33)	(5.92)	(6.25)	(6.78)	(7.09)
No. of Issues	-0.09	-0.52	-0.32	-0.35	-0.41	-0.41	-0.55
	(0.46)	(0.55)	(0.51)	(0.51)	(0.54)	(0.51)	(0.56)
Debt Concentration	7.55	4.08	7.09	2.14	6.58	2.61	1.03
	(10.93)	(11.39)	(11.20)	(11.33)	(11.16)	(10.81)	(11.18)
Tangibility	-0.73	1.24	3.75	3.17	2.15	0.33	1.61
	(9.88)	(10.06)	(10.58)	(10.43)	(10.36)	(10.03)	(10.16)
AS	-1.03***	-1.65***	-1.73***	0.15	-1.42*		
	(0.40)	(0.47)	(0.44)	(0.72)	(0.82)		
Distress1	12.47					-18.86***	
	(9.11)					(5.56)	
Distress1a		8.18					-36.50***
		(7.70)					(5.94)
AS * Distress1	-1.08***						
	(0.36)						
AS * Distress1a		-1.15***					
		(0.37)					
Ind. Illiq1			0.07**				
			(0.03)				
AS * Ind Illiq1			-0.004***				
			(0.001)				
Ind. Illiq2				23.53**			
				(9.52)			
AS * Ind Illiq2				-1.42***			
				(0.41)			
Med. Ind. Leverage					16.93		
					(45.36)		
AS * Med Ind Leverage					-1.22		
					(2.52)		
Peer Firms						-0.02	-0.02
						(0.03)	(0.04)
Peer firms * Distress1						0.19**	
						(0.08)	
Peer firms * Distress1a							0.61***
							(0.10)
Seniority Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Collateral Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	778	778	754	729	762	778	778
R^2	0.54	0.53	0.55	0.56	0.54	0.54	0.54

Table 5 - OLS Estimates of Regression of Recovery Prices at emergence - Pehyld (Interaction Effects by Priority)

Pehyld is the price observed at emergence measured in cents per dollar for each debt instrument and discounted by the high yield index for the period between default and emergence. All firm-specific variables are measured as of the last fiscal year before the default and data is obtained from COMPUSTAT. Log (Assets) is the natural logarithm of the total assets. Profit Margin is the ratio of EBITDA to Sales. Leverage is the ratio of Long-Term Debt to Total Assets. Med.Ind.Q is the median, of the ratio of Market value of the firm (estimated as Book Value of total assets − book value of equity + market value of equity) to the book value of the firm (estimated as book value of total assets), of all the firms in the 3 digit SIC code of the defaulted firm. No. of issues is the total number of debt issues of the firm that is currently under default. Debt concentration is the Herfindahl index measure by amount of the debt issues of the firm that are under default. Tangibility is the ratio of Property Plant and Equipment to Total Assets. All the above variables are included as controls in all specifications, but are not reported to conserve space. Distress1 is a dummy variable that takes a value 1 if the median stock return of all the firms in the 3-digit SIC code of the defaulted firm is less than -30% and 0 otherwise. Distress1a is a dummy variable that takes a value 1 if the median stock return (measured for the year at the midpoint between default and emergence for each firm) of all the firms in the 3-digit SIC code of the defaulted firm is less than -30% and 0 otherwise. Asset specificity (AS) is defined as the ratio of machinery and equipment as percentage of total assets and follows Stromberg(2000) for all firms in COMPUSTAT over the sample period and using the S and P industry classification. All Industry variables are measured in the year of default. All regressions have seniority, collateral and industry dummies. Bank, Senior and Junior are dummy variables representing the priority of the debt issue. Secured and Unsecured are dummy variables representing the collateralization of the debt issue. No secured is a dummy variable that takes the value 1 if there is no secured debt in the debt structure of the defaulting firm and 0 otherwise. Ind.Specific equipment is a dummy variable that equals one if the collateral backing the debt is industry specific assets (Collateral Code 2 in Table 1 Panel D) and 0 otherwise. Current Assets is a dummy variable that equals one if the collateral backing the debt issue is the current assets of the firm and 0 otherwise. Cluster (based on each firm's debt instruments as a single cluster) and heteroscedasticity corrected standard errors are reported in parentheses. $***, **, *$ represent significance levels at 1%, 5%, and 10% respectively.

Table 5 - Determinants of Pehyld (Interaction Effects by Priority)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
AS			-0.97**		-0.98**		-0.95**
			(0.42)		(0.40)		(0.43)
Distress1	5.69					-3.64	-2.91
	(6.70)					(4.30)	(4.34)
Ind. Sp. Eqpt * Distress1	-23.58**						
	(9.84)						
Current Assets * Distress1	-6.82						
	(10.03)						
Unsecured * Distress1	-20.37**						
	(8.45)						
Bank * Distress1		1.41	-0.70		-1.16***		
		(6.42)	(11.05)		(.40)		
Bank * Distress1 * AS			0.17				
			(0.60)				
Senior * Distress1		-21.08***	4.43				
		(7.16)	(12.28)				
Senior * Distress1 * AS			-0.98**				
			(0.42)				
Junior * Distress1		-5.84	17.10				
		(6.53)	(15.48)				
Junior * Distress1 * AS			-1.17*				
			(0.68)				
Secured * Distress1				-0.71	-0.73		
				(5.64)	(9.84)		
Secured * Distress1 * AS					0.08		
					(0.56)		
Unsecured * Distress1				-14.46***	13.15		
				(5.17)	(10.63)		
Unsecured * Distress1 * AS					-1.16***		
					(0.40)		
No Secured * Distress1 * Unsecured						-19.98**	11.90
						(9.39)	(20.53)
No Secured * Distress1 * Unsecured * AS							-1.09*
							(0.62)
Seniority Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Collateral Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	778	778	778	778	778	778	778
R^2	0.54	0.54	0.55	0.54	0.54	0.54	0.54

Table 6 Panel A: Industries in Distress. Industry Distress, Distress1, is a dummy variable that takes a value 1 if the median stock return of all the firms in the 3 digit SIC code of the defaulted firm in the default year is less than −30% and 0 otherwise. The following table lists the S and P Industry Code, the description of the industry, and the year in which it was classified as distressed using the above criterion.

S and P Code	Description	Year
4	Transportation	1984
12	Energy and Natural Resources	1986
5	Financial Institutions	1987
6	Healthcare/Chemicals	1987
2	Insurance and Real Estate	1990
4	Transportation	1990
5	Financial Institutions	1990
6	Healthcare/Chemicals	1990
7	High Technology/Office Equipment	1990
8	Aerospace/Auto /Capital goods	1990
9	Forest, Building Products/Home Builders	1990
10	Consumer/Service Sector	1990
11	Leisure Time/Media	1990
5	Financial Institutions	1991
10	Consumer/Service Sector	1993
2	Insurance and Real Estate	1994
6	Healthcare/Chemicals	1994
11	Leisure Time/Media	1994
6	Healthcare/Chemicals	1995
10	Consumer/Service Sector	1995
11	Leisure Time/Media	1995
10	Consumer/Service Sector	1996
6	Healthcare/Chemicals	1998

Table 6 Panel B: Pattern of Recovery Prices at Emergence (Pehyld) for Distressed and Non-distressed industries. Pehyld is the price observed at emergence discounted by the high yield index for the period between default and emergence. All recoveries are measured in cents per dollar for each debt instrument. The table lists the recoveries as average over the entire sample, average over the sample whose industry is in distress in a given year, and average over the remaining sample. The medians are shown within brackets. Industry Distress is a dummy variable that takes a value 1 if the median stock return of all the firms in the 3-digit SIC code of the defaulted firm in the default year is less than −30% and 0 otherwise. The t–statistic tests for difference of means (B)-(C). The z–statistic tests for differences in medians (B)-(C) using the Wilcoxon rank sum test. $***, **, *$ represent significance levels at 1%, 5%, and 10% respectively.

Recovery rates	Full sample	Obs	No Industry Distress (B)	Obs	Distress (C)	Obs	t-statistic (z- statistic)
Pehyld	50.8	1443	52.4	1285	37.8	158	4.77***
	(48.4)		(50.3)		(24.9)		(4.92)***
Pehyld (excl. 1990)	52.8	1209	53.2	1167	40.2	42	2.30**
	(50.5)		(51.2)		(27.5)		(2.33)**
Pehyld (excl. utilities and finl instns)	49.0	1293	51.1	1154	31.9	139	5.92***
	(43.4)		(47.6)		(18.5)		(6.07)***

Table 7: Pattern of Recovery Prices at Emergence, Pehyld and Asset Specificity within each Industry. Pehyld is the price observed at emergence discounted by the high yield index for the period between default and emergence. All recoveries are measured in cents per dollar for each debt instrument. Specific assets is defined as the ratio of machinery and equipment as percentage of total assets and follows Stromberg(2000) for all firms in Compustat over the sample period and using the S and P industry classification. The table lists the recoveries as average and median values over the entire sample when there is no industry distress, average over the sample whose industry is in distress in a given year. Industry Distress is a dummy variable that takes a value 1 if the median stock return of all the firms in the 3-digit SIC code of the defaulted firm in the default year is less than -30% and 0 otherwise. Panel A is for Pehyld. Panel B displays the correlation between specific assets and one of the recovery measures (mean Pehyld or median Pehyld). Correlations are calculated separately for years when the industry in in distress and when it is not. $***, **, *$ represent significance levels at 1% , 5% , and 10% respectively for the test that correlation is not equal to zero.

Panel A

Panel (Pehyld)	Specific Assets		No Industry Distress		Industry Distress	
Description	Mean	Median	Mean	Median	Mean	Median
Utility	14.9%	14.1%	73.99	76.80	no data	no data
Insurance and Real Estate	8.4%	1.6%	36.06	26.17	42.42	30.73
Telecommunications	36.5%	30.0%	53.01	49.49	no data	no data
Transportation	46.1%	44.2%	47.35	47.93	9.46	3.02
Financial Institutions	2.7%	0.0%	50.42	40.35	81.35	100.00
Healthcare / Chemicals	16.8%	14.6%	60.85	71.63	33.29	14.85
High Technology / Computers / Office Equipment	18.6%	15.8%	43.31	28.59	72.77	75.40
Aerospace / Automotive / Capital Goods / Metals	18.5%	16.5%	53.37	50.09	36.81	32.91
Forest and Building Products / Homebuilders	19.7%	16.9%	56.04	56.64	36.73	23.96
Consumer / Service Sector	26.3%	23.6%	48.54	42.91	34.37	34.10
Leisure Time / Media	19.8%	16.3%	52.99	47.79	28.74	25.86
Energy / Natural Resources	29.6%	25.0%	60.80	58.80	14.88	15.54

Panel B

(Correlations)	No Industry Distress	Industry Distress
Specific Assets (mean), Pehyld (mean)	-0.015	-0.763^{***}
Specific Assets (median), Pehyld (median)	0.200	-0.626^{**}
Specific Assets (mean), Pe (mean)	-0.066	-0.800^{***}
Specific Assets (median), Pe (median)	0.224	-0.579^{**}
Specific Assets (median), Pehyld (median) (excl. utilities and finl instns)	0.271	-0.508^{***}

Table 8: Pattern of Recovery Prices at Emergence, Pehyld and Pe by Outcome and Industry Distress. Pehyld is the price observed at emergence Pe, discounted by the high yield index for the period between default and emergence. All recoveries are measured in cents per dollar for each debt instrument. The table lists the recoveries as median values over the entire sample when there is no industry distress, and over the sample whose industry is in distress in a given year. Industry Distress is a dummy variable that takes a value 1 if the median stock return of all the firms in the 3-digit SIC code of the defaulted firm in the default year is less than -30% and 0 otherwise. Firm is the number of firms with the outcome and Defaults is the number of instruments that defaulted. Panel B shows the median time in default in years. Note that this information is not available for all firms in the sample. $***, **, *$ represent significance levels at 1% , 5% , and 10% respectively for the test that difference of medians of Pehyld (and Pe) when industry is in distress and not in distress is equal to zero.

Panel A:

Regression Sample

	No Industry Distress			Industry Distress		
Outcome	Defaults	Pehyld	Pe	Defaults	Pehyld	Pe
Acquired	131	76.80	100.00	0	na	na
Emerged***	585	54.23	67.13	64	20.89	31.89
Liquidated	56	13.79	14.50	1	55.77	102.25
Unknown	93	34.42	40.00	9	3.97	6.75
Total***	865	53.93	68.50	74	18.52	30.01

Overall Sample

	No Industry Distress			Industry Distress		
Outcome	Defaults	Pehyld	Pe	Defaults	Pehyld	Pe
Acquired	131	76.80	100.00	5	82.89	99.27
Emerged***	896	54.25	71.00	145	38.38	52.53
Liquidated	109	26.59	26.59	7	22.09	23.14
Unknown	149	27.75	40.00	11	9.39	14.00
Total***	1285	48.53	63.15	168	38.16	53.00

Panel B:

Regression Sample

No Industry Distress		Industry Distress	
Firm	Time in Default	Firm	Time in Default
249	1.37***	30	2.16

Overall Sample

No Industry Distress		Industry Distress	
Firm	Time in Default	Firm	Time in Default
332	1.27***	30	2.16

Table 9 - OLS Estimates of Regression of Recovery Prices at emergence on Determinants including Macro Variables - Pehyld

Pehyld is the price observed at emergence measured in cents per dollar for each debt instrument and discounted by the high yield index for the period between default and emergence. All firm-specific variables are measured as of the last fiscal year before the default and data is obtained from COMPUSTAT. The fundamental value variables include: Log (Assets) is the natural logarithm of the total assets. Profit Margin is the ratio of EBITDA to Sales. Leverage is the ratio of Long-Term Debt to Total Assets.Med.Ind.Q is the median, of the ratio of Market value of the firm (estimated as Book Value of total assets − book value of equity + market value of equity) to the book value of the firm (estimated as book value of total assets), of all the firms in the 3 digit SIC code of the defaulted firm. The liquidation variable values include: No. of issues is the total number of debt issues of the firm that is currently under default. Debt concentration is the Herfindahl index measure by amount of the debt issues of the firm that are under default. Tangibility is the ratio of Property Plant and Equipment to Total Assets. Distress1 is a dummy variable that takes a value 1 if the median stock return of all the firms in the 3-digit SIC code of the defaulted firm is less than -30% and 0 otherwise. All Industry and Macro variables are measured in the year of default. All regressions have seniority, collateral and industry dummies . Cluster (based on each firm's debt instruments as a single cluster) and heteroscedasticity corrected standard errors are reported in parentheses. $***, **, *$ represent significance levels at 1%, 5%, and 10% respectively. SR, GDP, BDA and BDR are the macro variables used by Altman et.al (2002). SR is the annual return on the SandP 500 stock index. GDP is the annual GDP growth rate. BDA is the total amount of high yield bonds defaulted amount for a particular year (measured at mid-year in trillions of and represents the potential supply of defaulted securities. BDR is the weighted average default rate on bonds in the high yield bond market. Weights are based on the face value of all high yield bonds outstanding each year.

Table 9 - Determinants of Pehyld including Macro Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Const.	96.51***	116.17***	93.27***	112.94***	92.94***	112.75***	95.61***	115.35***
	(22.54)	(22.98)	(22.53)	(23.00)	(22.38)	(22.78)	(22.51)	(22.91)
Coupon	0.15	-0.06	0.18	-0.03	0.17	-0.04	0.21	0.02
	(0.43)	(0.47)	(0.44)	(0.47)	(0.44)	(0.47)	(0.44)	(0.46)
Log(issue Size)	2.33**	2.69***	1.90*	2.16**	2.15**	2.41**	1.84*	1.99**
	(0.96)	(0.99)	(1.00)	(1.01)	(0.99)	(1.01)	(0.99)	(1.00)
Log(assets)	-1.03	-1.79	-1.14	-1.85	-0.88	-1.50	-0.70	-1.25
	(1.92)	(1.97)	(1.99)	(2.01)	(1.97)	(2.01)	(1.95)	(1.98)
Profit Margin	15.98***	16.10***	16.42***	16.86***	15.12***	15.21***	15.47***	15.72***
	(4.26)	(4.44)	(4.23)	(4.43)	(4.16)	(4.37)	(4.19)	(4.38)
Leverage	-3.02	-3.18	-4.71	-4.23	-4.04	-3.16	-4.52	-3.89
	(5.40)	(5.46)	(5.32)	(5.33)	(5.35)	(5.36)	(5.35)	(5.34)
Med Ind Q	17.37***		16.22**		16.73***		16.11**	
	(6.51)		(6.41)		(6.42)		(6.41)	
No. of Issues	-0.50	-0.56	-0.46	-0.55	-0.34	-0.37	-0.39	-0.44
	(0.48)	(0.51)	(0.46)	(0.50)	(0.45)	(0.48)	(0.44)	(0.47)
Debt Concentration	3.67	3.89	1.95	1.75	3.49	3.59	3.06	3.04
	(10.26)	(10.41)	(10.36)	(10.48)	(10.22)	(10.24)	(10.23)	(10.25)
Tangibility	-0.01	1.19	0.35	1.02	0.79	1.36	-0.25	-0.06
	(9.22)	(9.64)	(9.11)	(9.43)	(9.12)	(9.39)	(9.04)	(9.28)
Distress1	-13.60***		-11.36***		-10.11**		-9.54**	
	(4.67)		(4.34)		(4.34)		(4.29)	
SR	-19.35	-11.07						
	(12.98)	(13.02)						
GDP			158.69	190.12*				
			(99.66)	(103.55)				
BDA					-308.12	-448.82*		
					(232.50)	(238.40)		
BDR							-84.58*	-112.54**
							(44.75)	(45.88)
Seniority Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Collateral Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	778	778	778	778	778	778	778	778
R^2	0.54	0.51	0.54	0.52	0.54	0.52	0.54	0.52

Table 10: OLS estimates of regression of Recovery Prices at emergence on determinants including risk factors that explain default - Pehyld.

Pehyld is the price observed at emergence measured in cents per dollar for each debt instrument and discounted by the high yield index for the period between default and emergence. All firm-specific variables are measured as of the last fiscal year before the default and data is obtained from COMPUSTAT and used in the computation of default risk measures and hence excluded. The fundamental value variables include: Med.Ind.Q is the median, of the ratio of Market value of the firm (estimated as Book Value of total assets − book value of equity + market value of equity) to the book value of the firm (estimated as book value of total assets), of all the firms in the 3 digit SIC code of the defaulted firm. The liquidation variable values include: No. of issues is the total number of debt issues of the firm that is currently under default. Debt concentration is the Herfindahl index measure by amount of the debt issues of the firm that are under default. Tangibility is the ratio of Property Plant and Equipment to Total Assets. Distress1 is a dummy variable that takes a value 1 if the median stock return of all the firms in the 3-digit SIC code of the defaulted firm is less than −30% and 0 otherwise. Distress2 is a dummy variable that takes on a value 1 if distress1 is 1 and if the median sales growth of all the firms in the 3-digit SIC code of the defaulted firm is negative in any of the 2 years before the default date. All Industry variables are measured in the year of default. BDR is the macro variable used by Altman et.al (2002). BDR is the weighted average default rate on bonds in the high yield bond market. Weights are based on the face value of all high yield bonds outstanding each year. Z–Score is the Altman Z–score as modified by Mackie-Mason(1990). Zmij.Score is the Zmijeswki (1984) Score. Distance to default is the measure obtained by solving the Merton(1974) model for each firm following Vassalou and Xing(2004). Merton V and Merton Asset Vol are the asset value and asset volatility from the same model. All regressions have seniority, collateral and industry dummies . Cluster (based on each firm's debt instruments as a single cluster) and heteroscedasticity corrected standard errors are reported in parentheses. $***, **, *$ represent significance levels at 1%, 5%, and 10% respectively.

Table 10: Determinants including risk factors that explain default - Pehyld.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Const.	77.70***	78.42***	84.53***	86.41***	67.22**	67.40***	54.44	51.77
	(19.03)	(19.93)	(18.28)	(19.18)	(26.20)	(25.67)	(35.14)	(36.26)
Coupon	-0.07	-0.10	0.13	0.09	0.41	0.53	0.50	0.64
	(0.50)	(0.51)	(0.49)	(0.49)	(0.69)	(0.69)	(0.69)	(0.68)
Log(issue Size)	1.55	1.55	1.90	1.84	2.10	1.68	1.29	0.71
	(1.11)	(1.10)	(1.18)	(1.17)	(1.80)	(1.82)	(1.88)	(1.91)
Med Ind Q	19.15***	19.99***	17.33**	18.25**	14.49**	11.43	16.17**	13.34*
	(6.89)	(7.18)	(7.32)	(7.60)	(6.92)	(7.54)	(7.34)	(7.95)
No. of Issues	-0.009	-0.14	-0.19	-0.31	1.48***	1.4***	1.31***	1.26***
	(0.48)	(0.53)	(0.47)	(0.51)	(0.42)	(0.43)	(0.40)	(0.41)
Debt Concentration	10.68	10.83	12.05	11.51	9.53	9.62	11.20	12.74
	(10.54)	(10.82)	(10.21)	(10.48)	(14.67)	(14.49)	(15.55)	(15.67)
Tangibility	6.90	9.06	3.04	4.07	-30.00	-25.39	-25.33	-20.09
	(11.62)	(11.70)	(10.75)	(10.81)	(20.15)	(20.71)	(20.02)	(20.94)
Distress1	-12.29**		-11.74**		-0.36		-4.14	
	(5.53)		(5.04)		(12.94)		(13.13)	
Distress2		-23.02**		-19.75**		-23.10*		-27.20**
		(8.95)		(8.90)		(12.41)		(12.25)
BDR	-110.63**	-116.09**	-135.79***	-142.43***	-80.48	-76.21	-67.25	-62.10
	(50.21)	(50.25)	(47.93)	(48.18)	(69.54)	(66.38)	(77.52)	(73.13)
Z-Score	2.77**	2.72**						
	(1.29)	(1.27)						
Zmij. Score			-0.92***	-0.88***				
			(0.34)	(0.33)				
Distance to Default					2.78	2.56		
					(2.13)	(2.19)		
Log(Merton V)							1.99	2.26
							(2.49)	(2.56)
Merton Asset Vol							-3.70	-3.86
							(8.92)	(9.06)
Seniority Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Collateral Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	601	601	612	612	239	239	239	239
R^2	0.55	0.55	0.54	0.54	0.68	0.68	0.67	0.68