What Determines Creditor Recovery Rates?

By Nada Mora

The 2007-09 financial crisis illustrated the importance of healthy banks for the overall stability of the financial system and economy. Because banking is inherently risky, the health of banks depends importantly on their ability to manage risk and the associated exposure to losses. The crisis revealed that risk management at banks and other financial institutions had shortcomings. As a result, the riskiness of their loans and other investments resulted in large losses that arguably contributed to the severity of the recession.

An important component of a strong risk management system is a bank's ability to assess the potential losses on its investments. One factor that determines the extent of losses is the recovery rate on loans and bonds that are in default. The recovery rate measures the extent to which the creditor recovers the principal and accrued interest due on a defaulted debt. While financial companies, their regulators, and researchers commonly assume that the recovery rate is constant, in practice, actual recovery rates vary significantly. Moreover, recovery rates are systematically related to default rates. For example, recovery rates on corporate bonds are inversely related to the aggregate corporate default

---

Nada Mora is an economist at the Federal Reserve Bank of Kansas City. This article is on the bank's website at ***www.KansasCityFed.org.***

rate. As a result, assuming constant recovery rates can lead to an incorrect assessment of potential losses, which in turn, would reduce the effectiveness of risk management programs.

One reason why recovery and default rates may be inversely related is that they are both likely to be strongly influenced by the economy. For example, the same adverse economic conditions that cause defaults to rise—such as a recession—can cause recoveries to fall. Drawing on more than 30 years of recovery data on defaulted debt instruments, this article shows that the state of the economy does indeed help determine creditor recovery rates. Industry distress also drives recovery rates, and evidence suggests that industry distress can be triggered by an overall weak economy.

Section I examines why the recovery rate is an important input to credit risk models. Section II analyzes recovery rates on U.S. corporate debt securities. It shows that recoveries vary considerably across time, sectors, seniority, and security type of the defaulted debt instrument. The variation in the recovery rate across time is also related to the aggregate default rate and to the business cycle. Section III examines in detail the different potential factors that explain recoveries, including bond market conditions, the macroeconomy, industry distress, and their interrelationships.

I. THE RECOVERY RATE

The goal of risk management is to reduce the risk of large losses and to increase a financial firm's resilience to large losses. One key assumption in risk management is how the recovery rate is determined. This assumption is important because additional risk is introduced when the recovery rate is not constant. Weaknesses in modeling this risk may cause common measures of credit risk to be understated.

The recovery rate in credit risk

Credit risk is the dominant source of risk for banks (Pesaran, Schuermann, Treutler, and Weiner). Credit risk is the risk of changes in value from unexpected changes in credit quality (Duffie and Singleton).[1] Unexpected changes in credit quality can come from changes to the likelihood of default, the exposure at default, and the loss given default (where loss given default is 1 minus the recovery rate). Credit risk therefore comprises both default risk and recovery risk, where recovery risk is the chance of recovering less than the full amount of principal and accrued interest due, given a default event.[2] Recovery is uncertain and often less than the full amount due, meaning that the recovery rate varies between zero and 100 percent.

A common assumption in analyzing credit risk, however, is that the recovery rate is known with certainty, so that the analysis focuses on modeling the likelihood of default. For example, the recovery rate is often a constant based on historical averages, such as between 40 percent and 50 percent on debt issued by U.S. corporate borrowers and 25 percent on debt issued by sovereign borrowers (Das and Hanouna).[3] Essentially, certain recovery means that recovery risk is assumed away. The expected default loss rate on a particular credit portfolio is then calculated as the default probability multiplied by a constant loss given default.

For example, Giesecke, Longstaff, Schaefer, and Strebulaev focus on explaining default rates over a 150-year period, applying a long-run average loss rate of 50 percent. Realized corporate bond defaults are shown to cluster at various times over the historical period they examine, including the railroad crisis of 1873-75, the banking panics of the late 1800s, and the Great Depression. Default rates are modeled by a variety of factors. Macroeconomic factors such as GDP growth, stock returns, and stock return volatility are strong predictors of default rates.

Even when studies allow the recovery rate to vary randomly, they commonly assume it is not systematically related to factors like the default rate or the business cycle.[4] This assumption considerably simplifies the portfolio loss analysis because the correlation between defaults and recoveries does not have to be modeled. Moreover, researchers disagree about the need to model a systematic recovery in practice. For example, some have argued that since the recovery rate represents the outcome of a bargaining process between the debtor and the creditor, it is reasonable to assume that it is unsystematic (Longstaff and Schwartz).

Why recovery risk matters

While assuming a 40 percent to 50 percent certain recovery rate may be a good approximation for *average* losses, it can, nonetheless, bias estimates of credit risk. Specifically, when the recovery rate and the default probability are incorrectly assumed to be uncorrelated, key measures of credit risk can be misleadingly low. What makes the recovery rate and the default probability inversely related? An inverse relation between the recovery rate and default can arise from common dependence on an aggregate factor such as the business cycle. That is, economic downturns cause defaults to rise at the same time they push down the recovery rate. Intuitively, creditor recoveries will depend on the value of the debt collateral. But the collateral, and the economic worth of the defaulting firm's assets more generally, are expected to fall during a recession due to reduced business opportunities.[5]

To understand how key measures of credit risk can be underestimated, it is important to first provide an intuition for measuring credit risk. Suppose, for example, that a bank's credit portfolio consists of 100 identical $1 loans to U.S. businesses with a one-year maturity. If the likelihood of default and the recovery rate both were certain (say 50 percent each), the bank's risk manager would know for sure that the one-year ahead loss would be $25. Thus, risk is removed in this unrealistic example because the credit loss will always be 25 percent. But in practice, losses will be distributed over the range of zero to $100. So, while the likelihood that the loss will be less than or equal to $100 is 1, the likelihood of any particular loss value is not 1.

The risk of loss can be measured in a variety of ways. One common measure is known as Value at Risk (VaR). The VaR can be thought of as measuring the risk of a large loss. A large loss can be thought of as the level of loss that has a pre-specified low likelihood, say 1 percent, of being exceeded in practice. For example, in the situation described above, the bank might estimate that the likelihood of a loss of $90 or more might be 1 percent (see Appendix 1 for details). In some applications, such as the Federal Reserve's recent stress tests of the largest banking organizations, the likelihood of a large loss is conditioned on adverse macroeconomic outcomes. The accompanying Box describes how recovery rates were applied in these stress tests.

Altman, Brady, Resti, and Sironi simulate losses on a representative credit portfolio comparing the case when default probabilities and recoveries are assumed to be uncorrelated with the case where they are correlated. They find that potential large losses are understated in the uncorrelated case by roughly 30 percent, meaning that banks may hold insufficient capital buffers to absorb large losses that could occur if

BOX

STRESS TESTING—AN EXAMPLE OF HOW RECOVERY RATES ARE USED IN PRACTICE

To help protect the economy from future financial instability, financial policymakers and regulators have made broad changes to how the financial sector is monitored and regulated. One change is to use stress testing, particularly of the largest banking organizations. The purpose of stress tests is to understand how adverse macroeconomic conditions would affect the losses, revenues, and capital levels of these companies, individually and as a group, and then to require specific actions to ensure that the companies could remain viable should such adverse conditions occur.

Robust stress test scenarios simulate the most likely of the unlikely bad economic outcomes over a specified future horizon. A banking organization "passes" the stress test if it has sufficient capital to absorb losses and maintain lending under bad outcomes throughout the planning horizon. The Federal Reserve recently conducted stress tests on the largest 19 bank holding companies and determined that most banks would be able to maintain capital above minimum levels during a severe economic crisis characterized by unemployment rising to 13 percent, house prices falling by 21 percent, and stock prices plunging by 50 percent.[1]

Recovery rates were a key input in the estimation of potential losses in the stress test. A typical loss on a loan portfolio was projected by multiplying the exposure at default by the probability of default and by the loss given default (Appendix B in Board of Governors of the Federal Reserve System). Different models of the loss given default, which is 1 minus the recovery rate, were developed for different loan and securities portfolios. For example, a loss given default for large commercial and industrial (C&I) loans in the wholesale lending portfolio was estimated on historical data, depending on the C&I borrower's country, business line, and loan collateralization, among other characteristics. Another methodology was applied to loss given default for residential mortgages in the retail lending portfolio. Federal Reserve analysts developed a statistical model relating loss on private-label mortgage-backed securities to historical data on house prices. In this case, the projected lower path for house prices in the stress test scenario results in a higher loss given default path. The model also contains a property value discount associated with distressed sales. These models provide examples of how recovery rates are actually used to estimate a financial institution's vulnerability to large losses.

[1]See the March 13, 2012 press release available on the Federal Reserve System Board of Governors website at *http://www.federalreserve.gov/*. Also see concurrent media coverage, such as *The Wall Street Journal*, "Stress Tests Buoy U.S. Banks," March 14, 2012, and *The New York Times*, "Questions as Banks Increase Dividends," March 15, 2012.

defaults and recoveries are in fact correlated. Similarly, Bruche and Gonzalez-Aguado show that the VaR can be 40 percent higher when default probabilities and recovery rates are assumed to commonly depend on an underlying credit cycle.

II. DESCRIPTIVE STATISTICS OF CREDITOR RECOVERIES

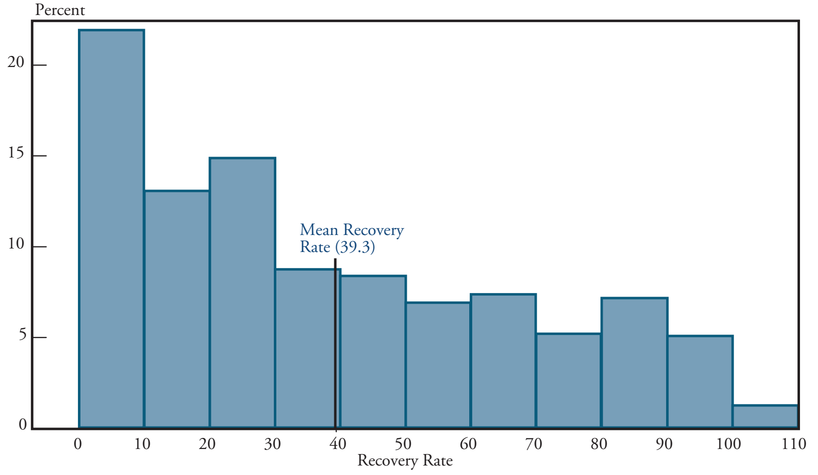
Do recovery rates vary in practice? This section shows the answer is yes. Recovery rates vary considerably across types of debt instrument and industry sectors, and, crucially, recovery rates vary across time in a systematic manner that is related to such factors as the aggregate default rate and the business cycle.

Variation across debt instrument type

Chart 1 shows the distribution of recoveries for debt instruments based on trading-price recovery on defaulted securities over about 40 years (Moody's Default Risk Service).[6] Recovery is measured by the

Chart 1

THE DISTRIBUTION OF RECOVERY RATES



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

market value of defaulted debt as a percentage of par, one month after default. The recovery rate distribution shown in the chart does not consider specific factors that may impact recovery rates, such as seniority type, industry type, or state of the economy. In addition, the distribution is not centered on the average recovery rate, meaning that recoveries are often either low or high (Schuermann). As a result, imposing a 40 percent to 50 percent average recovery assumption is problematic (the average recovery rate in Chart 1 is 39 percent and its standard deviation is 29 percent). Note that recoveries can be somewhat greater than 100 percent when the coupon on the debt is large relative to the prevailing term structure of interest rates.

Seniority, collateral, and industry are also important for recovery (Table 1). Average recovery rates have differed widely by sector, ranging from 25 percent to 58 percent. For example, from 1970 to 2008, defaulted debt in the utilities sector had a near 58-percent recovery rate, which was 19 percentage points higher than the average of 39 percent (Panel A). Utilities are natural monopolies and some economists suggest that their ability to charge customers higher rates can explain their higher recovery rate relative to other sectors. Moreover, the utilities sector has many tangible assets that can be easily sold, boosting

Table 1

DESCRIPTIVE STATISTICS OF RECOVERY RATES

Panel A. Industry Characteristics

Industry	Defaults	Firm Defaults	Mean	Median	Standard Deviation
Overall	4,422	1,307	39.3	30.5	29.1
A. Agriculture, Forestry and Fishing	18	6	39.9	46.5	25.6
B. Mining	81	38	50.8	48.6	26.0
C. Construction	36	14	28.7	20.0	31.4
D. Manufacturing	726	293	43.7	41.4	29.1
E1. Transportation	475	33	32.7	28.3	16.3
E2. Communications	331	87	39.6	30.0	31.0
E3. Utilities	164	22	57.5	62.9	31.8
F. Wholesale Trade	87	37	43.2	48.5	33.2
G. Retail Trade	235	91	43.3	41.0	29.8
H. Finance, Insurance and Real Estate	1,020	64	24.6	10.0	27.7
I. Services	339	115	49.3	56.8	31.2

Panel B. Seniority Characteristics

Seniority	Defaults	Firm Defaults	Mean	Median	Standard Deviation
Overall	4,422	1,307	39.3	30.5	29.1
Senior Secured	1,274	221	56.4	55.0	28.0
Senior Unsecured	1,918	432	36.5	26.0	29.0
Senior Subordinated	364	216	30.5	23.0	25.8
Subordinated	724	408	32.2	29.0	22.7
Junior Subordinated	34	11	27.1	15.3	25.8
Preferred Stock	99	16	10.1	4.2	21.1

Source: Author's calculations based on Moody's DRS 1970-2008. The industry divisions are based on 1-digit SIC codes (except for division E, which is further divided by 2-digit SIC codes: Transportation SIC 40-47, Communications SIC 48, and Utilities SIC 49).
Note that not all securities are reported with an industry SIC code or a seniority type in Moody's DRS.

recovery rates (Schuermann).[7] In contrast, the financial sector appears to be associated with low recovery, although this mainly reflects the recent financial crisis when most of the defaults in this sector occurred.

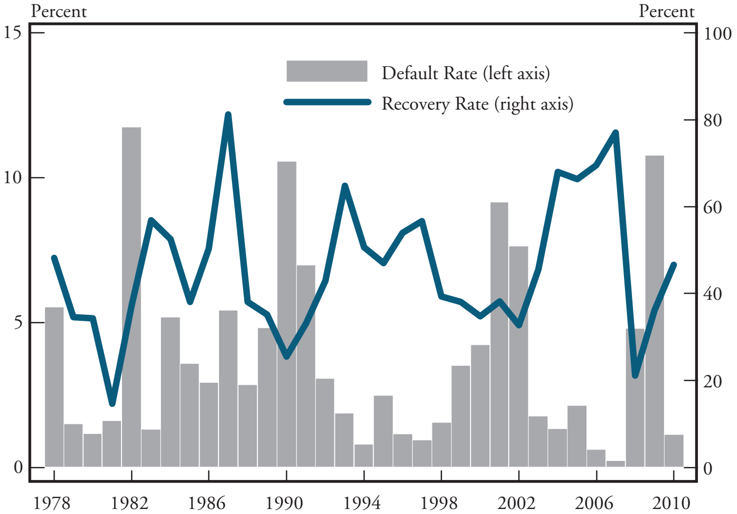
Security and seniority also matter. For example, senior secured instruments recovered 56 percent compared with 37 percent for senior unsecured instruments, highlighting the importance of collateral (Table 1, Panel B). The relative share of secured debt issued in 2009-11 has increased from the pre-crisis period, leading Fitch Ratings to expect higher recovery rates when debt issued during the crisis defaults. Moreover, more seniority (first priority during bankruptcy and debt restructurings) is generally associated with higher recovery. For example, senior unsecured debt, subordinated debt, and junior subordinated debt recovered 37 percent, 31 percent, and 27 percent, respectively.

Studies have also shown that bank loans have a higher recovery rate than bonds. Loans are typically senior to other liabilities. Banks also have more access to information by monitoring borrower deposits, cash flows, and covenant compliance. Indeed, banks can force bankruptcy filing sooner and take control. As a result, the overall recovery rate on a firm that has only bank debt will be higher than on a firm that has no bank debt. Such a firm is more likely to be deeply insolvent by the time it defaults (Carey and Gordy). For example, recovery on U.S. bank loans is roughly 80 percent on average (Acharya, Bharath, and Srinivasan; Khieu, Mullineaux, and Yi).

Different types of default and reorganization also result in different recoveries. While there is no standard definition of what represents a default (Schuermann), Moody's, for example, considers the following three credit events to be default: 1) a missed or delayed disbursement of interest or principal; 2) a bankruptcy filing or other legal stops on the timely payment of interest or principal; or 3) the occurrence of a distressed exchange. The third event is an out-of-court negotiated restructuring where debt holders are offered a new security that results in a reduced financial obligation, such as a debt with a lower coupon rate or a lower par value. Distressed exchanges have a higher recovery rate than bankruptcies (Franks and Torous).[8] Intuitively, firms and creditors only enter formal bankruptcy after having exhausted informal alternatives. Moreover, bankruptcies that result in an ongoing but reorganized company (Chapter 11) produce higher recovery than those that result in a company that closes and liquidates its assets (Chapter 7) (Bris, Welch, and Zhu; Acharya, Bharath, and Srinivasan).

Chart 2

THE DEFAULT RATE AND THE RECOVERY RATE ON DEFAULTED SECURITIES



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

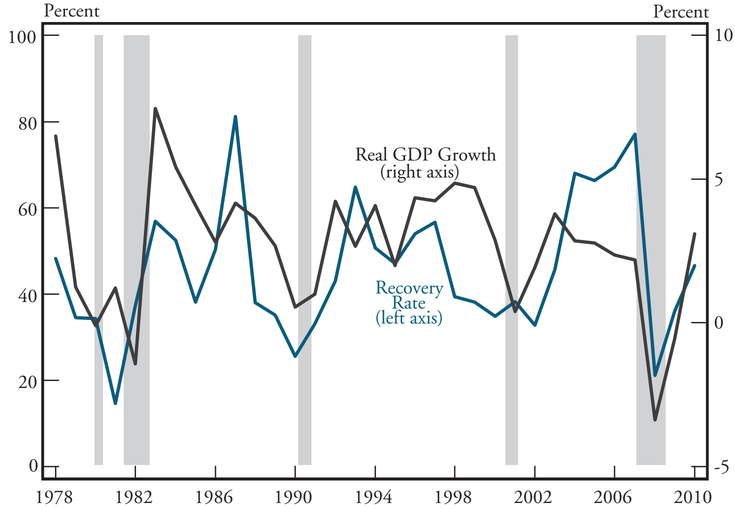
Finally, legal systems across countries give creditors different legal power to influence outcomes. For example, the United Kingdom is more creditor-friendly than Germany, which is more creditor-friendly than France. As a result, the median recovery rate on bank loans is 92 percent in the United Kingdom, 67 percent in Germany, and 56 percent in France (Davydenko and Franks).[9]

Variation over time

Recovery rates also vary systematically over time. Recovery rates are lower when the aggregate default rate inches up (Chart 2).[10] The average default rate over 1978-2010 was 3.8 percent, and the average recovery rate was 45.7 percent. Defaults were clustered during 1982, the early 1990s, the early 2000s, and 2008-09—periods of low recovery rates.[11] The two series are negatively correlated with a correlation coefficient equal to -0.4.

The recovery rate also is procyclical. As shown in Chart 3, the aggregate recovery rate closely tracks the business cycle. For example, the recovery rate is positively correlated with real GDP growth (correlation

Chart 3
THE RECOVERY RATE AND THE BUSINESS CYCLE



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

coefficient equal to 0.45 over 1978-2010). Previous studies also reveal a similar macroeconomic dependence, whereby recessions depress bond recoveries by up to one-third from normal-year averages (Frye; Schuermann; Chart 3). However, while researchers agree that the recovery rate and the economy are correlated, they do not agree on the underlying drivers.

III. EXPLAINING RECOVERY RATES

As previously discussed, the economy can directly affect recoveries through declines in asset and collateral values during recessions. Poor business prospects in recessions can lead to lower values for a company's assets. Two other reasons for the variation in recovery rates are illiquidity in the distressed bond market (Altman, Brady, Resti, and Sironi) and illiquidity in the market for the sale of a firm's real assets (Acharya, Bharath, and Srinivasan). This section describes these market specific explanations and shows how, together with macroeconomic effects, they influence recovery rates.

Market specific explanations for variation in recovery rates

Recovery rates can vary over time because of illiquidity in the market for distressed and defaulted securities. Proponents of this view argue that the recovery rate is a function of the supply and demand for defaulted securities, so that when the supply of defaulted bonds goes up, secondary market prices are driven down. This result relies on demand for distressed bonds not being very sensitive to prices. Such a condition may arise when investor capacity to absorb defaulted securities is limited. For example, only specialized investors such as vulture funds and hedge funds may be willing to buy distressed debt.[12] Therefore, in high default years when distressed debt is in excess supply relative to the typical investor capacity, secondary market prices fall to equilibrate the market. For example, during the 1990-91 and 2000-01 periods, the ratio of the supply to the demand for distressed and defaulted securities reached 10-to-1 (Altman, Brady, Resti, and Sironi).

Alternatively, illiquidity in the market for a defaulted firm's real assets can affect recovery rates over and above the fundamental economic worth of these assets. A key reason driving illiquidity in the market for the defaulting firm's real assets is industry distress (Shleifer and Vishny; Acharya, Bharath, and Srinivasan). This distress can produce a "fire sale," which is a forced asset sale at a "dislocated" price. The price is dislocated because the highest bidders are industry peers, but they cannot bid the price up to the value that reflects the best use of the assets because the industry is also financially distressed. A classic example is the sale of used airplanes by financially distressed airlines, where the asset is highly specific to the airline industry (Pulvino; Benmelech and Bergman).

To summarize, both views rely on market illiquidity determining a particular equilibrium for recovery rates. One view is that illiquidity in the financial market for the sale of defaulted securities is mainly responsible. The other view is that illiquidity in the market for the sale of specific real assets is mainly responsible. In neither view does the aggregate state of the economy play a leading role.

An empirical assessment of aggregate and market specific determinants of recovery rates

The effects of the macroeconomy, bond market conditions, and industry conditions on recovery rates can be estimated using regression analysis. The effects are first estimated with annual data from 1978 to 2010 by regressing the overall recovery rate for defaulted debt on measures of macroeconomic and bond market conditions. Macroeconomic conditions are measured by real GDP growth and the S&P 500 stock return. Bond market conditions are measured by the dollar amount of defaulted debt and the default rate.

The results of the regression analysis, which initially follows that of Altman, Brady, Resti, and Sironi, are shown in Table 2. The first two columns are consistent with those authors' findings that a greater supply of defaulted debt or a higher default rate forces the recovery rate down. For example, a 1-percentage-point increase in the aggregate default rate, say from 4 percent to 5 percent, drives recovery rates down by close to 2 percentage points (column 2).[13]

However, including the effect of macroeconomic factors produces a mixed picture. When real GDP growth is included (column 5), it has a statistically significant effect on the recovery rate but the bond default rate is no longer significant. For example, a decrease in the GDP growth rate by 1 percentage point results in a 2.3-percentage-point fall in the recovery rate. In contrast, the bond default rate continues to be statistically significant when the stock market return is included in the regression (column 6). Therefore, the evidence in Table 2 is inconclusive and suggests that while bond market conditions are likely important, macroeconomic drivers cannot be dismissed outright.[14]

Because the regression models in Table 2 are based on aggregate recovery rates, they do not test for industry distress and the potential for illiquidity in the market for distressed asset sales. The direct impact of industry distress on industry recovery rates is shown in the first two columns of Table 3, where the methodology follows that of Acharya, Bharath, and Srinivasan. These regressions include the median industry Q, which is the ratio of the market value of firm assets to the book value of firm assets. Higher values of this variable are meant to reflect favorable growth opportunities for firms in a particular industry. The industry Q, therefore, captures the channel through which pure economic worth drives up recoveries in good economic times for a particular industry. As shown, this variable enters with the hypothesized significantly positive effect. All of the models also control for industry

Table 2

EXPLAINING RECOVERY RATES: CONDITIONS IN THE OVERALL MARKET FOR DEFAULTED DEBT

(Aggregate Time-Series Regressions: 1978-2010)

	(1)	(2)	(3)	(4)	(5)	(6)
Bond Defaulted Amount	-117.97*** (40.02)					
Bond Default Rate		-1.96*** (0.61)			-1.22 (0.89)	-1.84** (0.68)
Real GDP Growth			3.13*** (0.67)		2.34** (1.12)	
S&P 500 Stock Return				0.18 (0.15)		0.09 (0.17)
Observations	31	33	33	33	33	33
R^2	0.09	0.16	0.20	0.04	0.25	0.17

This table presents regressions of the aggregate annual weighted average recovery rate on conditions in the bond market, measured by the bond defaulted amount (trillions of dollars) and the bond default rate (percent), and on macroeconomic conditions measured by real GDP growth (percent) and the S&P 500 stock return (percent). Note that ***, **, *, indicate 1, 5, and 10 percent statistical significance, respectively. The standard errors used in calculating significance levels are robust to heteroscedasticity and are shown in parentheses.

Table 3

EXPLAINING RECOVERY RATES: DISTRESS CONDITIONS IN THE INDUSTRY OF DEFAULTING FIRMS

(Industry-Level Regressions: 1978-2008)

	(1)	(2)	(3)	(4)	(5)
Industry Q (Market to Book)	8.42* (4.57)	9.47** (4.37)			9.38** (4.19)
Industry Stock Return	9.65** (4.58)				
Industry Distress Indicator		-6.50** (2.84)			
Recession Indicator			-6.84*** (1.99)	-1.11 (2.48)	-0.58 (2.44)
Correlation of Industry Sales Growth with Real GDP Growth				9.89 (14.06)	10.66 (13.43)
Recession * Correlation of Industry Sales Growth with Real GDP Growth				-46.45*** (15.39)	-40.82*** (14.99)
Observations	375	375	375	375	375
R^2	0.09	0.09	0.08	0.08	0.10

This table presents regressions of the industry (2-digit SIC code) annual weighted average recovery rate on industry illiquidity conditions. The industry distress indicator equals one if the median stock return of all firms in the 2-digit industry of the defaulted firm in the year of default is less than -30 percent, and zero otherwise. The recession indicator is one in recession years and zero otherwise. Industry variables are calculated using Compustat data. Regressions also include primary industry dummies. Note that ***, **, *, indicate 1, 5, and 10 percent statistical significance, respectively. The standard errors used in calculating significance levels are robust to heteroscedasticity, clustered at the 2-digit SIC industry level, and are shown in parentheses.

dummy variables to capture industry unique factors, such as debt issued by utilities consistently recovering more than that of other industries.

The key variables of interest are industry distress-type variables. A common practice is to measure distress by adverse stock returns in a particular industry. Therefore, the variable of interest in the first column of Table 3 is the industry stock return, which is the median stock return of firms in a particular industry in a particular year. The estimated coefficient reflects the average effect that industry stock returns have on industry recovery rates. The coefficient has the hypothesized positive effect and is statistically significant at the 5 percent level. The estimated coefficient implies that a 30 percent industry stock return increases industry recovery rates by close to 3 percentage points (0.3 times 9.65). Similarly, a 30 percent industry stock decline decreases industry recovery rates by close to 3 percentage points.

Proponents of the industry illiquidity view, however, argue that the average relationship between industry stock returns and recovery rates does not effectively capture the impact of industry distress. For example, fire sales should only occur when industry peers are also experiencing financial distress, causing asset prices to fall below fundamental values. In other words, if the key driver is an industry fire-sales discount, a rise in industry stock returns of 30 percent would not be expected to increase the recovery rate to the same extent that a fall in industry stock returns of 30 percent will decrease the recovery rate. To account for this asymmetry, the industry distress variable in column 2 is set equal to 1 if the median industry stock return is less than -30 percent and zero otherwise. This -30 percent threshold is simply meant to reflect very adverse outcomes in a particular industry in a particular year.

As expected, industry distress has a significantly negative impact on industry recovery rates. Widespread financial distress in a particular industry depresses the recovery rate by 6.5 percentage points. This effect is about twice the effect implied by the average relationship in column 1, supporting an industry illiquidity view.[15] Moreover, in results not shown, industry distress retains its significance when controlling for GDP growth.

The models in the last three columns of Table 3 consider the possibility that industry distress is not necessarily independent of the aggregate state of the economy. In some cases industry distress is plausibly independent of the macroeconomy. Examples include the distress among health-care providers resulting from an unfavorable Medicare payments change in 1997, or more generally, industry-specific accounting fraud (Covitz and Han). However, in other cases, industry distress is often induced by macroeconomic downturns. Thus, the models in column 4 and column 5 allow for the possibility that industries vary in their sensitivity to the business cycle. Certain industries may be more sensitive to the business cycle than others and are, therefore, more likely to fall into financial distress during recessions. As a result, GDP growth may drive up recovery rates in different ways across different industries.

One measure of the differential sensitivity of different industries to the business cycle is the correlation of median industry sales growth with GDP growth. To the extent an industry's sales are perfectly synchronized with the business cycle, its recovery rate should be strongly procyclical. Examples of industries with high GDP correlations are furniture and fixtures, apparel and accessory stores, and durable goods wholesale trade; examples of industries with low GDP correlations are tobacco, local passenger transit, and food stores.[16] These industry correlations make sense because consumers are expected to cut back more on their purchases of furniture and apparel in recessions than on basic food goods. Similarly, consumers expand their purchases of furniture and apparel in good times by more than their purchases of basic food.

The findings help reconcile industry distress with the state of the economy as determinants of recoveries. The model in column 3 estimates the average relationship between industry recovery rates and a recession indicator (1 in recession years and 0 otherwise). On average, recessions are associated with a 6.8-percentage-point fall in the recovery rate. Column 4 estimates the sensitivity of different industries to the business cycle. The key variable of interest is the interaction of the recession indicator with the correlation of industry sales and GDP growth. The hypothesis is that the estimated coefficient on this term is negative. Industries that are more sensitive to the business cycle are more likely to be in a financially poor state during recessions. Thus, distress in a particular industry caused by a weak macroeconomy likely lowers recovery rates. The results support this hypothesis. For example, if industries are ranked by the correlation of their sales growth with GDP growth from highest to lowest, durable goods trade is at the 75th percentile (correlation of 0.18) and food stores is at the 25th percentile (correlation of 0.045). Based on the model in column 4, the recovery rate will be more than 6 percentage points less in durable goods trade than in food stores during a recession.[17] This economic magnitude is comparable to the direct effect of industry distress (column 2).

Finally, it is important to show that this macro-induced effect is closely related to industry illiquidity and not purely to changes in the fundamental worth of assets in a particular industry. The model in column 5, therefore, includes the median industry Q to control for shifts in fundamental asset values in different industries. The effect of median industry Q is similar to its effect in column 2 where it was included with the industry distress measure. The coefficient on the interaction term of the recession and industry sales correlation remains statistically significant at the 1 percent level and with a very similar economic effect. While the estimated effect is slightly lower, the results indicate that a significant part of industry distress is arguably induced by poor macroeconomic conditions.[18]

IV. CONCLUSION

In financial crises and ensuing downturns, defaults are often triggered in the financial, corporate, and even sovereign sectors. The 2007-09 global crisis and recession produced another cluster of defaults, adding to the historical record including the railroad crisis and banking panics of the late 1800s, the Great Depression, and other recent recessions. Accompanying a rise in defaults is a rise in default losses. How well financial institutions cope with the possibility of large losses depends on the robustness of their risk management process, including a proper assessment of recovery risk.

This article examined whether recovery rates are affected by systematic conditions in the economy—whether the overall performance of the economy, the conditions in the bond market for distressed debt, or industry illiquidity. The results suggest that the recovery rate depends on systematic and industrywide factors. It is more difficult, however, to precisely determine which factor is primarily responsible for driving recovery risk. Nonetheless, a plausible case can be made for the view that the state of the business cycle exerts an important influence on recoveries and at least part of this transmission shows up indirectly through industry distress and resulting fire sales of real assets.

It is, therefore, inappropriate to treat the recovery rate (or the loss given default) as certain, or random but not systematically related to aggregate and industrywide factors. Doing so will likely produce biased estimates of loss measures and may neglect specific risks altogether. The underestimation of extreme losses by risk managers and market participants is not of pure academic interest, but has effects on lending and investment activity in the real economy. For example, a financial institution that suffers larger losses than it was prepared for will likely cut back on needed credit to businesses and consumers. In an extreme outcome, the financial institution can fail and cause significant disruptions to its borrower and counterparty relationships. For these reasons, continuous improvements in risk management are needed.

APPENDIX 1

This appendix describes, in more technical terms, key loss measures produced by credit risk models. It then explains how a portfolio's risk can change, using analytical approximations of the distribution that a continuous loss variable can reasonably take. The appendix ends with a simplified example of a discrete loss variable in order to show how key risk measures can be understated when the recovery rate is assumed to be certain.

Loss measures

Potential losses on a portfolio are continuously distributed over a range from zero to full loss. Practitioners estimate loss distributions in two main ways. The first method is using Monte Carlo type simulations, where an empirical loss distribution is produced by simulating a large number of different possible loss realizations. The second method is using analytical approximations of the unknown loss distribution. Chart A1 illustrates reasonable examples of analytical loss distributions, where the loss is expressed as a fraction of the portfolio and ranges from 0 to 1. The two distributions in solid lines are beta distributions with a defined mean and a defined respective standard deviation.[19]

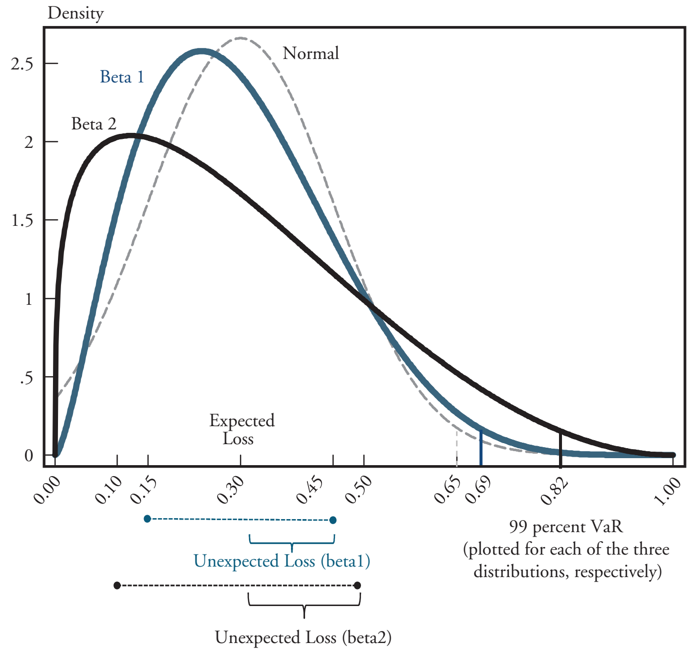
As illustrated in Chart A1, expected loss is the mean of the loss distribution and represents the amount the creditor can expect to lose over the forecast horizon. Both beta distributions match an expected loss rate of 0.3. For comparison purposes, a normal distribution with an expected loss rate of 0.3 is also plotted in the dashed line.

Notice, however, that while all three distributions have the same expected loss, the distributions are quite different. Unexpected loss is the deviation of losses from the expected loss and can be thought of as a measure of the risk of the portfolio. One common measure is the standard deviation of the loss distribution (Altman, Resti, and Sironi). For example, the beta distribution in the blue line (beta 1) has a smaller unexpected loss than the beta 2 distribution (0.15 versus 0.2).

But the main disadvantage to a standard deviation (or volatility) measure is that it does not do a good job at capturing the risk of large losses. For example, both the beta 1 distribution and the normal distribution have the same standard deviation of 0.15, but the likelihood of very large losses is greater with the beta distribution.

Chart A1

AN ILLUSTRATION OF A PORTFOLIO LOSS DISTRIBUTION



Notes: This chart plots analytical approximations of loss distributions, where the percentage portfolio loss is drawn from a beta distribution. Both distributions in the solid lines (beta 1 and beta 2) match a mean loss rate of 0.3 and a standard deviation of 0.15 and 0.20, respectively. For comparison, the normal distribution with a mean loss of 0.3 and standard deviation of 0.15 is plotted in the dashed line.

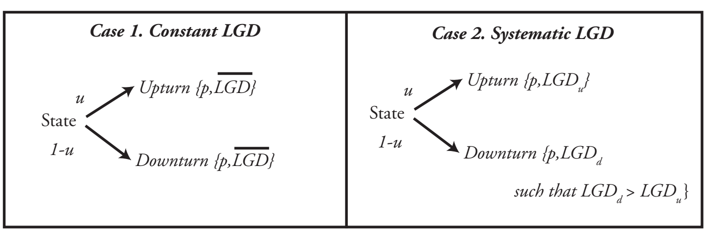
For this reason, other measures of the potential loss on the portfolio include the VaR. For example, the 99 percent VaR is the maximum loss over the forecast horizon such that there is a low probability (in this case 1 percent) that the actual loss will exceed it. The beta loss distributions in Chart A1 are realistic analytical approximations of true loss distributions because the beta distribution can be asymmetric and fat-tailed as shown. That is, in reality the likelihood of very large losses is greater than would be the case under, for example, a symmetric normal distribution. Note that while the normal distribution shares the same volatility as the beta 1 distribution, its VaR is less than the VaR of the beta 1 distribution (0.65 compared with 0.69). And not surprisingly, the higher volatility beta 2 distribution also has a considerably larger VaR (0.82).

Appropriate credit risk measures are important for policymakers overseeing financial institutions and not just for risk managers at these institutions. While optimal capital regulation is outside the scope of this article, provisions and capital buffers are intended to cover expected and unexpected loss, respectively, over a future horizon (Basel capital accord). The results of stress tests can be seen in this light. For example, the Federal Reserve's analysis of the capital plans recently submitted by the bank holding companies assessed the company's ability to maintain capital above a Tier 1 common capital ratio of 5 percent under both expected conditions and stressful conditions throughout the two-year planning horizon. One can think that expected macroeconomic conditions map to losses given by the expected loss in Chart A1. In contrast, stressful macroeconomic conditions map to a particularly large loss drawn from the right tail of the distribution.

A basic illustration of how credit risk can be understated

This example develops a simple discrete credit loss problem that shows how unexpected loss can be magnified when the recovery rate is positively related to the state of the business cycle. Suppose that there are only two states of the economy, upturns and downturns. Upturns occur with probability u and downturns occur with probability $d=1-u$. Suppose that there is a one unit loan outstanding, so that the exposure at default is equal to unity. For simplicity, further assume that the probability that the loan defaults is equal to p in both states. The only difference is that the loss given default (LGD) can be greater in downturns than in upturns in case 2, so that $LGD_d > LGD_u$. This key assumption makes LGD systematic (recall $LGD=1-recovery\ rate$).

How do losses compare in this systematic world with those in a constant LGD world? Let the loss variable be $L=1_{default}\ LGD$, where $1_{default}$ is an indicator variable, equal to one if the credit defaults and 0



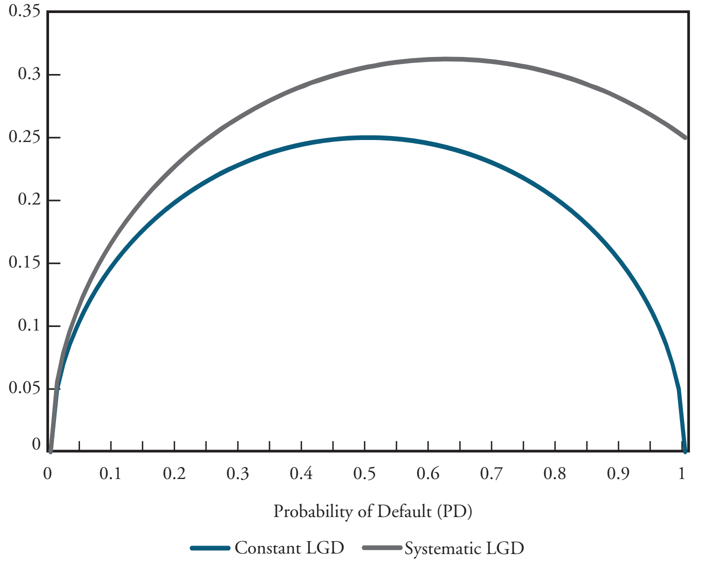
otherwise. Expected loss is, therefore, equal to $E[L]=p\overline{LGD}$ in case 1 and equal to $E[L]=upLGD_u+(1\text{-}u)pLGD_d$ in case 2. Intuitively, the state of the economy (and its likelihood, u) is irrelevant for losses in case 1, while in case 2 expected loss increases as the probability of a downturn increases (1-u) or as the severity of losses in a downturn increases (LGD_d).

Tracing unexpected loss for different values of default probability, p, provides additional insight. As discussed earlier, unexpected loss is a good summary measure of the risk of a credit portfolio, which is made up of one loan in this simple example. To make it clear how unexpected loss can differ even when expected loss is calibrated to be identical across the constant and systematic state, suppose that $uLGD_u+(1\text{-}u)LGD_d=\overline{\text{LGD}}$. For example, if the chance of an upturn is 50 percent and LGD in an upturn is only 25 percent while LGD in a downturn is 75 percent, this implies that the expected LGD in the systematic world is 50 percent. And if we calibrate $\overline{\text{LGD}}$ in the constant world to also equal 50 percent, then expected loss across the two cases will be identical.

However, the deviation of losses from expected loss will be different in the two cases. As shown in Chart A2, unexpected loss can be measured by the standard deviation of the loss variable. It can be shown that this equals the square root of $\overline{\text{LGD}}^2p(1\text{-}p)$ in the case of constant LGD, which is plotted in the blue line in Chart A2. First, before making a comparison with the systematic case, it is important to highlight the fact that for high values of default probability, unexpected loss goes down, so that unexpected loss is 0 if p, the default probability, is either 0 or 1. Intuitively, if a borrower is guaranteed to never fail or equally when it is guaranteed to always fail, there is no more risk associated with the loan because there is no chance that the payoff may vary unpredictably. As a result, the maximum unexpected loss in the case of a constant LGD is reached when the default probability is 50 percent so that there is an even chance that the credit defaults or does not default. The unexpected loss in the systematic case is plotted in the black line in Chart A2 and is greater than its value in the constant case (except when the default probability is 0 so that any systematic variation in LGD is no longer relevant). Note that unexpected loss does not approach 0 as the default probability goes to 1 because there is still recovery risk in this example from macroeconomic uncertainty even though default risk goes to 0 as the default probability goes to 1.[20]

Chart A2

AN ILLUSTRATION OF UNEXPECTED LOSS ON A ONE UNIT CREDIT EXPOSURE



Notes: This chart plots the standard deviation of a discrete loss variable, calibrated such that loss given default, LGD, equals 0.5 in the case of constant LGD, and expected LGD equals 0.5 in the case of an uncertain but systematic LGD. That is, LGD is systematically higher in an economic downturn than in an upturn, where each of the two economic states is assumed equally likely to occur.

APPENDIX 2

This appendix explains the distinction between different concepts of the recovery rate. There are three types of recovery, each with advantages and disadvantages to its application as a measure of the recovery rate.

The first concept is workout (or ultimate) recovery, which is the sum of the cash flows resulting from the workout process and measured at the time of resolution and emergence from default. In principle, this is the ideal measure of actual recovery, but because these cash flows are only realized at a future date, they should be properly discounted. This makes it problematic because the appropriate discount rate can be complicated to determine. One common method is to discount with the coupon of the bond (Metz and Sorensen). This is reasonable because if at resolution bondholders were to receive the full amount of principal and accrued interested due, then that amount discounted at the coupon rate back to the time of default corresponds to a 100-percent recovery rate. But in practice, it's not evident what discount rate to apply to workout recoveries. For example, Schuermann points out that the debt restructuring may have resulted in the issuance of two or more debt instruments—one a risky equity and one a less risky note or even cash.

The second measure is market recovery, which is based on the trading prices of defaulted securities soon after the default event occurs (roughly 30 days).[21] The analysis in Sections II and III of this article was based on trading price recoveries. While this measure may be an imperfect proxy of recovery, it has the advantage of being observed soon after default and, therefore, represents investors' expected recovery. Moreover, since many investors sell (or mark-to-market) debt instruments once default occurs, market price recovery represents actual recovery for many investors (Covitz and Han). Some studies have also shown that trading prices at default are unbiased predictors of discounted ultimate recoveries (Acharya, Bharath, and Srinivasan). But other studies find that trading prices are not unbiased predictors of ultimate recovery rates (Metz and Sorensen; Khieu, Mullineaux, and Yi). Although, reassuringly, the trading price recovery explains the level of ultimate recovery and a lot of its variation.

The third concept is the implied market recovery. These are recoveries derived from asset prices of tradable securities such as bonds and credit default swaps. So like the second concept, these are also based on market prices. But the difference is in the timing.[22] Because these securities have not (yet) defaulted, there is a much larger available sample size than the roughly 4,000 defaulted tradable U.S. corporate debt. Credit risk modelers can apply various theoretical asset pricing models to back out implied default probabilities and implied recovery rates. Indeed, spreads on corporate debt have been shown to be explained by realized recovery rates. That is, debt instruments with a higher default probability and a lower recovery rate are associated with a higher spread ex ante. Therefore, debt holders (at least partly) price in recovery risk (Liu, Miu, Chang, and Ozdemir).

But there are also disadvantages to market implied recovery rates because the implied recovery depends on the robustness of the asset pricing model used and the assumptions imposed. For example, because the spread on a corporate bond is a function of the default intensity and the loss given default, other information is needed to disentangle the implied recovery from the implied default intensity. Information could include other market data on equity prices or on derivatives securities with payoffs that depend in different ways on either the loss given default or the default intensity. Similarly, information from more than one bond could be exploited to the extent that junior debt shares the same default intensity as senior debt but has a different recovery profile (Duffie and Singleton). There are also additional problems with the use of corporate bond spreads to infer default intensity and loss given default. Specifically, corporate bond spreads likely include a risk premium, which is a compensation for the risk of default, as well as a liquidity premium because corporate bonds are not fully liquid.

ENDNOTES

[1]In their classification of risks, credit risk is one source of market risk. Market risk is defined as the risk of unexpected changes in prices, meaning it is broadly defined as the risk of changes in the market value of a particular portfolio of positions. To the extent that a credit portfolio is marked to market and liquid (easily traded without a substantial cost of adjusting the position), corporate bond spreads should price in the associated credit risk, otherwise the trading desk is either losing a valuable deal or taking on uncompensated credit exposures. However, Duffie and Singleton acknowledge that credit risk may not be fully captured in market prices because some credit-sensitive positions are less liquid, such as loan guarantees and lines of credit. Moreover, as shown by the financial crisis, some credit risk was entirely neglected by market participants, such as the risk that AAA-rated mortgage-backed securities had a greater likelihood of default than their rating would suggest.

[2]This classification of credit risk assumes that exposure at default is known; although in practice even exposure can be difficult to determine (Schuermann). For example, the exposure on a term loan is simpler to calculate than that on a credit line. As a firm approaches financial distress, it is likely to increase its drawdowns on unused credit lines to avoid defaulting. In the internal ratings based (IRB) approach introduced with Basel II, the exposure at default is set at 75 percent for irrevocable undrawn commitments. Moreover, exposure at default can be difficult to determine when credit exposures are hedged with other instruments such as credit default swaps. For example, the counterparty selling the credit insurance may not honor its obligations when the default event occurs. This risk is known as counterparty risk.

[3]Note that as with corporate defaults, there are large differences between creditor losses ("haircuts") across sovereign debt restructurings ranging from 13 percent in the case of Uruguay in 2003 to 73 percent in the case of Argentina in 2005 (Sturzenegger and Zettelmeyer). Private sector holders of Greek bonds took a 75 percent loss in their holdings in a deal announced March 9, 2012, which was the largest debt write-down in history (see *The New York Times*, "Next Time, Greece May Need New Tactics," March 9, 2012). Differences between countries arise from differences in bargaining power, the ability to pay, and the willingness to pay. The willingness to pay, in turn, depends on domestic political economy factors where the benefits of debt default are placed against the costs in terms of sanctions, reputational costs, and subsequent lack of access to international markets.

[4]A typical stochastic recovery rate is drawn from a beta distribution calibrated on the empirical mean and variance as done by Pesaran, Schuermann, Treutler, and Weiner. Applying a beta distribution to recovery rates has become a common industry practice because of a number of advantages, including it is 1) parsimonious as only two parameters (mean and variance) are needed; 2) bounded between 0 and 1; and 3) not necessarily symmetrical. However, the beta

distribution cannot be bimodal (two-humped) and does not allow for concentrations at specific recoveries, such as zero or 100 percent.

[5]Even ruling out common dependence on the state of the economy, the first generation structural model of credit risk developed by Merton (and extended by others) leads to a simple negative relationship between the likelihood of default and recovery. In Merton's model, default occurs when the market value of the firm's assets falls below its liabilities. Therefore, to the extent that the likelihood of default goes up when the market value of the firm's assets goes down (or when leverage goes up), recovery will decline, too. Further, increased asset volatility will mean a greater chance that realized asset values fall below the debt level, triggering default (and in later extensions of the structural model, a jump into default). In these cases, it is plausible that the recovery rate will also be low. For example, health-care providers that were hit by a reduction in cash flows from changes to Medicare reimbursements caused by the Balanced Budget Act of 1997 experienced low recovery rates (Covitz and Han).

[6]Trading price recovery measured soon after default is meant to proxy for eventual recovery on the defaulted debt when the issuer emerges from default. Moreover, this measure represents actual recovery for the many investors that sell their positions immediately following default. Appendix 2 describes, in detail, the different measures of the recovery rate that practitioners and financial economists have applied.

[7]Indeed, Moody's KMV proprietary LossCalc statistical model of loss given default includes a separate industry indicator for the utilities sector (Dwyer and Korablev).

[8]Many recent defaults have occurred through distressed exchanges triggered by private equity sponsors. For example, one-quarter of defaults during the January 2009 to August 2010 credit cycle were distressed exchanges compared with 16 percent on average as reported by Moody's. Moody's suggests that the larger share of distressed exchanges helps explain the relatively benign recovery rate in this period.

[9]These differences occur despite French creditors adjusting to the legal regime by requiring more collateral up front.

[10]The data are aggregate default rates and recovery rates. Specifically, the default rate is the weighted average default rate on securities in the high-yield market in the United States. Weights are based on the face value of all high-yield (subinvestment grade) securities outstanding each year (measured at midyear) and the size of each defaulting issue within a particular year. The recovery rate is the aggregate annual weighted average recovery on all defaulted U.S. corporate securities. The weights are based on the defaulted debt amounts. These measures follow closely those used by Altman and others. For example, the average default rate compiled by Altman and Kuehne for 1978-2010 is 3.6 percent and the average recovery rate is 44.8 percent. The trends are similar if the aggregate default rate is measured as a percent of all outstanding debt, not only the high-yield market; however, Altman and others use the high-yield bond market as the rel-

evant population base because most bonds migrate to default from this segment of the bond market.

[11]The 1982 peak in the default rate is less reliable because there was less outstanding high-yield debt in the 1970s and early 1980s. In addition, while 2008-09 saw a marked increase in the default rate from preceding years, the default rate peaked at a lower rate than observers expected at the beginning of the financial crisis. The default cycle was also short-lived, falling from a 10.8 percent default rate in 2009 to an average 1.3 percent in 2010-11 (Altman and Kuehne; Moody's and Fitch Ratings reports). One reason that defaults were fewer than expected is that the corporate sector was not at the center of the financial crisis (*The Economist*). Another reason may be that creditors such as banks wanted to avoid uncoordinated defaults and associated depressed recoveries. The choice of calling for default depends on creditors' incentives, in addition to borrowers' incentives (Carey and Gordy).

[12]Price deviations from fundamental debt values are not arbitraged away by other nonspecialized investors.

[13]This result is comparable to the -2.6 coefficient reported in Altman, Brady, Resti, and Sironi.

[14]In contrast, Altman, Brady, Resti, and Sironi find that the coefficients on GDP growth and the stock return are insignificant and sometimes enter with the wrong sign. Differences between the results in Table 2 and the results in Altman and others may be due to the different sample period (1978-2010 in Table 2 and 1982-2001 in the Altman and others study). However, replicating the basic Altman specifications using the data reported in Altman and Kuehne (also for 1978-2010) shows that bond market conditions are statistically significant in the presence of these two macro factors. Therefore, bond market conditions cannot be ruled out as important drivers of recoveries.

[15]For example, the average industry stock return conditioning on industry distress is roughly -40 percent, which implies a 3.9-percentage-point lower recovery rate (column 1) compared with a 6.5-percentage-point lower recovery rate associated with the industry distress indicator (column 2). Overall, the industry illiquidity effect is comparable to that found in Acharya, Bharath, and Srinivasan. They find that an industry in distress recovers roughly 10 percentage points less than otherwise. Note that differences arise from various factors including a different sample period, a different data set, and the fact that the specifications in Acharya, Bharath, and Srinivasan are at the instrument-level and, therefore, allow for additional debt contract and firm-level controls.

[16]The correlation measure is industry-specific (2-digit SIC codes) and is calculated using annual Compustat data from 1980.

[17]The differential effect on recovery during a recession equals -46.45*(0.18-0.045) = -6.3, where -46.45 is the estimated coefficient on the interaction term in column 4.

[18]In other robustness checks, the industry distress variable is also included in a similar empirical model to that shown in column 5. The coefficient on the recession interaction term falls slightly to -38.4 from -40.8 and remains statistically significant at the 1 percent level. The effect of industry distress also enters negatively as in column 2 but its effect is lower (-4.8 compared with -6.5) and not statistically significant at standard confidence levels. However, from a conceptual standpoint, such a specification is not ideal. That is, the underlying hypothesis is that industry distress is not independent but depends on the vulnerability of certain industries to the aggregate state. Therefore, including both terms may produce multicollinearity problems in the estimated regression.

[20]The beta distribution is a function of gamma distributions, where the loss variable, $L \sim \beta(a,b)$ such that a and b are the two shape parameters. Specifically,

$$E[L] = \frac{a}{a+b} \; and \;\; V[L] = \frac{ab}{(a+b)^2(a+b+1)}.$$

[21]Specifically, the variance of the loss variable in the constant LGD case is

$$Var[L]^{cst} = E[L^2] - \left[E[L]\right]^2 = p\overline{LGD}^2 - (p\overline{LGD})^2 = \overline{LGD}^2 p(1-p).$$

And in the systematic case,

$$Var[L]^{sys} = p(uLGD_u^2 + (1-u)LGD_d{}^2) - (p(uLGD_u + (1-u)LGD_d))^2.$$

Expanding the expressions and rearranging terms, it can be shown that

$$Var[L]^{sys} > Var[L]^{cst} \; if \;\; u(1-u)(LGD_u - LGD_d)^2 > 0$$

which is true for all $u \in (0,1)$. Chart A2 is plotted for a value of u=0.5.

[22]The 30-day after default is a market convention that has been shown to be a reasonable one. Metz and Sorensen show that the 30-day price is a better predictor of ultimate recoveries than prices closer to default. Interestingly, they also show that there are more observations available 30 days after default than directly after default. They attribute this feature to a change in the type of debt holders from institutional investors to investors specialized in distressed debt.

[23]Duffie and Singleton also make the additional distinction between recovery as a fraction of face value versus recovery as a fraction of market value. The latter concept measures recovery as a fraction of the market value of the bond just before default and is more tractable in asset pricing models because it can be computed using the same equations for default-free bonds but with default-adjusted parameters.

REFERENCES

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

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

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

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

Benmelech, Efraim, and Nittai K. Bergman. 2011. "Bankruptcy and the Collateral Channel," *Journal of Finance*, April.

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

Bris, Arturo, Ivo Welch, and Ning Zhu. 2006. "The Costs of Bankruptcy: Chapter 7 Liquidation versus Chapter 11 Reorganization," *Journal of Finance*, June.

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

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

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

Das, Sanjiv R., and Paul Hanouna. 2009. "Implied Recovery," *Journal of Economic Dynamics and Control*, November.

Davydenko, Sergei A., and Julian R. Franks. 2008. "Do Bankruptcy Codes Matter? A Study of Defaults in France, Germany, and the UK," *Journal of Finance*, April.

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

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

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

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

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

Franks, Julian R., and Walter N. Torous. 1994. "A Comparison of Financial Recontracting in Distressed Exchanges and Chapter 11 Reorganizations," *Journal of Financial Economics*, June.

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

_________. 2000. "Depressing Recoveries" *Risk*, November.

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

Khieu, Hinh D., Donald J. Mullineaux, and Ha-Chin Yi. 2011. "The Determinants of Bank Loan Recovery Rates," Journal of Banking and Finance, forthcoming.

Liu, Wenchien, Peter Miu, Yuanchen Chang, and Bogie Ozdemir. 2012. "Information Asymmetry and Bank Regulation: Can the Spread of Debt Contracts Be Explained by Recovery Rates?" *Journal of Financial Intermediation*, January.

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

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

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

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

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

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

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

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

_______________________________. 2011. "Fire Sales in Finance and Macroeconomics," *Journal of Economic Perspectives*, Winter.

Sturzenegger, Frederico, and Jeromin Zettelmeyer. 2008. "Haircuts: Estimating Investor Losses in Sovereign Debt Restructurings, 1998-2005," *Journal of International Money and Finance*, September.