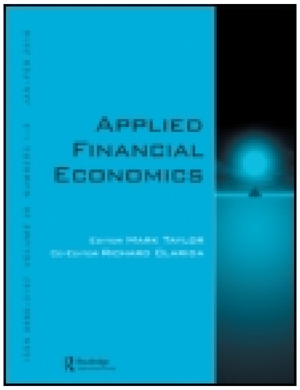

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An empirical study of the returns on defaulted debt

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An empirical study of the returns on defaulted debt†

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This study empirically analyses the historical performance of defaulted debt from Moody's Ultimate Recovery Database (1987–2010). Motivated by a stylized structural model of credit risk with systematic recovery risk, we argue and find evidence that returns on defaulted debt co-vary with determinants of the market risk premium, firm specific and structural factors. Defaulted debt returns in our sample are observed to be increasing in collateral quality or debt cushion of the issue. Returns are also increasing for issuers having superior ratings at origination, more leverage at default, higher cumulative abnormal returns on equity prior to default, or greater market implied loss severity at default. Considering systematic factors, returns on defaulted debt are positively related to equity market indices and industry default rates. On the other hand, defaulted debt returns decrease with short-term interest rates. In a rolling out-of-time and out-of-sample re-sampling experiment we show that our leading model exhibits superior performance. We also document the economic significance of these results through excess abnormal returns, implementing a hypothetical trading strategy, of around 5%–6% (2%–3%) assuming zero (1 bp per month) round-trip transaction costs. These results are of practical relevance to investors and risk managers in this segment of the fixed income market.

Keywords: distressed debt; recoveries; default; credit risk

JEL Classification: C15; C52; G24; G33; G34; G00; G10; G21

I. Introduction

There exists an economic argument that to the extent there may be opportunity costs associated with holding defaulted debt, and that the performance of such debt may vary systematically, the required return on the defaulted instruments should include an appropriate risk premium. Thus far, most research studying systematic variation in defaulted debt recoveries has focused on the influence of either macroeconomic factors (Frye, 2000a, b, c, 2003; Hu and Perraudin, 2002; Carey and Gordy, 2007; Jacobs, 2011), supply/demand conditions in the defaulted debt markets (Altman *et al*., 2003), or some combination thereof (Jacobs and Karagozoglu, 2011). Probably the reason for this focus is the conventional wisdom that determinants of recoveries (i.e. collateral values) are thought co-vary with such systematic

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macroeconomic measures. However, the results concerning systematic variation in recoveries have been mixed. We believe that this is due to the unmeasured factors influencing the market risk premium for defaulted debt. Adequately controlling for other determinants of defaulted debt performance, potentially imperfectly correlated with standard macroeconomic indicators, is critical to understanding these.

We propose to extend this literature in several ways. First, we quantify the systematic variation in defaulted debt returns with respect to factors which influence the market risk premium for defaulted debt, which are related to investors' risk aversion or investment opportunity sets[1]; in the process, we specify a simple stylized model of credit risk in structural framework (Merton, 1974), having testable implications that are investigated herein. Second, we are able to analyse defaulted debt performance in segments homogenous with respect to recovery risk, through controlling for both firm and instrument specific covariates, and examine whether these are associated with recoveries on defaulted debt securities. Third, departing from most of the prior literature on recoveries, having predominantly focused on measures around the time of default or at settlement, we will be studying the relationship amongst these in the form of returns. We believe that such focus is most relevant to market participants – both for traders and buy-and-hold investors (i.e. vulture funds, or financial institutions managing defaulted portfolios) – since this is an accepted measure of economic gain or loss. Finally, we are able to build parsimonious and robust econometric models, in the Generalized Linear Model (GLM) class, that are capable of explaining and predicting defaulted debt returns, and we use these to construct trading strategies demonstrating their economic significance.

In this study, we quantify the performance of defaulted debt relative to the previously and newly proposed determinants of corporate debt recoveries, through a comprehensive analysis of the returns on this asset class. The dataset that we utilize, Moody's *Ultimate Recovery Database*™ (MURD™), contains the market prices of defaulted bonds and loans near the time of default, and the prices of these instruments (or market value of the bundle of instruments) received in settlement (or at the resolution) of default. We have such data for 550 obligors and 1368 bonds and loans in the period 1987–2010. We examine the distributional properties of the individual annualized rates of return on defaulted debt across different segmentations in the dataset (i.e. default type, facility type, time period, seniority, collateral, original rating, industry), build econometric models to explain observed returns, and quantify potential trading gains to deploying such models.

Our principle results are as follows. We find returns to be in line with (albeit to the upper end of the range of results) what has been found in the previous literature, a mean of 28.6%.[2] We find returns on defaulted debt to vary significantly according to contractual, obligor, equity/debt markets and economic factors. At the facility structure level, there is some evidence that returns are elevated for defaulted debt having better collateral quality rank or in better protected tranches within the capital structure. At the obligor or firm level, returns are elevated for obligors rated higher at origination, more financially levered at default, or having higher Cumulative Abnormal Returns (CARs) on equity prior to default. However, we also find returns to be increasing in the market implied loss severity at default. We also find evidence that defaulted debt returns vary counter to the credit cycle, as they increase with industry default rates; however, they also increase with aggregate equity market returns. Further, we observe that short-term interest rates are inversely related to returns on defaulted debt. Finally, we document the economic significance of these results through excess abnormal returns, in a debt-equity arbitrage trading experiment, of around 5%–6% (2%–3%) assuming zero (1 bp per month) round-trip transaction costs.

In addition to the relevance of this research for resolving questions in the finance of distressed debt investing, and aiding practitioners in this space, our results have implications for recently implemented supervisory Basel II capital standards for financial institutions (BCBS, 2004). Our results indicate that time variation in the market risk premium for defaulted debt may be an important systematic factor influencing recoveries on such instruments (and by implication, their Loss-Given-Default (LGD)), which is likely to not be perfectly correlated with the business cycle. Hence, any financial institution, in making the decision about how much capital to hold as a safeguard against losses on corporate debt securities, should take into account factors such as the systematic variation in investor risk aversion

[1] Standard portfolio separation theory implies that, all else equal, during episodes of augmented investor risk aversion, a greater proportion of wealth is allocated to risk-free assets (Tobin, 1958; Merton, 1971), implying lessened demand, lower price, and augmented expected returns across all risky assets.
[2] The probable reason why we are closer to the higher end of estimates, such as Keenan *et al.* (2000), is that we have included several downturn periods, such as the early 1990s and the recent ones.

and investment opportunity sets.[3] Indeed, Basel II requires that banks quantify 'downturn effects' in LGD estimation (BCBS, 2005, 2006), and for the relevant kind of portfolio (i.e. large corporate borrowers having marketable debt), and our research provides some guidance in this regard.

II. Review of the Related Literature

Altman (1989) develops a methodology – at the time new to finance – for the measurement of risk due to default, suggesting a means of ranking fixed-income performance over a range of credit-quality segments. This technique measures the expected mortality of bonds, and associated loss rates, similarly to actuarial tabulations that assess human mortality risk. Results demonstrate outperformance by risky bonds relative to riskless Treasuries over a 10-year horizon and that, despite relatively high mortality rates, B-rated and CCC-rated securities outperform all other rating categories in the first 4 years after issuance, with BB-rated securities outperforming all others thereafter.

Gilson (1955) surveys the market practices of so-called 'vulture investors', noting that as the risks of such an investment style exposes one to a high level of idiosyncratic and nondiversifiable risk, and those who succeed in this space must have a mastery of legal rules and institutional setting that govern corporate bankruptcy. The author further argues that such mastery can result in very high returns. Hotchkiss and Mooradian (1997) study the function of this investor class in the governance and reorganization of defaulted firms using a sample of 288 public debt defaults. They attribute better relative operating performance after default to vulture investors gaining control of the target firm in either a senior executive or an ownership role. They also find positive abnormal returns for the defaulted firm's equity or debt in the 2 days surrounding the public revelation of a vulture purchase of such instruments. The authors conclude that vulture investors add value by disciplining managers of distressed firms.

The historical performance of the Moody's Corporate Bond index (Keenan *et al.*, 2000) shows an annualized return of 17.4% in the period 1982–2000. However, this return has been extremely volatile, as most of this gain (147%) occurred in the period 1992–1996. Keenan *et al.* (2000) and Altman and Jha (2003) both arrive at estimates of a correlation to the market on this defaulted loan index of about 20%, implying a market risk premium of 216 bps. Davydenko and Strebuleav (2002) report similar results for nondefaulted high-yield corporate bonds (BB rated) in the period 1994–1999.

From the perspective of viewing defaulted debt as an asset class, Guha (2003) documents a convergence in market value as a proportion of par with respect to bonds of equal priority in bankruptcy approaching default. This holds regardless of contractual features, such as contractual rate or remaining time-to-maturity. The implication is that while prior to default bonds are valued under uncertain timing of and recovery in the event of default, that varies across issues according to both borrower and instrument characteristics, upon default such expectations become one and the same for issues of the same ranking. There is cross-sectional variation in yields due to varied perceived default risk as well as instrument structures, but as default approaches the claim on the debt collapses to a common claim on the expected share of emergence value of the firm's assets due to the creditor class. Consequently, the contract rate on the debt pre-default is no longer the relevant valuation metric with respect to restructured assets. This was predicted by the Merton (1974) theoretical framework that credit spreads on a firm's debt approach the expected rate of return on the firm's assets, as leverage increases to the point when the creditors become the owners of the firm. Schuermann (2003) echoed the implications of this argument by claiming that cash flows post-default represent a new asset.

Altman and Jha (2003), regressing the Altman/Solomon Center defaulted bond index on the S&P 500 returns for the period 1986–2002, come up with an 11.1% required return (based upon a 20.3% correlation estimate.) Altman *et al.* (2003) examine the determinants of recoveries on defaulted bonds, in a setting of systematic variation in aggregate recovery risk, based on market values of defaulted debt securities shortly following default. The authors find that the aggregate supply of defaulted debt securities, which tends to increase in downturn periods, is a key determinant of aggregate as well as instrument level recovery rates. The authors' results suggest that while

[3] Our research also has a bearing on the related and timely issue of the debate about the so-called 'pro-cyclicality' of the Basel capital framework (Gordy, 2003), an especially relevant topic in the wake of the recent financial crisis, where a critique of the regulation is such that banks wind up setting aside more capital just at the time that they should be using capital to provide more credit to businesses or to increase their own liquidity positions, in order to help avoid further financial dislocations and help revitalize the economy.

systematic macroeconomic performance may be associated with elevated LGD, the principle mechanism by which this operates is through supply and demand conditions in the distressed debt markets. More recently, Altman and Karlin (2010) report that the Altman-NYU Salomon Center Index of defaulted bonds (bank loans) returned 12.6% (3.4%) over the period 1986–2009 (1989–2009).

Maclachlan (2004), in the context of proposing an appropriate discount rate for workout recoveries for regulatory purposes in estimating economic LGD (BCBS, 2005), outlines a framework that is motivated by a single-factor Capital Asset Pricing Model (CAPM) and obtains similar results in two empirical exercises. First, regressing Altman-NYU Salomon Center Index of Defaulted Public Bonds in the period 1987–2002 on the S&P 500 equity index, he obtains a 20% correlation, implying a Market Risk Premium (MRP) of 216 bps. Second, he looks at monthly secondary market bid quotes for the period April 2002–August 2003, obtaining a beta estimate of 0.37, which according to the Frye (2000c) extension of the Basel single factor framework, implies a recovery value correlation of 21% and an MRP of 224 bps.

Finally, considering studies of recovery rates (or LGDs), Acharya *et al*. (2007) examine the empirical determinants of ultimate LGD at the instrument level, and find that the relationship between the aggregate supply of defaulted debt securities and recoveries does not hold after controlling for industry level distress. They argue for a 'fire-sale effect' that results when most firms in a troubled industry may be selling collateral at the same time. These authors' results imply that systematic macroeconomic performance may not be a sole or critical determinant of recovery rates on defaulted corporate debt. Carey and Gordy (2007) examine whether there is systematic variation in ultimate recoveries at the obligor (firm-level default incidence) level, and find only weak evidence of systematic variation in recoveries. Recently, building upon these two studies, Jacobs and Karagozoglu (2011) empirically investigate the determinants of LGD and build alternative predictive econometric models for LGD on bonds and loans using an extensive sample of most major US defaults in the period 1985–2008. They build a simultaneous equation model in the Beta-Link Generalized Linear Model (BLGLM) class, identifying several that perform well in terms of the quality of estimated parameters as well as overall model performance metrics. This extends prior work by modelling LGD both at the firm and the instrument levels. In a departure from the extant literature, the authors find the economic and statistical significance of firm-specific, debt and equity-market variables; in particular, that information from either the equity or the debt markets at around the time of default (measures of either distress debt prices or cumulative equity returns, respectively) have predictive powers with respect to the ultimate LGD, which is in line with recent recovery and asset pricing research. They also document a new finding, that larger firms (loans) have significantly lower (higher) LGDs.

III. Theoretical Framework

In this section we lay out the theoretical basis for returns on post-default recoveries, denoted as r_s^D, where s denotes a recovery segment (i.e. seniority classes, collateral types, etc.). Following an intertemporal version of the structural modelling framework for credit risk (Merton, 1971; Vasicek, 1987, 2002),[4] we may write the stochastic process describing the instantaneous evolution of the ith firm's[5] asset returns at time t as

$$\frac{\mathrm{d}V_{i,t}}{V_{i,t}} = \mu_i \,\mathrm{d}t + \sigma_i W_{i,t} \tag{3.1}$$

where $V_{i,t}$ is the asset value, σ_i is the return volatility, μ_i is the drift (which can be taken to be the risk-free rate r under risk-neutral measure), and $W_{i,t}$ is a standard Weiner process that decomposes as (this is also known as a *standardized asset return*)

$$\mathrm{d}W_{i,t} = \rho_{i,X}\,\mathrm{d}X_t + \left(1 - \rho_{i,X}^2\right)^{1/2} \mathrm{d}Z_{i,t} \tag{3.2}$$

where the processes (also standard Weiners) X_t and $Z_{i,t}$ are the systematic risk factor (or standardized asset returns) and the idiosyncratic (or firm-specific) risk factor, respectively; and the factor loading $\rho_{i,X}$ is constant across all firms in a Probability-of-Default (PD) segment homogenous with respect to default risk (or across time for the representative firm).[6] It follows that the instantaneous asset-value correlation amongst firms (or segments) i and j is given by

$$\frac{1}{\mathrm{d}t}\mathrm{Cor}_{(i,j)}^{V}\left[\frac{\mathrm{d}V_{i,t}}{V_{i,t}}\frac{\mathrm{d}V_{j,t}}{V_{j,t}}\right] = \rho_{i,X}\rho_{j,X} \tag{3.3}$$

[4] Note that this is also the approach underlying the regulatory capital formulae (BCBS, 2004), as developed by Gordy (2003).
[5] This could also be interpreted as the ith PD segment or an obligor rating.
[6] Vasicek (2002) demonstrates that under the assumption of a single systematic factor, an infinitely granular credit portfolio, and LGD that does not vary systematically, a closed-form solution for capital exists that is invariant to portfolio composition.

Defining the recovery rate on the sth defaulted asset[7] at time t as $R_{s,t}$, we may similarly write the stochastic process describing its evolution as

$$\frac{\mathrm{d}R_{s,t}}{R_{s,t}} = \mu_s^R \mathrm{d}t + \sigma_s^R \mathrm{d}W_{s,t}^R \tag{3.4}$$

where μ_s^R is the drift (which can be taken to be the expected instantaneous return on collateral under physical measure, or the risk-free rate under risk-neutral measure), σ_s^R is the volatility of the collateral return, and $W_{s,t}^R$ is a standard Weiner process that for recovery segment S^R decomposes as

$$\mathrm{d}W_{s,t}^R = \rho_{s,X^R}\mathrm{d}X_t^R + \left(1-\rho_{s,X^R}^2\right)^{1/2}\mathrm{d}Z_{s,t} \tag{3.5}$$

where the two-systematic factors are bivariate standard normal, each standard normal, but with correlation r between each other

$$\left(\mathrm{d}X_t, \mathrm{d}X_t^R\right)^T \sim N\left(\begin{pmatrix}0\\0\end{pmatrix}, \begin{pmatrix}1 & r\\ r & 1\end{pmatrix}\right) \tag{3.6}$$

This set-up follows various extensions of the structural model framework for systematic recovery risk. What they have in common is that they allow the recovery process to depend upon a 2nd systematic factor, which may be correlated with the macro (or market) factor X_t (Frye, 2000a, b, c; Pykhtin, 2003; Dullman and Trapp, 2004; Giese, 2005; Rosch and Scheule, 2005; Hillebrand, 2006; Barco, 2007). In this general and more realistic framework, returns on defaulted debt may be governed by a stochastic process distinct from that of the firm. This is the case where the asset is secured by cash, third party guarantees, or assets not used in production. In this setting, it is possible that there are two salient notions of asset value correlation, one driving the correlation amongst defaults, and another driving the correlation between collateral values and the returns on defaulted assets in equilibrium. This reasoning implies that it is entirely conceivable that, especially in complex banking facilities, cash flows associated with different sources of repayment should be discounted differentially according to their level of systematic risk. In not distinguishing how betas may differ between defaulted instruments secured differently, it is quite probable that investors in distressed debt may misprice such assets.

It is common to assume that the factor loading in Equation 3.5 is constant amongst debt instruments within specified recovery segments, so that the recovery-value correlation for segment S^R is given by $\rho_{i,s^R}^2 \equiv R_{s^R}$.[8] If we take the further step of identifying this correlation with the correlation to a market portfolio – arguably a reasonable interpretation in the Asymptotic Single Risk-Factor (ASRF) framework (Vasicek, 1987; Gordy, 2003) – then we can write $R_{s^R}^2 = \rho_{s^R,M}^2$. It then follows from the standard CAPM that the relationship between the defaulted debt instrument and market rates of return is given by the beta coefficient

$$\frac{\mathrm{Cov}_{s^R,M}\left[\frac{\mathrm{d}R_{i,t}}{R_{i,t}}, \frac{\mathrm{d}V_{M,t}}{V_{M,t}}\right]}{\mathrm{Var}_M\left[\frac{\mathrm{d}V_{M,t}}{V_{M,t}}\right]} = \beta_{s^R,M} = \frac{\sigma_s^R\sqrt{R_{s^R}}}{\sigma_M} \tag{3.7}$$

where σ_M is volatility of the market return. We may now conclude that in this setting the return on defaulted debt on the sth exposure (or segment) r_s^D is equal to the expected return on the collateral, which is given by the sum of the risk-free rate r_{rf} and a debt-specific risk-premium δ_s

$$\begin{aligned} r_s^D &= r_{rf} + \frac{\sigma_s^R\sqrt{R_{s^R}}}{\sigma_M}\left(r_M - r_{rf}\right) \\ &= r_{rf} + \beta_{s^R,M}MRP = r_{rf} + \delta_{s^R} \end{aligned} \tag{3.8}$$

where the MRP is given by $\mathrm{MRP} \equiv r_M - r_{rf}$ (also assumed to be constant through time) and the debt-specific risk premium is given by $\delta_{s^R} = \beta_{s^R,M}\mathrm{MRP}$. This approach identifies the systematic factor with the standardized return on a market portfolio r_M, from which it follows that the asset correlation to the former can be interpreted as a normalized 'beta' in a single-factor CAPM (or just a correlation between the defaulted debt's and the market's return), which is given by $\rho_{i,s^R} \equiv (R_{s^R})^{1/2}$. In subsequent sections, we pursue estimation of $\hat{\rho}_{i,s^R}$, through regressing actual defaulted debt returns on some kind of market factor or other measure of systematic risk (i.e. aggregate default rates),[9] while controlling for firm or instrument specific covariates.

[7] We can interpret this as an LGD segment (or rating) or debt seniority class.

[8] Indeed, for many asset classes the Basel II framework mandates constant correlation parameters equally across all banks, regardless of particular portfolio exposure to industry or geography. However, for certain exposures, such as wholesale non-High Volatility Commercial Real Estate (non-HVCRE), this is allowed to depend upon the PD for the segment or rating (BCBS, 2004).

[9] Alternatively we can estimate the vector of parameters $(\mu, \mu_i^R, \rho_{i,s}, \rho_{i,s^R}, r)^{\mathrm{T}}$ by Full-Information Maximum Likelihood (FIML), given a time series of default rates and realized recovery rates. The resulting estimate $\widehat{\rho}_{i,s^R}$ can be used in Equation 3.8 – in conjunction with estimates of the market volatility σ_M, debt-specific volatility σ_i^R, the MRP $(r_M - r_f)$, and the risk-free rate r_f – in order to derive the theoretical return on defaulted debt within this model (Maclachlan, 2004). Also see Jacobs (2011) for how these quantities can be estimated from prices of defaulted debt at default and at emergence of different seniority instruments.

IV. Empirical Methodology

We adopt a simple measure, motivated in part by the availability of a rich dataset of defaulted bonds and loans available to us, which analyses the observable market prices of debt at two points in time: the default event (i.e. bankruptcy or other financial distress qualifying as a default) and the resolution of the default event (i.e. emergence from bankruptcy or liquidation under the provisions of the US legal codes Chapter 11 or Chapter 7, respectively). We calculate the annualized rate of return on the *i*th defaulted debt instrument in segment *j* as

$$r_{i,j}^{D} = \left(\frac{P_{i,j,t_{i,j}^{E}}^{E}}{P_{i,j,t_{i,j}^{D}}^{D}} \right)^{\frac{1}{t_{i,j}^{E} - t_{i,j}^{D}}} - 1 \tag{4.1}$$

where $P_{i,j,t_{i,j}^{D}}^{D}$ ($P_{i,j,t_{i,j}^{E}}^{E}$) are the prices of debt at time of default $t_{i,j}^{D}$ (emergence $t_{i,j}^{E}$). An estimate for the return, the *j*th segment (seniority class of collateral type), can then be formed as the arithmetic average across the loans in that segment

$$\bar{r}_{j}^{D} = \frac{1}{N_{j}^{D}} \sum_{i=1}^{N_{j}^{D}} \left[\left(\frac{P_{i,j,t_{i,j}^{E}}^{E}}{P_{i,j,t_{i,j}^{D}}^{D}} \right)^{\frac{1}{t_{i,j}^{E} - t_{i,j}^{D}}} - 1 \right] \tag{4.2}$$

where N_{j}^{D} is the number of defaulted loans in the recovery group *j*. A measure of the recovery uncertainty in recovery class *j* is given by the sample SE of the mean annualized return

$$\hat{s}_{\bar{r}_{j}^{D}} = \frac{1}{N_{j}^{D} - 1} \sqrt{ \sum_{i=1}^{N_{j}^{D}} \left[\left\{ \left(\frac{P_{i,j,t_{i,j}^{E}}^{E}}{P_{i,j,t_{i,j}^{D}}^{D}} \right)^{\frac{1}{t_{i,j}^{E} - t_{i,j}^{D}}} - 1 \right\} - \bar{r}_{j}^{D} \right]^{2} } \tag{4.3}$$

V. Empirical Results: Summary Statistics of Returns on Defaulted Debt by Segment

In this section and the following, we document our empirical results. These are based upon our analysis of defaulted bonds and loans in the Moody's Ultimate Recovery Database$^{\text{TM}}$ (MURD$^{\text{TM}}$) release as of August 2010. This contains the market values of defaulted instruments at or near the time of default,[10] as well as the values of such pre-petition instruments (or of instruments received in settlement) at the time of default resolution. This database is largely representative of the US large-corporate loss experience, from the late 1980's to the present, including most of the major corporate bankruptcies occurring in this period.

Table 1 summarizes basic characteristics of simple annualized Return on Defaulted Debt (RDD) in Equation 4.1 by default event type (bankruptcy under Chapter 11 versus out-of-court settlement) and instrument type (loans – broken down by term loans and revolving credits versus bonds). The bottom panel of Table 1 represents the entire Moody's database, whereas the top panel summarizes the subset for which we can calculate RDD measures. Here we also show the means and SEs of two other key quantities: the time-to-resolution (i.e. time from default to time of resolution) and the outstanding-at-default, for both the RDD sample as well as for the entire MURD$^{\text{TM}}$ database (i.e. including instruments not having trading prices at default). We conclude from this that our sample is for the most part representative of the broader database. Across all instruments, average time-to-resolution is 1.6 (1.4) years and average outstanding at default is US\$216.4 M (US\$151.7 M), for the analysis (broader) samples.

The version of MURD$^{\text{TM}}$ that we use contains 4050 defaulted instruments, 3500 (or 86.4%) of which are bankruptcies, and the remaining 550 are distressed restructurings. On the other hand, in the RDD subset, the vast majority (94.6% or 1322) of the total (1398) are Chapter 11. One reason for this is that the times-to-resolution of the out-of-court settlements are so short (about 2 months on average) that it is more likely that post-default trading prices at 30–45 days from default are not available. Second, many of these were extreme values of RDD, and were heavily represented in the outliers that we chose to exclude from the analysis (30 out of 35 statistical outliers).[11]

The overall average of the 1398 annualized RDDs is 28.6%, with a SE of the mean of 3.1%, and ranging widely from −100% to 893.8%. This suggests that there were some very high returns – as the 95th percentile of the RDD distributions is 191%, or that in well over 70 cases investors would have nearly tripled their money holding defaulted debt. We can observe this in Fig. 1, the distribution of RDD, which

[10] Experts at Moody' compute an average of trading prices from 30 to 45 days following the default event, where each daily observation is the mean price polled from a set of dealers with the minimum/maximum quote thrown out.

[11] Based upon extensive data analysis in the Robust Statistics package of the S-Plus statistical computing application, we determined 35 observations to be statistical outliers. The optimal cut-off was determined to be about 1000%, above which we removed the observation from subsequent calculations. There was a clear separation in the distributions, as the minimum RDD in the outlier subset is about 17 000%, more than double the maximum in the nonoutlier subset.

Table 1. Characteristics of RDD[a] observations by default and instrument type (Moody's ultimate recovery database 1987–2010)

			Bankruptcy					Out-of-court					Total				
			Count	Average	SE of the mean	Minimum	Maximum	Count	Average	SE of the mean	Minimum	Maximum	Count	Average	SE of the mean	Minimum	Maximum
Sub-population of Moody's recoveries database having trading price of debt at default	Bonds and team loans	RDD	1072	28.32%	3.47%	−100.00%	893.76%	59	45.11%	19.57%	−91.87%	846.73%	1131	29.76%	3.44%	−100.00%	893.76%
		Time-to-resolution[b]		1.7263	0.0433	0.0027	9.0548		6.65%	3.33%	0.27%	144.38%		1.6398	0.0425	0.0000	9.0548
		Principal at default[c]		207 581	9043	163	4 600 000		416 751	65 675	6330	2 250 000		218 493	9323	0	4 600 000
	Bonds	RDD	837	25.44%	3.75%	−100.00%	893.76%	47	44.22%	21.90%	−91.87%	846.73%	884	26.44%	3.74%	−100.00%	893.76%
		Time-to-resolution[b]		1.4089	0.0436	9.0548	9.0548		0.2044	0.0786	0.0027	1.4438		1.3194	0.0427	0.0027	9.0548
		Principal at default[c]		205 028	10 590	0	4 000 000		432 061	72 727	6330	2 250 000		207 647	10 325	0	4 000 000
	Revolvers	RDD	250	26.93%	7.74%	−100.00%	893.76%	17	10.32%	4.61%	−0.04%	61.18%	267	25.88%	7.26%	−100.00%	893.76%
		Time-to-resolution[b]		1.4089	0.0798	0.0548	9.0548		0.0027	0.0000	0.0027	0.0027		1.3194	0.0776	0.0027	9.0548
		Principal at default[c]		205 028	19 378	0	4 000 000		246 163	78 208	32 000	1 250 000		207 647	18 786	0	4 000 000
	Loans	RDD	485	32.57%	5.71%	−100.00%	893.76%	29	26.161%	18.872%	−91.87%	532.76%	514	32.21%	5.49%	−100.00%	893.76%
		Time-to-resolution[b]		1.4089	0.0548	0.0027	9.0548		18.12%	9.96%	0.0027	2.8959		1.2458	0.0743	0.0027	9.0548
		Principal at default[c]		193 647	11 336	0	4 000 000		291 939	78 628	24 853	1 750 000		199 192	16 088	0	4 000 000
	Total	RDD	1322	28.05%	3.17%	−100.00%	893.76%	76	37.33%	15.29%	−91.87%	846.73%	1398	28.56%	3.11%	−100.00%	893.76%
		Time-to-resolution[b]		1.6663	0.0384	0.0027	9.0548		0.0522	0.0260	0.0000	1.4438		1.5786	0.0376	0.0000	9.0548
		Principal at default[c]		207 099	8194	0	4 600 000		378 593	54 302	0	2 250 000		216 422	8351	0	4 600 000
Entie population of Moody's recoveries database	Bonds and team loans	Time-to-resolution[b]	2798	1.6982	0.0253	0.0027	9.3151	433	0.2084	0.0261	0.0027	3.8767	3231	1.4986	0.0239	0.0027	9.3151
		Principal at default[c]		149 623	4585	0	4 600 000		204 750	16 469	0	3 000 000		157 011	4553	0	4 600 000
	Bonds	Discounted LGD[c]	2162	48.57%	0.83%	−69.78%	100.00%	345	14.50%	1.37%	−27.66%	100.00%	2507	43.83%	0.78%	−69.78%	100.00%
		Time-to-resolution[b]		1.7786	0.0290	0.0027	9.3151		0.2084	0.0292	0.0027	3.8767		1.5620	0.0275	0.0027	9.3151
		Principal at default[c]		157 488	5608	0	4600 0		204 750	18 450	0	3 000 000		166 781	5551	0	4 600 000
	Revolvers	Discounted LGD[c]	702	39.47%	1.47%	−69.78%	100.00%	117	18.00%	2.76%	−3.58%	100.00%	819	36.40%	1.35%	−69.78%	100.00%
		Time-to-resolution[b]		1.3944	0.1062	0.0027	9.0548		0.1490	0.0476	0.0027	2.8959		1.2165	0.0407	0.0027	9.0548
		Principal at default[c]		131 843	21 396	0	4 000 000		124 199	17 836	347	1 250 000		130 751	226 241	0	4 000 000
	Loans	Discounted LGD[c]	1338	40.03%	1.08%	−69.78%	100.00%	205	17.20%	2.03%	−27.66%	100.00%	1543	37.00%	0.99%	−69.78%	100.00%
		Time-to-resolution[b]		1.4089	0.0330	0.0027	9.0548		0.1812	0.0375	0.0027	2.8959		1.2458	0.0309	0.0027	9.0548
		Principal at default[c]		127 586	5521	0	4 000 000		124 671	14 739	347	1 750 000		127 199	5171	0	4 000 000
	Total	Discounted LGD[c]	3500	45.31%	0.66%	−69.78%	100.00%	550	15.25%	1.13%	−27.66%	100.00%	4050	41.23%	0.61%	−69.78%	100.00%
		Time-to-resolution[b]		1.6373	0.0221	0.0027	9.3151		0.1958	0.0026	0.0027	3.8767		1.4415	0.0208	0.0027	9.3151
		Principal at default[c]		146 057	4064	0	4 600 000		187 615	13 576	0	3 000 000		151 701	3972	0	4 600 000

Notes: [a]'RDD': annnualized simple rate of return on defaulted debt from just after the time of default (1st trading date of debt) until the time of ultimate resolution.
[b]The total instrument outstanding at default.
[c]The time in years from the instrument default date to the time of ultimate recovery.

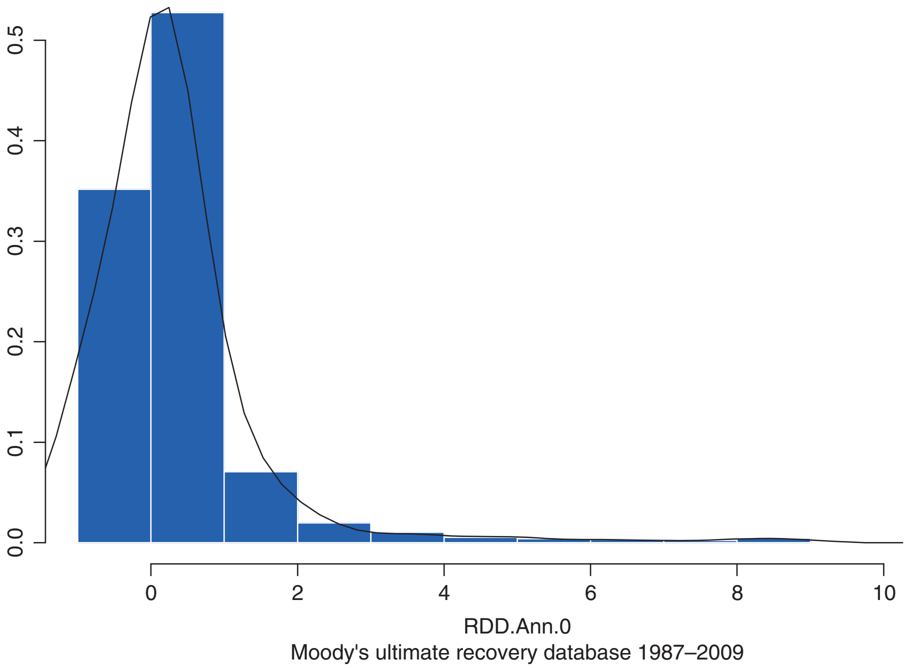

Fig. 1. Distribution of RDD (All instruments)

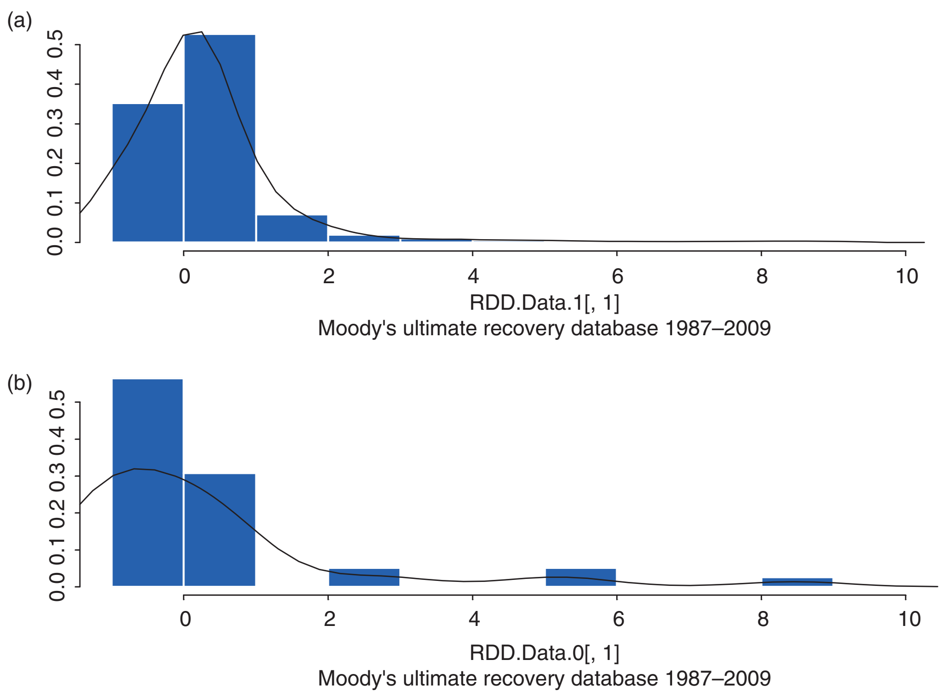

Fig. 2. Distribution of RDD: (a) Bankruptcies; (b) out-of-court settlements

has an extremely long tail to the right. We observe that the distribution of RDD is somewhat different in the case of out-of-court settlements as compared to bankruptcies, with respective mean RDDs of 37.3% for the former, and 28.1% in the latter. The SEs of mean RDDs are also much higher in the nonbankruptcy population, 15.3% for out-of-court versus 3.2% for bankruptcies. This large difference in distributional properties can be observed in the empirical distributions of RDDs by default type in Fig. 2(a) and (b). The data is well-represented by bank loans, 36.8% (38.1%) of the RDD (total MURD™) sample, or 514 (1543) out of 1398 (4050) instruments. Loans appear to behave

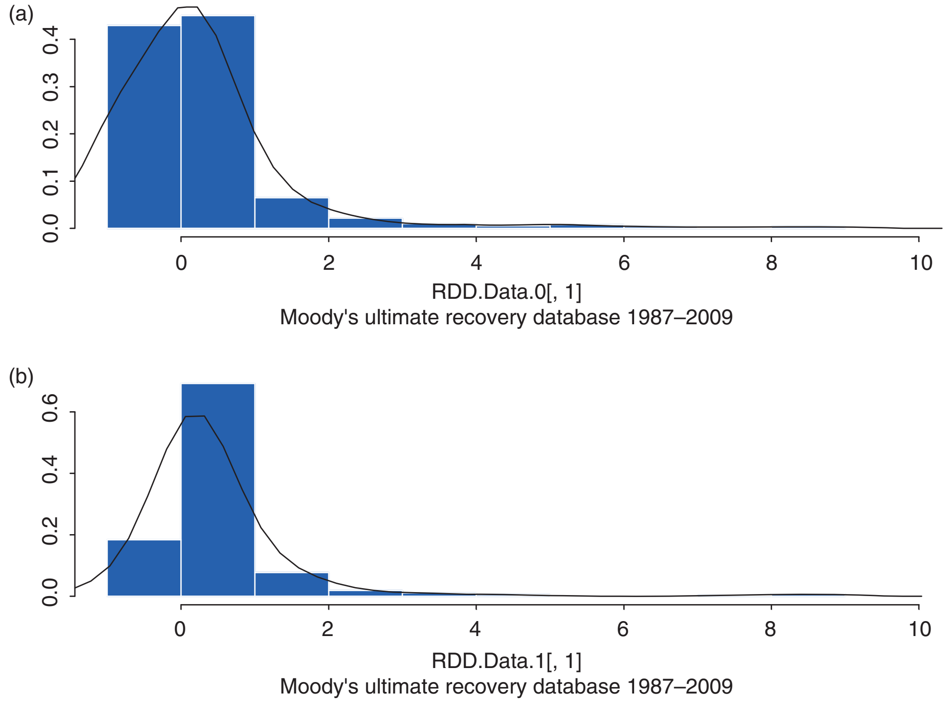

Fig. 3. Distribution of RDD: (a) bonds; (b) loans

somewhat differently than bonds, having slightly higher mean and SE of mean RDDs, 32.1% and 26.4%, respectively. Figure 3(a) and (b) show the distributions of RDD by instrument type.

Table 2 summarizes the distributional properties of RDD by seniority rankings (bank loans; senior secured, unsecured and subordinated bonds; and junior subordinated bonds) and collateral types.[12] Generally, while this does not hold monotonically across collateral classes or is consistent across recovery risk measures, better secured or higher ranked instruments exhibit superior post-default return performance. However, while the SE of mean RDD (which we can argue reflects recovery uncertainty) tends to be lower for more senior instruments, it tends to be higher for those which are better secured. Average RDD is significantly higher for secured as compared to unsecured facilities, 34.5% versus 23.6% respectively. Focusing on bank loans, we see a wider split of 33.0% versus 19.8% for secured and unsecured, respectively. However, by broad measures of seniority ranking, mean RDD exhibits a non-monotonic increasing pattern in seniority, while the SE of RDD is decreasing in seniority. Average RDD is 32.3% and 36.6% for loans and senior secured bonds, as compared to 23.7% and 33.2% for senior secured and senior subordinated bonds, decreasing to 15.6% for junior subordinated instruments. However, while unsecured loans have lower post-default returns than secured loans, within the secured loan class we find that returns exhibit a humped pattern as collateral quality goes down in rank, an increase in RDD from 22.6% for cash, to 46.2% for ‘All assets and real estate’, to 29.0% for ‘PP&E and second lien’.

Table 3 summarizes RDDs by two duration measures: the ‘Time-In-Distress’ (TID), defined as the time (in years) from the last cash pay date to the default state, and the ‘Time-To-Resolution’ (TTR), the duration from the date of default to the resolution or settlement date. Analysis of these measures helps us to understand the term-structure of the defaulted debt returns. We examine features of RDD by quintiles of the TTR and TID distributions, where the 1st refers to the bottom fifth of durations in length, and the 5th quintile the top longest.

[12] We have two sets of collateral types: the 19 lowest level labels appearing in MURD™ (Guarantees, Oil and Gas Properties, Inventory and Accounts Receivable, Accounts Receivable, Cash, Inventory, Most Assets, Equipment, All Assets, Real Estate, All Noncurrent Assets, Capital Stock, PP&E, Second Lien, Other, Unsecured, Third Lien, Intellectual Property and Intercompany Debt), and a 6-level grouping of that we constructed from these (Cash, Accounts Receivables and Guarantees; Inventory, Most Assets and Equipment; All Assets and Real Estate; Noncurrent Assets and Capital Stock; PP&E and Second Lien; and Unsecured and Other Illiquid Collateral). The latter high-level groupings were developed with in consultation with recovery analysis experts at Moody’s Investors Services.

Table 2. RDD[a] by seniority ranks and collateral types (Moody's ultimate recovery database 1987–2010)

		Revolving credit/term loan			Senior secured bonds			Senior unsecured bonds			Senior subordinated bonds			Subordinated bonds			Total instrument		
	Collateral type	Count	Average	SE	Count	Average	SE	Count	Average	SE	Count	Average	SE	Count	Average	SE	Count	Average	SE
Minor collateral category	Guarantees	2	−96.0%	4.0%	0	N/A	N/A	0	N/A	N/A	0	N/A	N/A	0	N/A	N/A	2	−96.0%	4.0%
	Oil and Gas Properties	2	77.5%	68.3%	0	N/A	N/A	0	N/A	N/A	0	N/A	N/A	0	N/A	N/A	2	77.5%	68.3%
	Inventory and Accounts Receivable	28	20.2%	23.4%	0	N/A	N/A	0	N/A	N/A	0	N/A	N/A	0	N/A	N/A	28	20.2%	23.4%
	Accounts Receivable	5	24.5%	28.5%	2	23.9%	40.6%	0	N/A	N/A	0	N/A	N/A	0	N/A	N/A	7	24.4%	21.6%
	Cash	2	114.8%	17.0%	0	N/A	N/A	0	N/A	N/A	0	N/A	N/A	0	N/A	N/A	2	114.8%	17.0%
	Inventory	1	−100.0%	N/A	1	29.3%	N/A	0	N/A	N/A	0	N/A	N/A	0	N/A	N/A	2	−35.3%	64.7%
	Most Assets	6	25.6%	30.4%	1	161.5%	N/A	0	N/A	N/A	0	N/A	N/A	1	72.1%	N/A	8	48.4%	28.1%
	Equipment	1	−100.0%	N/A	17	41.9%	8.9%	0	N/A	N/A	0	N/A	N/A	0	N/A	N/A	18	34.0%	11.5%
	All Assets	363	32.4%	6.9%	36	332.4%	23.8%	1	86.5%	N/A	0	N/A	N/A	0	N/A	N/A	400	32.6%	6.6%
	Real Estate	4	132.0%	73.6%	2	63.8%	110.9%	0	N/A	N/A	1	57.4%	N/A	0	N/A	N/A	7	101.8%	48.3%
	All Noncurrent Assets	2	−41.7%	58.3%	3	−60.7%	35.1%	0	N/A	N/A	0	N/A	N/A	0	N/A	N/A	5	−53.1%	27.0%
	Capital Stock	36	40.0%	15.4%	38	65.2%	19.1%	0	N/A	N/A	0	N/A	N/A	0	N/A	N/A	74	52.9%	12.3%
	PP&E	8	106.0%	70.7%	17	6.9%	17.4%	0	N/A	N/A	0	N/A	N/A	0	N/A	N/A	25	38.6%	26.3%
	Second Lien	21	23.2%	26.8%	17	24.1%	18.4%	1	119.6%	N/A	1	−46.0%	N/A	0	N/A	N/A	40	24.3%	16.2%
	Other	0	N/A	N/A	1	−24.7%	N/A	0	N/A	N/A	0	N/A	N/A	0	N/A	N/A	1	−24.7%	N/A
	Unsecured	32	19.8%	7.9%	3	−27.7%	36.6%	452	23.7%	4.9%	158	31.0%	10.2%	117	15.7%	11.1%	762	23.6%	4.0%
	Third Lien	1	106.1%	N/A	1	4.9%	N/A	7	3.5%	22.3%	1	439.4%	N/A	2	−21.8%	2.5%	12	44.3%	39.2%
	Intellectual Property	0	N/A	N/A	2	28.6%	43.9%	0	N/A	N/A	0	N/A	N/A	0	N/A	N/A	2	28.6%	43.9%
	Intercompany Debt	0	N/A	N/A	1	143.1%	N/A	0	N/A	N/A	0	N/A	N/A	0	N/A	N/A	1	143.1%	N/A
Major collateral category	Guarantees	39	22.6%	18.2%	2	23.9%	40.6%	0	N/A	N/A	0	N/A	N/A	0	N/A	N/A	41	22.6%	17.4%
	Inventory, Most Assets and Equipment	8	−5.8%	30.3%	19	47.5%	10.2%	0	N/A	N/A	0	N/A	N/A	1	72.1%	N/A	28	33.2%	11.7%
	All Assets and Real Estate	367	33.5%	6.9%	38	35.0%	22.9%	1	86.5%	N/A	1	57.4%	N/A	0	N/A	N/A	407	33.8%	6.6%
	NonCurrent Assets and Capital Stock	38	35.7%	15.0%	41	56.0%	18.6%	0	N/A	N/A	0	N/A	N/A	0	N/A	N/A	79	46.2%	12.0%
	PPE and Second Lien	29	46.1%	27.6%	35	14.3%	14.3%	1	119.6%	N/A	1	−46.0%	N/A	0	N/A	N/A	66	29.0%	13.9%
	Unsecured and Other Illiquid Collateral	33	22.4%	8.1%	7	17.4%	28.5%	459	23.4%	4.8%	159	33.6%	10.4%	119	15.1%	10.9%	777	24.1%	3.9%
	Total Unsecured	32	19.8%	7.9%	3	27.7%	36.6%	452	23.7%	4.9%	158	31.0%	10.2%	117	15.7%	11.1%	762	23.6%	4.0%
	Total Secured	482	33.0%	5.8%	139	38.0%	9.1%	9	25.6%	22.6%	3	150.3%	147.6%	3	9.5%	31.4%	636	34.5%	4.9%
	Total Collateral	514	32.2%	5.5%	161	36.6%	8.4%	461	23.7%	4.8%	161	33.2%	10.3%	120	15.6%	10.8%	1398	28.6%	3.1%

Note: [a]Annualized 'RDD' from the time of default until the time of ultimate resolution.

Table 3. RDD[a] of defaulted instruments by quintiles of TTR[b] and TID[c] from last cash pay to default date (Moody's ultimate recovery database 1987–2010)

		Quintiles of time from default to resolution date											
		1		2		3		4		5		Total	
		Average	SE of the mean	Average	SE of the mean	Average	SE of the mean	Average	SE of the mean	Average	SE of the mean	Average	SE of the mean
Quintiles of time from last cash pay to default data	1	64.19%	24.57%	25.75%	26.11%	38.32%	13.54%	29.75%	14.08%	–4.99%	9.21%	35.04%	9.66%
	2	22.10%	15.41%	38.34%	17.09%	28.24%	19.03%	26.69%	9.21%	8.23%	6.82%	25.93%	6.78%
	3	20.81%	12.16%	30.55%	18.16%	10.04%	8.12%	27.19%	11.21%	8.90%	5.06%	19.28%	5.26%
	4	91.53%	31.75%	41.38%	19.92%	19.79%	9.16%	23.55%	6.26%	8.96%	3.91%	28.67%	5.51%
	5	92.08%	34.68%	57.99%	20.85%	8.82%	8.21%	34.22%	20.16%	–2.97%	8.57%	38.32%	9.23%
	Total	58.90%	11.57%	39.71%	8.89%	20.02%	5.71%	27.32%	4.99%	6.03%	2.61%	28.56%	3.11%

Notes: [a]Annualized 'RDD' from just after the time of default (1st trading date of debt) until the time of ultimate resolution.
[b]TTR: Duration in years from the date of default (bankruptcy filing or other default) to the date of resolution (emergence from bankruptcy or other settlement of default).
[c]TID: Duration in years from the date of the last interest payment to the date of default (bankruptcy filing or other default).

Table 4. RDD[a] of defaulted defaulted instruments by credit rating at origination (Moody's ultimate recovery database 1987–2010)

		Count	Average of RDD	SE of mean RDD
Rating groups	AA-A	146	22.94%	5.04%
	BBB	586	45.09%	13.25%
	BB	285	17.92%	5.24%
	B	65	31.57%	5.66%
	CC-CCC	125	21.99%	8.29%
	Investment grade (BBB-A)	211	29.77%	8.43%
	Junk grade (CC-BB)	996	23.71%	5.94%
	Total	1398	28.56%	3.34%

Note: [a]Annualized 'RDD' from just after the time of default (1st trading date of debt) until the time of ultimate resolution.

Table 5. RDD[a] of defaulted instruments by Tranche Safety Index (TSI)[b] quintiles and categories (Moody's ultimate recovery database 1987–2010)

		Count	Average of RDD	SE of mean RDD
Debt tranche groups	1st Quintile TSI	172	35.06%	12.88%
	2nd Quintile TSI	373	10.98%	4.85%
	3rd Quintile TSI	413	25.77%	5.40%
	4th Quintile TSI	342	42.41%	6.33%
	5th Quintile TSI	98	47.48%	9.57%
	NDA/SDB[c]	449	42.77%	4.89%
	SDA/SDB[d]	259	24.06%	7.65%
	NDA/NDB[e]	164	25.23%	9.44%
	NDB/SDA[f]	526	19.67%	5.25%
	Total	1398	28.56%	3.11%

Notes: [a]Annualized 'RDD' from just after the time of default (1st trading date of debt) until the time of ultimate resolution.
[b]An index of the tranche safety calculated as TTS = (%Debt Below − %Debt Above + 1)/2.
[c]No debt above and some debt below.
[d]Some debt above and some debt below.
[e]No debt above and no debt below.
[f]No debt below and some debt above.

The patterns we observe are that RDD is decreasing (albeit nonmonotonically) in TTR, while it exhibits a U-shape in TID.

Table 4 summarizes RDD by the earliest available Moody's senior unsecured credit rating for the obligor. This provides some evidence that returns on defaulted debt are augmented for defaulted obligors that had, at origination (or time of first public rating), better credit ratings or higher credit quality. Mean RDD generally declines as credit ratings worsen, albeit unevenly. While the average is 22.9% for the AA-A category, it goes up to 45.1% for BBB, then down to 17.9% for BB, but up again to 31.6% for B, and finally down to 21.99% for the lowest category CC-CCC.

Table 5 summarizes RDD by measures of the relative debt cushion of the defaulted instrument. MURD™ provides the proportion of debt either above (degree of subordination) or below (debt cushion) any defaulted instrument, according to the seniority rank of the class to which the instrument belongs. It has been shown that the greater the level of debt below, or the less debt above, the better the *ultimate recovery* on the defaulted debt (Keisman and van de Castle, 2000). We can also think of this position in the capital structure in terms of 'tranche safety' – the less debt above, more debt below, then the more likely it is that there will be some recovery. While this is not the entire story, this measure has been demonstrated to be an important determinant of ultimate recovery, so we suspect that it will have some bearing on the performance of defaulted debt. Here, we offer evidence that returns on defaulted debt are increasing in the degree of tranche safety, or relative debt cushion, as measured by the difference between debt below and debt above. To this end, we define the

Tranche Safety Index (TSI) as

$$\mathrm{TSI} \equiv \frac{1}{2}[\%\text{Debt Below} - \%\text{Debt Above} + 1] \quad (5.1)$$

This ranges between zero and one. When it is near zero the difference between the debt above and below is greatest (i.e. the least debt cushion or the most subordinated tranche), and closest to unity when debt below is maximized and the debt above is nil (i.e. the most senior tranche or the greatest debt cushion). In Table 5, we examine the quintiles of the TSI, where the bottom 20th percentile of the TSI distribution represents the least protected instruments, and the top 20th percentile the most protected. Additionally, we define several dummy variables in order to capture this phenomenon, as in Brady *et al*. (2006). 'No debt above and some debt below' (NDA/SDB) represents a group that should be the best protected, while 'some debt above and some debt below' (SDA/SDB) and 'no debt above and no debt below' (NDA/NDB) represent intermediate groups, and 'no debt below and some debt above' (NDB/SDA) should be the least protected group. Table 5 shows that there is U-shape overall in average RDD with respect to quintiles of TSI: starting at 35.1% at the bottom quintile, having a minimum in the 2nd of 11.0%, and increasing thereafter to 25.8%, 42.3% and 47.5% at the top. With regards to the dummy variables, we observe a general decrease in average RDD, from the most to the least protected categories: 42.8%, 24.1%, 25.2% and 19.7% from NDA/SDB to NDB/SDA.

VI. Multivariate Regression Analysis of Defaulted Debt Returns

In this section, we discuss the construction and results of multiple regression models for RDD. In order to cope with the highly non-Gaussian nature of the RDD distribution, we turn to the various techniques that have been employed in the finance and economics literature to classify data in models having constrained dependent variables, either qualitative or bounded in some region. However, much of the credit risk-related literature has focused on qualitative-dependent variables, in which the case of PD estimation naturally falls into. Maddala (1983, 1991) introduces, discusses, and formally compares the different GLMs. Here we consider the case most relevant for RDD estimation, and the least pursued in the GLM literature. In this context, since we are dealing with a random variable in a bounded region, this is most conveniently modelled through employing a beta distribution. Consequently, we follow Mallick and Gelfand (1994), in which the GLM *link function*[13] is taken as a mixture of cumulative beta distributions, which we term as the BLGLM (see Jacobs and Karagozoglu (2011) for an application of the GLM model in estimating the ultimate LGD).

The coefficient estimates and diagnostic statistics for our 'leading' three models are shown in Table 6. These are determined through a combination of automated statistical procedures[14] and expert judgment, where we try to balance sometimes competing considerations of statistical quality of the estimates with the sensibility of the models. Essentially, the three models shown in Table 6 had the best fit to the sample data, while spanning what we thought was the best set of risk factors, based upon prior expectations as well as the univariate analysis.[15] Note that there is much overlap between the models, as Model 2 differs from Model 1 by two variables (it has market value/book value-MV/BV instead of total liabilities/total assets-TL/TA, and has relative size), and Model 3 from Model 2 by two variables (Free Asset Ratio (FAR) in lieu of TSI and LGD).

Across the three candidate models, we observe that all coefficients estimates attain a high degree of statistical significance, in almost all cases at better than the 5% level,[16] and in many cases at much better than the 1% level. The number of observations for which we had all of these explanatory variables is the same for Models 1 and 2 (968), but there is a sizable drop-off for Model 3 to only 792 observations. In all cases, the likelihood functions converged to a stable global maximum.[17] Model 3 achieves the best in-sample fit by McFadden pseudo R-squared of 41.7%, followed by Model 2 (38.8%), and Model 1 (32.5%). In terms of maximized log-likelihood, Model 3 is far better than the others (−504.0), and Model 1 is slightly better than Model 2 (−592.3 versus −594.7) in spite of having one less explanatory variable.

[13] In the terminology of GLMs, the link function connects some function of a response variable (usually the random variable weighted by density, in the case of the expected value) to a linear function of explanatory variables.
[14] To this end, we employ an alternating direction stepwise model selection algorithm in the mass() library of R statistical software. There were five candidate leading models that were tied as best, we eliminated two of them that we judged to have economically unreasonable features.
[15] These are described in Jacobs (2011).
[16] Moody's investment grade rating in Model 3 is on the borderline, having a p-value of 0.06, with significance at the 5% level.
[17] The estimation was performed in S+ 8.0 using built-in optimization routines.

Table 6. BLGLM for annualized returns on defaulted debt[a] (Moody's ultimate recovery database 1987–2010)

	Model 1		Model 2		Model 3	
Variables	Partial effect	*p*-value	Partial effect	*p*-value	Partial effect	*p*-value
Intercept	0.3094	1.42E−03	0.5101	9.35E−04	0.4342	6.87E−03
Moody's 12 month lagging speculative grade default rate by industry	2.0501	1.22E−02	2.2538	6.94E−03	2.1828	1.36E−02
Fama–French excess return on market factor	1.3814	8.73E−03	1.5085	6.35E−03	1.5468	9.35E−03
Collateral rank secured	0.2554	7.21E−03	0.2330	1.25E−02	0.2704	9.36E−04
Tranche safety index	0.4548	3.03E−02	0.4339	3.75E−02		
Loss given default	0.3273	1.44E−02	0.2751	3.88E−02		
Cumulative abnormal returns on equity prior to default	0.3669	1.51E−03	0.3843	1.00E−03	0.4010	9.39E−04
Total liabilities to total assets	0.2653	5.22E−08				
Moody's original rating investment grade	0.2118	2.80E−02	0.2422	6.84E−03	0.1561	6.25E−02
1-Month treasury yield	−0.4298	3.04E−02	−0.3659	1.01E−02	−0.4901	3.36E−02
Size relative to the market			0.0366	4.76E−02	0.0648	3.41E−03
Market value to book value			0.1925	2.64E−05	0.1422	5.63E−03
Free-asset ratio					−0.2429	2.25E−02
Degrees of freedom	959		958		783	
Log-likelihood	−592.30		−594.71		−503.99	
McFadden pseudo *R*-squared (in-sample)	32.48%		38.80%		41.73%	
McFadden pseudo *R*-squared (out-of-sample) – bootstrap mean	21.23%		12.11%		17.77%	
McFadden pseudo *R*-squared (out-of-sample) – bootstrap SE	2.28%		1.16%		1.70%	

Note: [a]Annualized 'RDD' from just after the time of default (1st trading date of debt) until the time of ultimate resolution.

However, as these models are not nested this may not be so meaningful a comparison. Overall, we deem these to signify good fit, given the nonlinearity of the problem, the relatively high dimension, as well as the high level of noise in the RDD variable.

We now turn to the signs and individual economic significance of the variables, note that we report Partial Effects (PEs), which are akin to straight coefficient estimates in an Ordinary Least Squares (OLS) regression. Roughly speaking, this represents a change in the dependent variable for a unit change in a covariate, holding other variables fixed at their average sample values.[18]

First, we consider the systematic risk variables. In the case of the Moody's speculative default rate by industry, appearing in all models, we see PE's ranging in 2.05–2.25. This implies that a percentage point elevation in aggregate default rates adds about 2% in return on defaulted debt on average, all else equal, which can be considered highly significant in an economic sense. For example, the near quadrupling in default rates between 1996 and 2001 would imply an increase in expected RDD of about 12%. On the other hand, the PE's on the 1-month Treasury yield are in the range of −0.49 to −0.37, so that debt defaulting when short-term rates are about 2% higher will experience close to 1% deterioration in performance, *ceteris paribus*. Second, across all three regression models, RDD has a significant (at the 5% level) and positive loading on the Fama–French-excess return on the market (Fama and French, 1992), with PE's ranging from 1.38 to 1.55, implying that a 5% increase in the aggregate equity market return augments defaulted debt returns by about 8%.

Next, we consider the contractual variables. The dummy variable for secured collateral has PE's ranging in 0.23–0.27 across models, suggesting that the presence of any kind of security can be expected to augment expected RDD by about 25%, which is an economically significant result. The TSI, appearing only in Models 1 and 2, has a PE ranging in 0.43–0.45, suggesting that going up a single decile in this

[18] See Maddala (1981) for a discussion of this concept in the context of probit and logit regressions.

Table 7. Excess abnormal trading returns[a] of BLGLM for annualized returns on defaulted debt[b] (Moody's ultimate recovery database 1987–2010)

	Model 1		Model 2		Model 3	
	Mean	*p*-value	Mean	*p*-value	Mean	*p*-value
Zero transaction costs	0.0051	3.65E−03	0.0049	2.79E−04	0.0062	1.98E−03
1 bp per month round trip transaction costs	0.0032	7.76E−02	0.0019	7.90E−03	0.0025	6.45E−02

Notes: [a]We formulate a trading strategy as follows. At the time of default, if forecasted returns according to the model over the expected time-to-resolution in excess of returns of returns on equity in the 3 months prior to default are positive (negative), then we form a long (short) position in the debt. Abnormal excess returns are then measured relative to a market model (3-factor Fama–French) from the time of default to resolution.
[b]Annualized 'RDD' from just after the time of default (1st trading date of debt) until the time of ultimate resolution.

measure can increase RDD by anywhere between 4% to 5%.

Turning to the credit quality/market variables, for LGD at default, only in Models 1 and 2, PE's are about 0.28–0.33, implying that a 10% lower expected recovery rate by the market at default can lead to about 3% higher expected RDD. The dummy variable for a Moody's investment grade rating at origination, appearing in all models, has PE's ranging from 0.16 in Model 3 to 0.24 in Model 2. This tells us that 'fallen angels' are expected to have about 15%–25% better return on their defaulted debt. On the other hand, the single relative stock price performance variable Cumulative Abnormal Return (CAR), in all three models, has PE's ranging in 0.37–0.40. This says that, for example, a firm with 10% better price performance relative to the market in the 90 days prior to default will experience about 4% better return on its defaulted debt.

In the case of the financial ratios, TL/TA appears only in Model 1, having a PE of 0.27. This means that the debt of a defaulted firm having 10% higher leverage at default will have about 3% greater return on its debt. MV/BV appears in Models 2 and 3, with respective PEs of 0.19 and 0.14, so a 10% higher market valuation translate on average into nearly a 2% better return on defaulted debt. Finally in this group, the cash-flow measure FAR only appears in Model 3, with a PE of −0.24. This implies that if a defaulted firm has 10% greater cash generating ability by this measure, then holding other factors constant its RDD should return about 2.5% less. Finally, the size of the firm relative to the market appears in only Models 2 and 3, with PE's of about 0.06 to 0.04. As this is in logarithmic terms, we interpret this as if a defaulted firm doubles in relative market capitalization, we should expect its RDD to be augmented by around 5%, all other factors being held constant.

In order to settle upon a 'favoured' or 'leading' model, we perform an out-of-sample and out-of-time analysis. We re-estimate the models for different subsamples of the available data, starting from the middle of the dataset in year 1996. We then evaluate how the model predicts the realized RDD a year ahead. We employ a re-sampling procedure (a 'nonparametric bootstrap'), sampling randomly with replacement from the development dataset (i.e. the period 1987–1996), and in each iteration re-estimating the model. Then from the year ahead, we resample with replacement (i.e. the 1997 cohort), and evaluate the goodness-of-fit for the model. This is performed 1000 times, then a year is added, and this is repeated until the sample is exhausted. At the end of the procedure, we collect the *R*-squared values, and study their distribution for each of the three models. The results of this show that the mean out-of-sample *R*-squared in Model 1 is highest, at 21.2%, followed by Model 3 (17.8%), and Model 2 (12.1%). On the basis of the numerical SEs (of the order 1%–2%), we deem these to be significantly distinct. Given the best performance on this basis, in conjunction with other considerations, we decide that Model 1 is the best. The other reasons for choosing Model 1 are its parsimony relative to Model 2, and that it contains a credit market variable (LGD), the latter we believe makes for a more compelling story. Note that this procedure is robust to structural breaks, as the model is redeveloped over an economic cycle, in each iteration the same variables are chosen, and the models display the same relative performance over time.

Finally, in Table 7, we evaluate the economic significance of these results. We formulate a trading strategy as follows. At the time of default, if forecasted returns according to the model over the expected time-to-resolution exceed cumulative excess of returns equity in the 3 months prior to default, then we form a long position in the debt, else we form a short position on the defaulted instrument. Abnormal excess returns are then measured relative to a market model (three-factor Fama–French) from the time of default to resolution. The results show excess abnormal returns, in this defaulted debt trading experiment, of around 5%–6% (2%–3%) assuming zero (1 bp per month) round-trip transaction costs. These are statistically significant, and understandably lower and having higher p-values when we factor in transaction costs. Also, results are not highly differentiated across models, with Model 3 performing about 1% better assuming no transaction costs, and Model 1 having a similar margin of outperformance relative to the other models assuming transaction costs. Given that the latter is arguably a more realistic scenario, we still favour Model 1 because it generates superior excess returns in this trading strategy.

VII. Conclusion

In this article, we have empirically studied the market performance of a long history of defaulted debt. We examined the distributional properties of the RDD measure across different segmentations in the dataset (i.e. default type, facility type, time period, seniority, industry), and developed multiple regression models for RDD in the GLM class.

We found that defaulted debt returns vary significantly according to certain different factors. There is some evidence that RDD is elevated for debt having better collateral quality rank or better protected tranches within the capital structure; and for obligors rated higher at origination, larger in market capitalization relative to the market, more financially levered, or having higher CARs on equity at default. However, RDD is increasing in market implied loss severity at default (LGD). We also find evidence that returns vary counter-cyclically, as they are positively correlated with industry default rates. Furthermore, they are inversely related to short-term interest rates, and positively related to returns on the equity market. We identify a leading econometric model of RDD that performs well out-of-time and out-of-sample. Finally, we document the economic significance of these results through excess abnormal returns, in a debt-equity arbitrage trading experiment, of around 5%–6% (2%–3%) assuming zero (1 bp per month) round-trip transaction costs.

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