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Part 1

Part 2

Empirical Analysis, Trading Strategies, and Risk Models for Defaulted Debt Securities

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Abstract

This study empirically analyzes 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 covary 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 resampling 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 percent (2-3 percent) assuming zero (1bp 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.

1 The views expressed herein are those of the author and do not necessarily represent a position taken by the Office of the Comptroller of the Currency or the U.S. Department of the Treasury.

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 (2000 a,b,c; 2003), Hu and Perraudin (2002) Cary 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 covary with such systematic 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 this.

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; 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 analyze 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 percent.[3] 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 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 while defaulted debt returns vary counter to the credit cycle, as they increase with industry default rates, 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 percent (2-3 percent) assuming zero (1bp 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 and

2 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.

3 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 recently.

investment opportunity sets.[4] 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.

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 ten-year horizon and that, despite relatively high mortality rates, B-rated and CCC-rated securities outperform all other rating categories in the first four years after issuance, with BB-rated securities outperforming all others thereafter.

Gilson (1995) 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 non-diversifiable risk, 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 two 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 percent in the period 1982-2000. However, this return has been extremely volatile, as most of this gain (147 percent) 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 percent, implying a market risk premium of 216 bps. Davydenko and Strebuleav (2002) report similar results for non-defaulted 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 is 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 percent required return (based upon a 20.3 percent 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 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 (2010) reports that the Altman-NYU Salomon Center Index of defaulted bonds (bank loans) returned 12.6 percent (3.4 percent) over the period 1986-2009 (1989-2009).

Machlachlan (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 CAPM model 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 percent 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 0.21 and an MRP of 224 bps.

4 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.

Finally, considering studies of recovery rates (orLGDs), 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 U.S. 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 modeling 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.

Theoretical framework

In this section we lay out the theoretical basis for returns on post-default recoveries, denoted 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)[5]], we may write the stochastic process describing the instantaneous evolution of the i^{th} firm's[5] asset returns at time t as: $dV_{i,t}/V_{i,t} = \mu_i dt + \sigma_i W_{i,t}$ (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): $dW_{i,t} = \rho_{i,X} dX_t + (1- \rho^2_{i,X})^{1/2} dZ_{i,t}$ (2), where the processes (also standard Weiners) X_t and $Z_{i,t}$ are the systematic risk factors (or standardized asset returns) and the idiosyncratic (or firm-specific) risk factors, respectively; and the factor loading $\rho_{i,X}$ is constant across all firms in a PD segment homogenous with respect to default risk (or across time for the representative firm).[7] It follows that the instantaneous asset-value correlation amongst firms (or segments) i and j is given by: $1/dt \cdot Cor^V_{i,j} [dV_{i,t}/V_{i,t} , dV_{j,t}/V_{j,t}] = \rho_{i,X}\rho_{j,X}$ (3).

Defining the recovery rate on the ith defaulted asset[8] at time t as $R_{i,t}$, we may similarly write the stochastic process describing its evolution as: $dR_{i,t}/R_{i,t} = \mu_i^R dt + \sigma_i^R dW^R_{i,t}$ (4), where μ_i^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_i^R is the volatility of the collateral return, and $W^R_{i,t}$ is a standard Weiner process that for recovery segment S^R decomposes as: $dW^R_{i,t} = \rho_{i,s^R}\, dX^R_t + (1 - \rho^2_{i,s^R})^{1/2}\, dZ^R_{i,t}$ (5), where the two-systematic factors are bivariate standard normal, each standard normal, but with correlation r between each other:

$$\left(dX_t, dX_t^R\right)^T \sim N\left(\begin{pmatrix}0\\0\end{pmatrix}, \begin{pmatrix}1 & r\\ r & 1\end{pmatrix}\right) \tag{6}$$

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 second systematic factor, which may be correlated with the macro (or market) factor X_t [Frye (2000 a, b, c), Pyktin (2003), Dullman and Trapp (2004), Giese (2005), Rosch and Scheule (2005), Hillebrand (2006), Barco (2007), Jacobs (2011)]. 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 (5) is constant amongst debt instruments within specified recovery segments, so that the recovery-value correlation for segment SR is given by $\rho^2_{i,s^R} \equiv R_{s^R}$.[9] If we take the further step of identifying this correlation with the correlation to a market portfolio – arguably a reasonable interpretation in the asymptotic

5 Note that this is also the approach underlying the regulatory capital formulae [BCBS (2003)], as developed by Gordy (2003).

6 This could also be interpreted as the ith PD segment or an obligor rating.

7 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.

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

9 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, this is allowed to depend upon the PD for the segment or rating [BCBS (2004]).

single risk-factor (ASRF) framework [(Vasicek (1987), Gordy (2003)] – then we can write $R^2_{s^R} = \rho^2_{s^R_{,M}}$. It then follows from the standard capital asset pricing model (CAPM) that the relationship between the defaulted debt instrument and market rates of return is given by the beta coefficient:

$$\frac{Cov_{s^R,M}\left[\frac{dR_{i,t}}{R_{i,t}},\frac{dV_{M,t}}{V_{M,t}}\right]}{Var_M\left[\frac{dV_{M,t}}{V_{M,t}}\right]} = \beta_{s^R,M} = \frac{\sigma_i^R\sqrt{R_{s^R}}}{\sigma_M} \tag{7}$$

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:

$$r_s^D = r_{rf} + \frac{\sigma_i^R\sqrt{R_{s^R}}}{\sigma_M}\left(r_M - r_{rf}\right) = r_{rf} + \beta_{s^R,M}MRP = r_{rf} + \delta_{s^R} \tag{8}$$

Where the market risk premium is given by MRP ≡ $r_M - r_{rf}$ (also assumed to be constant through time) and the debt-specific risk premium is given by $\delta_{s^R} = \beta_{s^R_{,M}}$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 alternative estimations $\hat{\rho}_{i,s^R}$, through regressing actual defaulted debt returns on some kind of market factor or other measure of systematic risk (i.e., aggregate default rates),[10] while controlling for firm or instrument specific covariates.

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 analyzes 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 under Chapter 11 or liquidation under Chapter 7). We calculate the annualized rate of return on the ith defaulted debt instrument in segment j as:

$$r_{i,j}^D = \left(\frac{P^E_{i,j,t^E_{i,j}}}{P^D_{i,j,t^D_{i,j}}}\right)^{\frac{1}{t^E_{i,j}-t^D_{i,j}}} - 1 \tag{9}$$

where $P^D_{i,j,t^D_{i,j}}$ ($P^E_{i,j,t^E_{i,j}}$) are the prices of debt at time of default $t^D_{i,j}$ (emergence $t^E_{i,j}$). An estimate for the return, the jth segment (seniority class of collateral type), can then be formed as the arithmetic average across the loans in that segment:

$$\bar{r}_j^D = \frac{1}{N_j^D}\sum_{i=1}^{N_j^D}\left[\left(\frac{P^E_{i,j,t^E_{i,j}}}{P^D_{i,j,t^D_{i,j}}}\right)^{\frac{1}{t^E_{i,j}-t^D_{i,j}}} - 1\right] \tag{10}$$

Where N_j^D is the number of defaulted loans in the recovery group j. A measure of the recovery uncertainty in recovery class s is given by the sample standard error of the mean annualized return:

$$s_{\bar{r}_j^D} = \frac{1}{N_j^D - 1}\sqrt{\sum_{i=1}^{N_j^D}\left[\left\{\left(\frac{P^E_{i,j,t^E_{i,j}}}{P^D_{i,j,t^D_{i,j}}}\right)^{\frac{1}{t^E_{i,j}-t^D_{i,j}}} - 1\right\} - \bar{r}_j^D\right]^2} \tag{11}$$

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™ (MURD™) release as of August, 2010. This contains the market values of defaulted instruments at or near the time of default,[11] 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 U.S. large-corporate loss experience, from the late 1980s to the present, including most of the major corporate bankruptcies occurring in this period.

Table A1, in the Appendix, summarizes basic characteristics of simple annualized return on defaulted debt (RDD) in (10) by default event type (bankruptcy under Chapter 11 versus out-of-court settlement) and instrument type (loans – broken down by term and revolving versus bonds). Here we also show the means and standard deviations 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™ 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 U.S.$216.4M (U.S.$151.7M) for the analysis (broader) samples.

10 Alternatively, we can estimate the vector of parameters $(\mu, \mu_i^R, \rho_{i,s}, \rho_{i,s^R}, r)^T$ by full-information maximum likelihood (FIML), given a time series of default rates and realized recovery rates. The resulting estimate $\hat{\rho}_{i,s^R}$ can be used in equation (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 [Machlachlan (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.

11 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.

		Quintiles of time from default to resolution date											
		1		2		3		4		5		Total	
		Average (%)	Std error of the mean (%)	Average (%)	Std error of the mean (%)	Average (%)	Std error of the mean (%)	Average (%)	Std error of the mean (%)	Average (%)	Std error of the mean (%)	Average (%)	Std error of the mean (%)
Quintiles of time from last cash pay to default date	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

Table 1 – Returns on defaulted debt (RDD)[1] of defaulted instruments by quintiles of time-to-resolution (TTR)[2] and time-in-distress (TID)[3] from last cash pay to default date (Moody's Ultimate Recovery Database 1987-2010)

1 – Annualized "return on defaulted debt" from just after the time of default (first trading date of debt) until the time of ultimate resolution.

2 – 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).

3 – TID: Duration in years from the date of the last interest payment to the date of default (bankruptcy filing or other default).

The bottom panel of Table A1 represents the entire Moody's database, whereas the top panel summarizes the subset for which we can calculate RDD measures. The version of MURD™ that we use contains 4,050 defaulted instruments, 3,500 (or 86.4 percent) of which are bankruptcies, and the remaining 550 are distressed restructurings. On the other hand, in the RDD subset, the vast majority (94.6 percent or 1,322) of the total (1,398) 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 of 35 statistical outliers).[12]

The overall average of the 1,398 annualized RDDs is 28.6 percent, with a standard error of the mean of 3.1 percent, and ranging widely from -100 percent to 893.8 percent. This suggests that there were some very high returns – as the 95th percentile of the RDD distributions is 191 percent, or that in well over 70 cases investors would have more than doubled their money holding defaulted debt. We can observe this in Figure 1, the distribution of RDD, which 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 percent for the former, and 28.1 percent in the latter. The standard errors of mean RDDs are also much higher in the non-bankruptcy population, 15.3 percent for out-of-court versus 3.2 percent for bankruptcies. The data is well-represented by bank loans, 36.8 percent (38.1 percent) of the RDD total MURD™ sample, or 514 (1543) out of 1398 (4050) instruments. Loans appear to behave somewhat differently than bonds, having slightly higher mean and standard error of mean RDDs, 32.1 percent and 26.4 percent, respectively.

Table A2 summarizes the distributional properties of RDD by seniority rankings (bank loans; senior secured, unsecured and subordinated bonds; and junior subordinated bonds) and collateral types.[13] Generally, since 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 standard error 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 percent versus 23.6 percent respectively. Focusing on bank loans, we see a wider split of 33.0 percent versus 19.8 percent for secured and unsecured, respectively. However, by broad measures of seniority ranking, mean RDD exhibits a non-monotonic increasing pattern in seniority, while the standard error of RDD is decreasing in seniority. Average RDD is 32.3 percent and 36.6 percent for loans and senior secured bonds, as compared to 23.7 percent and 33.2 percent for senior secured and senior subordinated bonds, decreasing to 15.6 percent for junior subordinated instruments. However, while unsecured loans have lower post-default

12 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 cutoff was determined to be about 1,000%, 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 non-outlier subset.

13 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 Non-current Assets, Capital Stock, PP&E, Second Lien, Other, Unsecured, Third Lien, Intellectual Property and Intercompany Debt), and a six level high level grouping of that we constructed from the (Cash, Accounts Receivables & Guarantees; Inventory, Most Assets & Equipment; All Assets & Real Estate; Non-Current Assets & Capital Stock; PP&E & Second Lien; and Unsecured & Other Illiquid Collateral). The latter high-level groupings were developed with in consultation with recovery analysis experts at Moody's Investors Services.

		Count	Average of RDD	Standard error 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%

Table 2 – Returns on defaulted debt[1] of defaulted instruments by credit rating at origination (Moody's Ultimate Recovery Database 1987-2010)

1 – Annualized "Return on defaulted debt" (RDD) from just after the time of default (first trading date of debt) until the time of ultimate resolution.

		Count	Average of RDD	Standard error 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[1]	449	42.77%	4.89%
	SDA / SDB[2]	259	24.06%	7.65%
	NDA / NDB[3]	164	25.23%	9.44%
	NDB / SDA[4]	526	19.67%	5.25%
	Total	1398	28.56%	3.11%

1 – No debt above and some debt below.
2 – Some debt above and some debt below.
3 – No debt above and no debt below.
4 – No debt below and some debt above.

Table 3 – Returns on defaulted debt[5] of defaulted instruments by Tranche Safety Index[6] (TSI) quintiles and categories (Moody's Ultimate Recovery Database 1987-2010)

5 – Annualized "return on defaulted debt" (RDD) from just after the time of default (first trading date of debt) until the time of ultimate resolution.
6 – An index of the tranche safety calculated as TTS = (% debt below – % debt above + 1)/2.

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 percent for cash, to 46.2 percent for "All assets and real estate," to 29.0 percent for "PP&E and second lien."

Table 1 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 first refers to the bottom fifth of durations in length, and the fifth quintile the top longest. The patterns we observe are that RDD is decreasing (albeit non-monotonically) in TTR, while it exhibits a U-shape in TID.

Table 2 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 percent for the AA-A category, it goes up to 45.1 percent for BBB, then down to 17.9 percent for BB, but up again to 31.6 percent for B, and finally down to 21.99 percent for the lowest category CC-CCC.

Table 3 summarizes RDD by measures of the relative debt cushion of the defaulted instrument. MURDTM 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 et al. (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:

$$TSI \equiv \tfrac{1}{2}[\%\text{debt below} - \%\text{debt above} + 1] \quad (12)$$

This ranges between zero and 1. When it is near zero the difference between the debt above and below is greatest (i.e., the thinnest tranche or the most subordinated), and closest to unity when debt below is maximized and the debt above is nil (i.e., the thickest tranche or the greatest debt cushion). In Table 3, 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 3 shows that there is there is U-shape overall in average RDD with respect to quintiles of TSI: starting at 35.1 percent at the bottom quintile, having a minimum in the second of 11.0 percent, and increasing thereafter to 25.8 percent, 42.3 percent and 47.5 percent 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 percent, 24.1 percent, 25.2 percent, and 19.7 percent from NDA/SDB to NDB/SDA.

Summary statistics and distributional properties of covariates

In this section we first analyze the independent variables available to us and calculated from MURD™, as well as data attached to this from Compustat and CRSP, and then discuss a multivariate regression model to explain RDD. Table A3 in the Appendix summarizes the distributional properties of key covariates in our database and their univariate correlations to RDD. We have grouped these into the following categories: financial statement and market valuation, equity price performance, capital structure, credit quality/credit market, instrument/contractual, macro/cyclical, and durations/vintage.

The financial variables, alone or in conjunction with equity market metrics, are extracted from Compustat or CRSP. The Compustat variables are taken from the date nearest to the first instrument default of the obligor, but no nearer than one month, and no further than one year, to default. These are shown in the top panel of Table A3 in the Appendix. First, we see some evidence that leverage is positively related to RDD, suggesting that firms that were nearer to their "default points" prior to the event had defaulted debt that performed better over the resolution period, all else equal. This is according to an accounting measure, book value of total liabilities/book value of total assets, which has a substantial positive correlation of 17.2 percent.

Next, we consider a set of variables measuring the degree of market valuation relative to stated value, or alternatively the degree of intangibility in assets: Tobin's Q, market value of total assets/book value of total assets (MVTA/BVTA), book value of intangibles/book value of total assets, and the price/earnings ratio. In this group, there is evidence of a positive relationship to the RDD, which is strongest by far for MVTA/BVTA, having a correlation of 18.5 percent. This enters into some of our candidate regression models significantly, but not the final model chosen. We speculate that the intuition here is akin to a "growth stock effect" – such types of firms may have available a greater range of investment options, that when come to fruition result in better performance of the defaulted debt on average.

We display 3 covariates in Table A3 that measure the cash-flow generating ability of the entity: free asset ratio (FAR), free cash flow/book value of total assets, and the cash flow from operations/book value of total assets. Results show generally a negative correlation between cash flow ratios and RDD, notably a strong negative correlation for FAR of 9.0 percent. The intuition here may be considered strained, as it is natural to think that the ability to throw off cash may signal a firm with an underlying business model that is viable, which is conducive to a successful emergence from default and well performing debt; however, this may also be taken to mean an "excess" of cash with not good investments to apply it to and a basically poor economic position.

Finally for the financials, we have a set of variables that measure some notion of accounting profitability: net income/book value of total assets, net income/market value of total assets, retained earnings/book value of total assets, return on assets, and return on equity. These have generally a modest inverse relation to RDD. As with other dimensions of risk considered here, we resort to a "backward story," relative to the expectation that least-bad profitability mitigates credit or default risk: that is, if already in default, then better accounting profitability may be a harbinger of deeper woes for the firm, as reflected in the better returns on the debt from default to resolution of default. However, none of these enter the multiple regressions.

Equity price performance metrics were extracted from CRSP at the date nearest to the first default date of the obligor, but no nearer than on month to default. These are shown in the second from top panel of Table A3. The 1-month equity price volatility, the standard deviation of daily equity returns in the month prior to default, exhibits a small modest positive correlation of 2.5 percent to RDD. This sign is explainable by an option theoretic view of recoveries, since the value of a call-option on the residual cash flows of the firms to creditors are expected to increase in asset value volatility, which is reflected to some degree in equity volatility. On the other hand, the one-year expected equity return, defined as the average return on the obligor's stock in excess of the risk-free rate the year prior to default, exhibits a modest degree of negative correlation (-6.4 percent) which we find to be somewhat puzzling. The cumulative abnormal returns on equity, the returns in excess of a market model in the 90 days prior to default, have the strongest positive relationship to RDD of the group, 10.3 percent. This is understandable, as the equity markets may have a reasonable forecast of the firm's ability to become rehabilitated in the emergence from default, as reflected in "less poor" stock price performance relative to the market. Note this is one of two variables in this group that enters the candidate regression models, and is also the basis of our trading analysis. Market capitalization of the firm relative to the market as a whole, defined as the logarithm of the scaled market capitalization,[14] also has a significant negative univariate correlation to the RDD of -8.6 percent, and enters all of the regressions, as does CAR. We have no clear a priori expectation for this variable, as

14 The scale factor is defined as the market capitalization of the stock exchange where the obligor trades times 10,000.

perhaps we would expect larger companies to have the "resiliency" to better navigate financial distress, counter to what we are measuring. The stock price relative to the market, which is the percentile ranking or the absolute level of the stock price in the market, has a moderate negative correlation to RDD of -4.4 percent. As this variable is intended to capture the delisting effect when a stock price goes very low, we might expect the opposite sign on this correlation. Finally, the stock price trading range, defined as the stock price minus its three-year low divided by the difference between its three-year high and three-year low, is showing only a small negative correlation to RDD of -2.9 percent. This is another counterintuitive result, as one might expect that when a stock is doing better than its recent range that it should be a higher quality firm whose debt might have a better performance in default, but the data is not showing that, or much less of any kind of relationship here.

Capital structure metrics, extracted from the MURD™ data at the default date of the obligor, are shown in the third from top panel of Table A3. The two measures of capital structure complexity, number of instruments (NI) and number of creditor classes (NCC), show an inverse relationship to defaulted debt performance. NI (NCC) has a modest negative correlation to RDD of -4.0 percent (-3.0 percent). We might expect a simpler capital structure to be conducive to favorable defaulted debt performance according to a coordination story. Note that neither of these variables enters the final regression models. While most companies in our database have relatively simple capital structures, with NI and NCC having medians of 6 and 2, respectively, there are some rather complex structures (the respective maxima are 80 and 7).

We have three variables in this group that measure the nature of debt composition: percent secured debt (PSCD), percent bank debt (PBD) and percent subordinated debt (PSBD). The typical firm in our database has approximately 40 percent to 50 percent of its debt either secured, subordinated, or bank funded. All of these exhibit moderate positive correlation to RDD of 8.8 percent, 9.4 percent, and 8.7 percent for PSCD, PBD, and PSBD, respectively. The result on PBD may be attributed to either a monitoring on the one hand, or alternatively an "optimal foreclosure boundary choice," kind of story [Carey and Gordy (2007), Jacobs (2011)]. However, as with the complexity variables, none of these appear in the regression model.

The credit quality/credit market metrics were extracted from the MURD™ database and Compustat just before the default date of the obligor. These are shown in the fourth from top panel of Table A3. Two of the variables in this group have, what may seem to be at first glance, counterintuitive relationships to RDD. First, the Altman Z-Score, which is available in Compustat, has a relatively large negative correlation of -8.8 percent (note that higher values of the Z-score indicate lower bankruptcy risk). Second, the LGD implied by the trading price at default, which forms the basis for the RDD calculation, exhibits a moderate positive correlation to RDD of 11.3 percent. As this variable has been shown to have predictive power for ultimate LGD [Emery et al. (2007), Jacobs and Karagozoglu (2011)], at first glance this relationship may seem difficult to understand. But note that the same research demonstrates that LGD at default is also an upwardly biased estimate of ultimate LGD in some sense. Consequently, we might just as well expect the opposite relationship to hold, as intuitively it may be that otherwise high quality debt may perform better on average if it is (perhaps unjustifiably) "beaten down." Indeed, LGD enters all of our regression models with this sign, and as a more influential variable than suggested by this correlation, but the Z-score does not make it to any of our regression models. The remaining variables in this group are reflective of the Moody's ratings at the first point that the debt is rated. These are the Moody's Original Credit Rating Investment Grade Dummy (MOCR-IG), Moody's Original Credit Rating – Major Code (MOCR-MJC; i.e., numerical codes for whole rating classes), Moody's Original Credit Rating – Minor Code (MOCR-MNC; i.e., numerical codes for notched rating classes) and Moody's Long Run Default Rate – Minor Code (MLRDR-MNC; i.e., empirical default rates associated with notched rating classes). The only meaningful univariate result here is the small positive correlation of 2.4 percent in the case of MOCR-IG. This variable enters significantly into all of our candidate regression models.

Next we consider instrument/contractual metrics, extracted from the MURD™ database at the default date of the obligor. These are shown in the third from bottom panel of Table A3. Consistent with the analysis of the previous section, the correlations with RDD in this group reflect the extent to which instruments which are more senior, better secured, or in a safer tranches experience better performance of defaulted debt. The seniority rank (SR) and collateral rank (CR) codes both have negative and reasonably sized correlation coefficients with RDD, -9.6 percent and -10.0 percent for SR and CR, respectively. Percent debt below and percent debt above are positively (negatively) correlated to RDD, coefficients of 9.4 percent (-5.2 percent). And the TSI, constructed from the latter two variables as detailed in the previous section, has a significant positive correlation with RDD of 9.7 percent. TSI enters into two of our three candidate regression models.

In this section we consider macroeconomic/cyclical metrics measured near the default date of the obligor. These are shown in the second from bottom panel of Table A3. These correlations are evidence that defaulted debt returns vary counter-cyclically with respect to the credit cycle, or that debt defaulting in downturn periods tends to perform better. We have measures of the aggregate default rate, extracted from Moody's Default Rate Service (DRS™) database. These are lagging 12-month default rates, with cohorts formed on an overlapping quarterly basis.[15] The

15 For example, the default rate for the fourth quarter of 2008 would represent the fraction of Moody's rated issuers in the beginning of 4Q07 that defaulted over the subsequent year. We follow the practice of adjusting for withdrawn ratings by subtracting one-half the number of withdrawn obligors from the number of available-to-default (or the denominator of the default rate.)

Variables	Model 1		Model 2		Model 3	
	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
One-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 standard error	2.28%		1.16%		1.70%	

Table 4 – Beta-link generalized linear model for annualized returns on defaulted debt[1] (Moody's Ultimate Recovery Database 1987-2008)

1 – Annualized "return on defaulted debt" (RDD) from just after the time of default (first trading date of debt) until the time of ultimate resolution.

four versions of this are for the all-corporate and speculative grade segments, both in aggregate and by industry. All of these have a mild, albeit significant, positive linear correlations with RDD. The Moody's All-Corporate Quarterly Default Rate (MACQDR), having a 6.7 percent correlation with RDD, is one of the systematic risk variables to enter the candidate regression models.

The next set of variables represent measures of aggregate equity and money market performance, the Fama and French (FF) portfolio returns commonly used in the finance literature, measured on a monthly basis in the month prior to instrument default.[16] These are excess return on the market (FF-ERM), relative return on small stocks[17] (FF-ERSS), and the relative return on value stocks[18] (FF-ERVS). We see that RDD is somewhat positively associated with aggregate return on the market factor FF-ERM, having a modest correlation of 7.2 percent.[19] Similarly, RDD is positively but weakly related to FF-RRSS, a correlation of only 2.8 percent. On the other hand, RDD seems to have a small negative correlation to FF-RRVS of -4.3 percent. We have one more aggregate equity market variable, two-year stock market volatility, defined as the standard deviation of the S&P 500 return in the two years prior to default, which shows a modest positive linear correlation to RDD of 5.7 percent. Note that FF-ERM is the only of these aggregate equity market variables to enter significantly in the multiple regression models. Another set of systematic variables are aggregate interest rates, the one-month treasury bill yield and the ten-year treasury bond yield, which exhibit moderate negative correlation to RDD of -10.2 percent and -7.0 percent, respectively. However, only the one-month treasury bill yield appears in the final regressions. The intuition here may be that defaulted debt performs better in low interest rate environments, which is associated with lower aggregate economic activity, as well as a higher marginal utility of consumption on the part of investors.[20]

The final set of variables that we consider in this section are duration/vintage metrics, based on calculations from extracted dates in the MURD™ database. These are shown in the bottom panel of Table A3. We can conclude from this section that the duration/vintage measures that would be in one's information set at the time of instrument default are largely

16 These can be downloaded from Kenneth French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

17 This is more commonly termed the "small minus large" (SML) portfolio [Fama and French (1992)].

18 This is more commonly termed the "high minus low" (HML) portfolio, meaning high versus low book-to-market ratio [Fama and French (1992)].

19 Results for the S&P 500 return, not shown, are very similar.

20 The term spread, or the difference in a long and short term treasury yield, was neither significant on a univariate basis nor in the regressions. This held across several different choices of term structures. Consequently, we do not show these results.

uninformative regarding the performance of defaulted debt. The variables that we have chosen to display include time from origination to default, time from first rating to default, time from last cash pay date to default, time from default to emergence, and time from origination to maturity.

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-normal 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 with constrained dependent variables, either qualitative or bounded in some region. However, much of the credit risk related literature has focused on qualitative dependent variables, which the case of probability-of -default (PD) estimation naturally falls into. Maddala (1991, 1983) introduces, discusses, and formally compares the different generalized linear models (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 modeled through employing a beta distribution. Consequently, we follow Mallick and Gelfand (1994), in which the GLM link function[21] is taken as a mixture of cumulative beta distributions, which we term the beta-link GLM (BLGLM) [see Jacobs and Karagozoglu (2011) for an application of the GLM model to estimating the ultimate LGD].

The coefficient estimates and diagnostic statistics for our "leading" three models are shown in Table 4. These are determined through a combination of automated statistical procedures[22] 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 4 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. Note that there is much overlap between the models, as Model 2 differs from Model 1 by two variables (it has MV/BV instead of TL/TA, and has RSIZ), and Model 3 from Model 2 by two variables (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 percent level,[23] and in many cases at much better than the 1 percent 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.[24] Model 3 achieves the best in-sample fit by McFadden pseudo r-squared of 41.7 percent, followed by Model 2 (38.8 percent), and Model 1 (32.5 percent). In terms of maximized log-likelihood, Model 3 is far better than the others (-504.0), and Model 1 is only slightly better than Model 2 (-592.3 versus -594.7) in spite of having one less explanatory variable. 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 non-linearity 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 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.[25]

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 PEs ranging in 2.05-2.25. This implies that a percentage point elevation in aggregate default rates adds about 2 percent 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 percent. On the other hand, the PEs on the one-month treasury yield are in the range of -0.49 to -0.37, so that debt defaulting when short-term rates are about 2 percent higher will experience close to 1 percent deterioration in performance, ceteris paribus. Second, across all three regression models, RDD has a significant (at the 5 percent level) and positive loading on the FF-ERM, with PEs ranging from 1.38 to 1.55, implying that a 5 percent increase in the aggregate equity market return augments defaulted debt returns by about 6 percent.

Next, we consider the contractual variables. The dummy variable for secured collateral has PEs 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 percent, 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 measure can increase RDD by anywhere between 4 percent to 5 percent.

21 In the terminology of GLMs, the link function connects the expectation of some function of the data (usually the random variable weighted by density, in the case of the expected value) to a linear function of explanatory variables.

22 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.

23 Moody's investment grade rating in Model 3 is on the borderline, having a p-value of 0.06, just shy of significance at the 5 percent level.

24 The estimation was performed in S+ 8.0 using built-in optimization routines.

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

	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

Table 5 – Excess abnormal trading returns[1] of beta-link generalized linear model for annualized returns on defaulted debt[2] (Moody's Ultimate Recovery Database 1987-2008)

1 – 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 three 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.

2 – Annualized "return on defaulted debt" (RDD) from just after the time of default (first trading date of debt) until the time of ultimate resolution.

Turning to the credit quality/market variables, for LGD at default, only in Models 1 and 2, PEs are about 0.28-0.33, implying that a 10 percent lower expected recovery rate by the market at default can lead to about a 3 percent higher expected RDD. The dummy variable for a Moody's investment grade rating at origination, appearing in all models, has PEs 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 percent better return on their defaulted debt. On the other hand, the single relative stock price performance variable CAR, in all three models, has PEs ranging in 0.37-0.40. This says that, for example, a firm with 10 percent better price performance relative to the market in the 90 days prior to default will experience about 4 percent 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 percent higher leverage at default will have about 3 percent greater return on its debt. MV/BV appears in Models 2 and 3, with respective PEs of 0.19 and 0.14, so that a 10 percent higher market valuation translate on average into nearly a 2 percent better return on defaulted debt. Finally in this group, the cashflow measure FAR only appears in Model 3, with a PE of -0.24. This implies that if a defaulted firm has 10 percent greater cash generating ability by this measure, then holding other factors constant its RDD should return about 2.5 percent less.

Finally, the size of the firm relative to the market appears in only Models 2 and 3, with PEs 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 percent, all other factors being held constant.

In order to settle upon a "favored" or "leading" model, we perform an out-of-sample and out-of-time analysis. We reestimate 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 resampling procedure (a "non-parametric bootstrap"), sampling randomly with replacement from the development dataset (i.e., the period 1987-1996), and in each iteration reestimating 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-squareds, 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 percent, followed by Model 3 (17.8 percent), and Model 2 (12.1 percent). On the basis of the numerical standard errors (on the order of 1-2 percent), 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 5, 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 three 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 (3-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 percent (2-3 percent) assuming zero (1bp 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 percent 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 favor Model 1 because it generates superior excess returns in this trading strategy.

Conclusion

In this paper, we have empirically studied the market performance of a long history of defaulted debt. We examined the distributional properties of the return on defaulted debt (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 generalized linear model (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 cumulative abnormal returns on equity (CARs) at default. However, RDD is increasing in market implied loss severity at default (loss given default – LGD). We also find evidence that returns vary countercyclically, 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 percent (2-3 percent) assuming zero (1bp per month) round-trip transaction costs.

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			Bankruptcy					Out-of-court					Total				
			Cnt	Average	Std Err of the mean	Minimum	Maximum	Cnt	Average	Std Err of the mean	Minimum	Maximum	Cnt	Average	Std Err of the mean	Minimum	Maximum
Sub-population of Moody's recoveries database having trading price of debt at default	Bonds and term loans	RDD	1072	28.32%	3.47%	-100.00%	893.76%	59	45.11%	19.57%	-91.87%	846.73%	1131	29.19%	3.44%	-100.00%	893.76%
		Time-to-resolution[2]		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[3]		207,581	9,043	163	4,600,000		416,751	65,675	6,330	2,250,000		218,493	9,323	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[2]		1.4089	0.0436	0.0548	9.0548		0.2044	0.0786	0.0027	1.4438		1.3194	0.0427	0.0027	9.0548
		Principal at default[3]		205,028	10,590	0	4,000,000		432,061	72,727	6,330	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[2]		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[3]		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[2]		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[3]		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[2]		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[3]		207,099	8,194	0	4,600,000		378,593	54,302	0	2,250,000		216,422	8,351	0	4,600,000
Entire population of Moody's recoveries database	Bonds and term loans	Time-to-resolution[2]	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[3]		149,623	4,585	0	4,600,000		204,750	16,469	0	3,000,000		157,011	4,553	0	4,600,000
	Bonds	Discounted LGD[3]	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[2]		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[3]		157,488	5,608	0	4,600,000		204,750	18,450	0	3,000,000		166,781	5,551	0	4,600,000
	Revolvers	Discounted LGD[3]	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[4]		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[5]		131,843	21,396	0	4,000,000		124,199	17,836	347	1,250,000		130,751	####	0	4,000,000
	Loans	Discounted LGD[3]	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[4]		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[5]		127,586	5,521	0	4,000,000		124,671	14,739	347	1,750,000		127,199	5,171	0	4,000,000
	Total	Discounted LGD[3]	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[4]		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[5]		146,057	4,064	0	4,600,000		187,615	13,576	0	3,000,000		151,701	3,972	0	4,600,000

1 – "Return on defaulted debt": annualized simple rate of return on defaulted debt from just after the time of default (first trading date of debt) until the time of ultimate resolution.

2 – Total instrument outstanding at default.

3 – The time in years from the instrument default date to the time of ultimate recovery.

Table A1 – Characteristics of return on defaulted debt (RDD)[1] observations by default and instrument type (Moody's Ultimate Recovery Database 1987-2010)

		Revolving credit/term loan			Senior secured bonds			Subordinated bonds			Senior unsecured bonds			Senior subordinated bonds			Total instrument		
	Collateral Type	Cnt	Avg (%)	Std Err (%)	Cnt	Avg (%)	Std Err	Cnt	Avg (%)	Std Err (%)	Cnt	Avg (%)	Std Err	Cnt	Avg (%)	Std Err	Cnt	Avg (%)	Std Err
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	33.4	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 non-current 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	Cash, accounts receivables and 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
	Non-current 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	12.3	1	119.6	N/A	1	-46.0	N/A	0	N/A	N/A	66	29.0	13.9
	Unsecured & 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

Table A2 – Return on defaulted debt (RDD[1]) by seniority ranks and collateral types (Moody's Ultimate Recovery Database 1987-2010)

1 – Annualized "return on defaulted debt" from the time of default until the time of ultimate resolution.

Category	Variable	Count	Minimum	Median	Mean	Maximum	Std err of the mean	Correlation with RDD	P-value of correlation
Financial statement and market valuation	Book value total liabilities/book value total assets	1106	38.00%	115.00%	137.42%	392.00%	2.33%	17.20%	4.32E-04
	Market-to-book (market value assets/book value assets)	1106	44.00%	123.00%	152.61%	673.00%	2.71%	18.50%	6.34E-05
	Intangibles ratio (book value intangibles/book value assets)	773	0.00%	18.34%	21.02%	87.85%	0.75%	11.91%	4.20E-04
	Free asset ratio	941	-95.51%	9.24%	5.89%	95.86%	1.18%	-8.97%	2.34E-03
	Free cash flow/book value of total assets	1006	-107.64%	-1.41%	-10.77%	34.61%	0.70%	-2.42%	6.11E-04
	Cash flow from operations/book value of total assets	1014	(669.12)	(0.48)	57.09	7,778.00	30.65	-3.32%	8.33E-04
	Retained earnings/book value of total assets	1031	-757.97%	-25.80%	-61.21%	56.32%	3.01%	-5.91%	1.47E-03
	Return on assets	1031	-159.12%	-8.52%	-22.18%	36.35%	0.92%	-6.50%	1.62E-03
	Return on equity	1031	-2950.79%	3.10%	23.11%	6492.67%	17.19%	-4.31%	1.07E-03
Equity price performance	One-year expected return on equity	1106	-132.00%	-80.00%	-72.40%	161.00%	1.26%	-6.42%	1.07E-03
	One-month equity price volatility	1106	13.00%	209.00%	259.49%	6116.00%	11.18%	2.48%	1.14E-04
	Relative size (market cap of firm to the market)	1106	-17.3400	-12.7200%	-13.0487	-6.9300	0.0599	8.60%	1.31E-03
	Relative stock price (percentile ranking to market)	1106	0.47%	11.00%	13.76%	81.00%	0.42%	-4.36%	1.05E-03
	Stock price trading range (ratio of current to 3 Yr high/low)	1106	0.00%	0.71%	2.95%	88.00%	0.22%	-2.92%	7.02E-04
	Cumulative abnormal returns (90 days to default)	1171	-127.70%	0.00%	-4.87%	147.14%	0.84%	10.30%	2.42E-03
Capital structure	Number of instruments	4050	0.0000	6.0000	9.9511	80.0000	0.1938	-4.04%	5.07E-04
	Number of creditor classes	4050	0.0000	2.0000	2.4669	7.0000	0.0188	-2.98%	3.74E-04
	Percent secured debt	4050	0.00%	47.79%	47.13%	100.00%	0.56%	8.76%	1.10E-03
	Percent bank debt	4050	0.00%	44.53%	45.23%	100.00%	0.54%	9.44%	1.19E-03
	Percent subordinated debt	4050	0.00%	41.67%	43.26%	100.00%	0.53%	8.68%	1.09E-03
Credit quality/credit market	Altman Z-score	793	-8.5422	0.3625	-0.3258	4.6276	0.0804	-8.75%	2.49E-03
	LGD at default	1433	-8.50%	59.00%	55.05%	99.87%	0.83%	-11.28%	2.38E-04
	Moody's original credit rating investment grade dummy	3297	0.0000	0.0000	0.2014	1.0000	0.0070	12.40%	2.37E-04
	Moody's original credit rating (minor code)	3342	3.0000	14.0000	12.4054	20.0000	0.0588	3.63%	5.01E-04
Instrument/ contractual	Seniority rank	4050	1.0000	1.5000	1.7262	7.0000	0.0142	-9.60%	2.28E-04
	Collateral rank	4050	1.0000	6.0000	4.5879	6.0000	0.0254	-10.00%	5.29E-04
	Percent debt below	4050	0.00%	9.92%	25.89%	100.00%	0.48%	9.36%	1.18E-03
	Percent debt above	4050	0.00%	0.00%	21.41%	100.00%	0.45%	-5.16%	6.48E-04
	Tranche safety index	4050	0.00%	50.00%	52.24%	100.00%	0.40%	9.70%	1.04E-03
Macro/cyclical	Moody's all-corporate quarterly default rate	1322	0.00%	7.05%	7.14%	13.26%	0.09%	6.68%	1.47E-03
	Moody's speculative quarterly default rate	1322	1.31%	7.05%	7.16%	13.26%	0.09%	6.40%	1.41E-03
	Fama-French excess return on market factor	4050	-1076.00%	77.00%	31.06%	1030.00%	7.20%	7.22%	3.02E-04
	Fama-French relative return on small stocks factor	4050	-2218.00%	31.00%	20.15%	843.00%	6.00%	2.81%	3.52E-04
	Fama-French excess return on value stock factor	4050	-912.00%	54.00%	79.35%	1380.00%	5.75%	-4.27%	5.35E-04
	Short-term interest rates (1-month treasury yields)	1322	6.00%	32.00%	31.75%	79.00%	0.46%	-10.22%	2.26E-03
	Long-term interest rates (10-month treasury yields)	1106	332.00%	535.00%	538.42%	904.00%	3.61%	-7.00%	1.69E-03
	Stock-market volatility (2-year IDX)	1106	4.00%	9.00%	10.03%	19.00%	0.12%	5.70%	1.37E-03
Durations/ vintage	Time from origination to default	3521	0.2500	2.9096	4.0286	29.9534	0.0631	0.57%	7.68E-05
	Time from last cash-pay date to default	4050	0.0000	0.2384	0.3840	4.3808	0.0075	4.49%	5.63E-04
	Time from default to resolution	4050	0.0027	1.1534	1.4415	9.3151	0.0208	-13.41%	1.70E-03
	Time from origination to maturity date	3521	0.1000	7.5890	8.9335	50.0329	0.1111	-0.85%	1.14E-04

Table A3 – Summary statistics on selected variables and correlations with RDD[1] (Moody's Ultimate Recovery Database 1987-2010)

1 – Annualized "return on defaulted debt" (RDD) from just after the time of default (first trading date of debt) until the time of ultimate resolution.