Financial Innovation and Corporate Default Rates

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ABSTRACT

Corporate default rates have been unusually low in recent years, both relative to historical rates and to forecasts of economists and ratings agencies. We examine the hypothesis that financial innovation has provided new financing options for distressed firms, which are consequently able to postpone or avoid default. Consistent with this hypothesis, we find that in recent years the incidence of early default has decreased, even after controlling for business cycle effects. Next, we estimate a model for predicting aggregate monthly defaults and find that, if financial innovation is ignored, there is evidence of a structural break in recent years. Focusing on the most recent sample, we find that increased structured financing (i.e., high-yield CLO and CDO issuances) predict increased distance to default. Moreover, the component of distance to default explained by financing is positively related to future defaults, whereas the residual unexplained part is negatively related to future defaults. In contrast, increased traditional financing (i.e., banks' commercial and industrial lending and commercial paper issuance) is negatively related to the distance to default. These results are consistent with more stringent monitoring of borrowers by traditional lenders. However, incorporation of both structured and traditional financing improves the default prediction model, especially in the recent sample. Our findings highlight the important role of financing in credit risk modeling and management.

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I. Introduction

Corporate default rates in recent years were at historically low levels. The Moody's 12-month trailing default rate for U.S. issuers of corporate bonds was 0.41% in December 2007, compared to an average of 1.4% since 1970. Strikingly, the default rate had fallen since January 2007, while many measures of economic fundamentals had worsened over this period. For example, option-implied equity volatility had more than doubled, and high-yield corporate bond spreads had increased more than 100 basis points. In fact, it appears that actual default rates had been lower than predictions by forecasters and ratings agencies at least since 2006.[1]

Default rates could be low due to cyclical factors. Alternatively, models may be over-predicting default rates because of a structural break in the historical relationship between existing model variables. For example, it may be that default rates have become less sensitive to equity volatility and more sensitive to corporate profits, which continued to grow in early 2007, according to flow of funds data. Or, the models may suffer from an omitted variable bias, such as changes in financing. This is the possibility that we explore in this paper.

We examine whether default prediction risk models should incorporate changes in sources of financing. In particular, increased access to financing for high credit risk firms may allow such firms to avoid or delay defaults. In recent years, financial innovations in debt markets have been a source of new financing. For example, high-yield collateralized loan obligations (CLO) issuances were used for "rescue financing," or

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[1] See "Junk keeps defying gravity," by Jane Sasseen, *BusinessWeek*, January 29, 2007.

loans to distressed firms that are unable to tap traditional financing sources.[2] While previously rescue financing was geared towards firms near bankruptcy, in recent years it has been used by firms wishing to substitute bonds with loans in their capital structure, ostensibly due to the greater financial flexibility of loans terms.[3]

Structured financing vehicles have helped in the growth of CLO issuance. For example, managers of CLOs are major buyers of such loans. In addition, repackaging of risky bonds or loans into collaterized debt obligation (CDO) products, which re-distribute the risk and return of the portfolio through "tranching," allows investors who traditionally stay away from distress investing to invest in the safe tranche of a CDO investment product. As more capital becomes available to even highly risky borrowers, companies that might have had to default otherwise can survive longer.

We hypothesize that one effect of financial innovation is a reduction in the incidence of early defaults observable in recent years when the availability of alternative financing increased. We investigate yearly cumulative default rates for annual cohorts of speculative-grade issuers from 1980 to 2007 and find that, since 2002, cumulative default rates have declined consistently in the initial years after cohort formation compared to earlier cohort years. In particular, the cumulative default rates for the 2004-2006 cohorts are particularly low. While 2004-2006 were years of economic expansion, the default rates were low even when compared to those of cohorts formed during prior expansionary periods such as 1983-1986 and 1992-1996. This finding suggests an

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[2] "Rescue finance for troubled firms," by Bernard Wysocki Jr., *The Wall Street Journal*, June 12 2007.
[3] A main reason why such loans may afford greater flexibility is that they are privately negotiated. See "Banks warn of risk to rescuers," by Heidi Moore, Financial News Online US, August 15 2007.

unusual slowing down of default rates for the most recent years, even after accounting for business cycle effects.

To examine the dynamics of default behavior more formally, we estimate a prediction model for monthly aggregate corporate default rates of speculative-grade firms using structural variables such as the distance to default, credit quality, and macroeconomic variables to account for business cycle conditions. We include variables identified in earlier studies to be informative in predicting default rates (Fons (1991), Jonsson and Fridson (1996), Helwege and Kleiman (1997), Keenan, Sobehart and Hamilton (1999), Duffie, Saita and Wang (2007)). Since we cannot reject the null of unit roots in default rate levels, we predict *changes* in default rates. Although the model has an adjusted R-squared of almost 50%, we find that it consistently over-predicts the default rate since 2006. Further, structural break analysis indicates breaks in the estimated relationship of default rates after 2003.

INSERT FIGURE 1 HERE

INSERT FIGURE 2 HERE

Financial innovation may be one reason for the structural break in default rates models since 2004. For example, global issuance of high-yield collaterized loan obligations (CLO) has grown from essentially zero in 1995 to $35 billion in 2004 and to $150 billion in 2006 (Figure 1).[4] US issuance of collaterized debt obligations (CDO) also grew rapidly, as may be observed from data available since 2005 (Figure 2).[5]

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[4] High-yield loans are defined as transactions of borrowers with senior unsecured debt ratings at financial close below Baa3 from Moody's or BBB- from S&P. The data source is Lehman Brothers.

[5] The underlying collateral for CDOs includes investment grade and high yield bonds and loans, structured finance collateral (such as RMBS, CMBS, CMOs, ABS, CDOs, and CDS). Data and definitions are from SIFMA http://www.sifma.org/research/pdf/SIFMA_CDOIssuanceData2008q3.pdf.

The availability of structured financing is likely to increase the distance to default as the new financing effectively pushes firms away from their default boundary through changes in the terms of financing (i.e. more flexible or cheaper terms and longer maturities). Consistent with our hypothesis, we find that during the period 2005 to 2007 (for which we have monthly structured finance issuance data) increases in US issuances of high-yield CLOs and of CDOs predict an increase in the distance to default, and these effects last up to four months. These results explicitly link the distance to default to the financial innovation of recent years.

What are the implications of new financing for default rates? Financial innovations could either raise or lower default rates depending on the mechanisms that dominate, and the impact could be either transitory or permanent. For example, if the marginal firms affected are those in need of funding for available positive-NPV investment opportunities, additional capital should have permanent positive benefits for the company. On the other hand, if the marginal firms tend to be distressed borrowers without viable investment opportunities, innovations might simply fund a temporary "survival" option to the borrowers who ultimately default later with poorer recovery. An even worse potential outcome for the second type of the firm, as discussed in Jensen and Meckling (1976), is that given the newly available capital, the close-to-distress companies might have an incentive to take on even more risk, in which case the net effect of innovations could be an increase the default risk.

We find that financial innovation affects default rates in two ways. The direct effect of structured finance issuances is mixed, but more likely to reduce default rates. However, financial innovation also impacts default rates indirectly, via its effect on the distance to default. The component of distance to default that is explained by past financing is positively related to default rates. In contrast, the residual component of distance to default unrelated to financing is a negative predictor of defaults, consistent with traditional structural default models without financing.

In contrast to structured financing, traditional forms of financing (e.g., banks' commercial and industrial loans, and commercial paper issuance) are negatively related to the distance to default. A possible explanation for this result is that structured finance lenders are more distant from the ultimate borrowers and thus may have reduced incentives to monitor (Rajan, Seru and Vig (2008)). Moreover, traditional financing appears to have only a weak direct relation to default rates. Nevertheless, for the most recent sample, incorporating financing into the default model is informative. In particular, it remains true that the component of distance to default that is related to financing has a positively predicts future defaults, whereas the residual component negatively predicts future defaults.

Our paper is related to recent papers on the mortgage market that examine the relation of financing to credit risk. Rajan, Seru and Vig (2008) argue that mortgage default prediction models under-predicted defaults in recent years due to ignoring of "soft information," due to the increased distance between structured finance lenders and ultimate borrowers. Mian and Sufi (2008) relate the expansion of mortgage supply to defaults. Keys et al (2008) argue that securitization reduces screening by lenders. Our results demonstrate a relation between types of financing and credit risk for corporate default rates. We further identify the direct and indirect channels by which financing impacts default rates.

To the best of our knowledge, we provide the first systematic evidence that financial innovations are significantly related to changes in the default boundary and to default rates. In doing so, we also contribute to the literature of credit risk. Existing structural models of default risk have not taken into explicit consideration the role of financing in determining default rate dynamics. Although many structural models have the flexibility to incorporate exogenous changes brought about by financial innovation, the current literature does not have clear implications regarding which parameters should be used for this. For example, innovations could be viewed as exogenous shifts that lower the debt financing cost of the borrower, extend the effective maturity of the existing debt (like a debt rollover), or lower the default threshold parameter by replacing existing debt with cheaper debt financing. Several papers have addressed the latter channel by making the default threshold endogenous (e.g., Leland and Toft (1996) and Anderson, Sundaresan, and Tychon (1996)). However, the evidence we present suggests a different mechanism that could be used.

The rest of the paper is organized as follows. In Section II, we provide descriptive evidence of delayed defaults in the most recent sample. In Section III, we present summary statistics and stylized facts on delayed defaults in recent years. In Section IV, we estimate a default prediction model without financing. In Section V, we explicitly link the distance to default and aggregate default rates to financial innovation. In Section VI, we investigate the relation between traditional financing sources and default rates. Section VII concludes.

II. Early Defaults: Descriptive Statistics

New sources of financing for distressed firms allow such firms to avoid or delay a default event. Following a period of high growth in financing sources, we expect to observe a lower incidence of defaults compared to historical periods, and after controlling for business cycle effects. Whether default rates revert to higher levels in subsequent periods will depend on the later performance of firms that initially avoided default. In this section, we investigate the path of default rates for speculative-grade issuers for yearly cohorts starting in 1980.

We use data from Moody's Investors Service to measure corporate default rates. In particular, we focus on calculations of annual cumulative default rates by yearly cohort for speculative-grade bonds, which Moody's published in a 2008 report. "Moody's definition of default includes three types of credit events:

- A missed or delayed disbursement of interest and/or principal;
- Bankruptcy, administration, legal receivership, or other legal blocks (perhaps by regulators) to the timely payment of interest and/or principal; or
- A distressed exchange occurs where: (i) the issuer offers debt holders a new security or package of securities that amount to a diminished financial obligation (such as preferred or common stock, or debt with a lower coupon or par amount, lower seniority, or longer maturity); or (ii) the exchange had the apparent purpose of helping the borrower avoid default."

Moody's calculates cumulative issuer-weighted default rates at the end of every calendar year, both for the set of all issuers with bonds outstanding at the beginning of the year and for individual cohorts representing sets of issuers with bonds outstanding at the beginning of each prior calendar year. For example, the year 2000 speculative-grade cohort consists of all issuers with speculative-grade long-term ratings, and corporate bonds outstanding, as of January 1, 2000.[6] For the year 2000 cohort, the cumulative default rate for the second year is the portion of the original cohort that has defaulted by the end of 2001. Consequently, for each annual cohort, the cumulative default rate is monotonically increasing with the number of years after cohort formation.

INSERT FIGURE 3 HERE

Figure 3 shows the cumulative default distributions by year, with 1980-1989 in grey, 1990-1999 in black and 2000-2006 in red. A flatter slope in the early years indicates lower incidences of default at that time. The three curves with the flattest slopes are the three red curves at the bottom for the yearly cohorts 2004 to 2006. However, the flatter slopes may be mainly due to the fact that all three years were part of an economic expansion. Indeed, we observe relatively flat slopes for many of the 1990s cohorts, when the economy was also in expansion for much of the decade.

INSERT FIGURE 4 HERE

In controlling for business cycle effects, we note that different years of a particular cohort may represent different business cycle phases. For example, for the 1991 cohort, the first year represents a recession year but the second year (i.e. 1992) represents an expansionary year. To account for this complication, we limit the time range of each cohort to five years and then calculate the average of the yearly defaults for the 1983-1985 and 1992-1996 cohorts. For these cohorts, the defaults occur in expansionary periods for each of the first five years, similar to the 2004-2006 cohorts.

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[6] The year 2000 cohort typically includes many of the same firms as the 1999 speculative-grade cohort.

These default distributions are shown in Figure 4. We find that cumulative default rates have declined for each annual cohort of speculative-grade issuers formed since 2002. Moreover, the slope of the default curve for 2004-2006 is flatter even when compared to 1983-1985 and 1992-1996. This pattern suggests the decline in early defaults may be more than just a cyclical effect.[7]

These stylized facts are broadly consistent with an unusually low incidence of early defaults in the most recent years (i.e. 2004 and later). While we have compared default rates in expansionary years, there are other variables that are known to impact default rates, such as stock returns, that we have ignored so far. We now formally model aggregate default rates at the monthly level.

IV. Predicting Aggregate Default Rates

In this section, we develop a model for predicting aggregate defaults for speculative-grade issuers at the monthly level, incorporating distance to default, macroeconomic conditions, credit quality and stock returns. The aim of this analysis is two-fold. We show that there is a tendency for the model to over predict default rates from 2005 onwards, and we further show the existence of a structural break in the estimated default relationship at this point. Since this period coincides with the time of a

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[7] In unreported analysis, we also calculate our own forward-looking measures of default rates using bond-level data from Moody's Default Risk Service. We focus on bonds that are domestically outstanding by industrial and financial issuers during the period of 1984-2006. The sample includes only "regular" bonds which excludes bonds with nonstandard features such as convertibility. Our ratings cohorts are formed at the beginning of June of each year using all outstanding bonds, and we follow each cohort for two years. Our rating-specific analysis of two-year cumulative default rates is also suggestive of a recent pattern of delayed default. For example, bonds rated Ba and B have exhibited unusually low forward default rates in 2005 and 2006, the most recent years for which 2-year subsequent default data is available, after adjusting for business cycle effects.

boom in structured financing, this result provides circumstantial evidence of a link between the break-down of the default model and the structural changes in financing. In the next section, we explicitly relate the distance to default and default rates to measures of financial innovation.

Aggregate default rates, obtained from Moody's, are trailing 12-month default rates. They are calculated, for month *t*, as

$$D_t = \frac{\sum_{t-11}^{t} Y_t}{I_{t-11}}, \tag{1}$$

where D_t is the trailing 12-month default rate, Y_t is the number of defaulting long-term debt issuers and I_t is the number of issuers remaining in month *t*. The number of issuers is adjusted to reflect withdrawal from the market for some issuers so that the denominator reflects the number of issuers who could potentially have defaulted in the subsequent 12-month period.[8] The set of issuers comprises the entire Moody's-rated universe (all-corporate) but we will mostly focus on the speculative-grade issuers. Thus, the calculations do not include the non-rated sector, which is a small market segment and for which accurate default information is difficult to obtain, according to Moody's.

INSERT FIGURE 5 HERE

The monthly aggregate defaults for speculative-grade issuers tend to exhibit a cyclical pattern (see Figure 5). Just after the 1990-91 recession, the monthly default rate peaked at more than 12%. Subsequently, defaults declined to a low of 1.66% during the expansionary years of the mid-1990s, before rising again to hit 11% just after the 2001

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8 See Keenan, Sobehart and Hamilton (1999) for further details of how the adjustment for withdrawals is implemented.

recession. Since 2004, default rates have declined markedly, falling to historically low levels in 2006 and 2007. Default rates touched its all-time low of 1% in November 2007 before starting to rise in 2008.

Since we cannot reject the null hypothesis of unit roots in the time series of default levels, we predict *changes* in default rates rather the level. Thus, our dependent variable is:

$$\Delta D_t = D_t - D_{t-1} = \frac{\sum_{t-11}^{t} Y_t}{I_{t-11}} - \frac{\sum_{t-12}^{t-1} Y_t}{I_{t-12}}. \tag{2}$$

In general, the change in default rates depends on changes in Y_t for the entire prior 12-month period. However, according to Keenan, Sobehart and Hamilton (1999), the numerator of (2) is a slow moving value and so, approximately, $I_t \approx I_{t-1}$. Therefore, we can rewrite (2) as:

$$\Delta D_t = D_t - D_{t-1} \approx \frac{Y_t - Y_{t-12}}{I_{t-12}}. \tag{3}$$

In other words, we expect the explanatory variables to impact ΔD_t at long lags of up to 12 months. We estimate a prediction model for ΔD_t using variables identified in earlier studies to have strong predictive power. All data are from Haver, except for the distance to default and corporate leverage, which are described below. The variable definitions are summarized in Table 1.

INSERT TABLE 1 HERE

The explanatory variables may be grouped as follows:

Distance to default. In standard structural models (Black and Scholes (1973), Merton (1974), Fisher, Heinkel and Zechner (1989), and Leland (1994)), the default rate is completely determined by the distance to default. The latter is defined as the number of standard deviations of asset growth by which the asset level exceeds the firm's liabilities. Following equation (19) in Duffie, Saita and Wang (2007), the distance to default is:

$$DDEF_t = \frac{Ln(V_t / L_t) + (\mu_A - 0.5 * \sigma_A^2) * 12}{\sigma_A \sqrt{12}}, \tag{4}$$

V_t is the sum of equity market value (from CRSP) and the book value of debt L_t (short term plus long-term debt, from Compustat). μ_A is the sample mean and σ_A is the sample standard deviation of V_t. For the aggregate level analysis, $DDEF_t$ is obtained for each firm and then averaged. *DDEF* is obtained at the quarterly level and then interpolated to obtain monthly values. We use the one lag of $DDEF_t$.

Macroeconomic conditions. Aggregate default rates tend to be high just prior to and during economic recessions and relatively low during economic expansions. We use the term spread, defined as the difference between constant maturity 10-year rates and the 3-month rate. The 12-month lagged value of the term spread has been shown to be a reliable predictor of recessions (Estrella and Hardouvelis (1991)). In addition, we use one lag of consumer expectations, which are forwarding looking indicators of aggregate consumer expenditure growth (Ludvigson, 2004).[9] Finally, we use three lags of the change in the civilian unemployment rate which is a strong predictor of the correlation between consumption and equity returns (Sarkar and Zhang, 2008).

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9 The Michigan survey asks consumers questions on expected business conditions—both over the next year and over the next five years—and expected changes in the respondent's financial situation over the next year.

We also tried other macroeconomic variables previously used in the literature, such as growth in GDP, industrial production and personal income, but none of these variables were significant in the regressions.

Credit quality. Fons (1991) found that 51% of the variation in historical default rates could be explained by credit quality and economic conditions. Credit quality is typically measured as the relative weight of high-yield bonds in the economy, where the weight could be high-yield default rates (Fons (1991)) or the relative size of speculative-grade issuers (e.g. the percent of issuers rated B3 or lower, as in Jonsson, Fridson and Zhong (1996)). We use a measure related to that of Fons (1991): the difference in credit spreads between high-yield and investment-grade issuers. We use 10 monthly lags of the change in this variable.

Stock returns. Duffie, Saita and Wang (2007) use the trailing one-year return of the S&P 500 index and find it statistically significant (although the sign is counter-intuitively positive, indicating higher returns increase default rates). We use 6 monthly lags of returns on the Wilshire 3000 index.

Growth in corporate sector debt. Firms where leverage is growing quickly are likely to hit the default threshold quicker. This is an aspect of the strong non-linearities between model inputs and the default rate found in calibration exercises (Tarashev (2008)). We use the quarterly debt growth reported in the Flow of Funds database and interpolate to obtain monthly numbers. We use the one-month lagged value of debt growth.

A. Results

INSERT TABLE 2 HERE

Table 2 shows results from regressing the change in default rates on the various explanatory variables. As there is persistence even in the change series, we include 12 lags of changes in default in all specifications. To determine the number of lags for the explanatory variables, we use the Akaike and Schwartz information criteria. The estimation is carried out sequentially on the distance to default, the macroeconomic variables, the credit quality and stock return variables, and finally the corporate leverage variable. The results are reported in Table 2 following the above pattern.

We find that an increase in the distance to default is unrelated to changes in the default rate; in fact, the sign is positive indicating that as firms move closer to their default boundary, the aggregate default rate is lower! This result is the opposite of Duffie, Saita and Wang (2007), who find that the default rate is negatively related to distance-to-default. The difference in our results appears to stem mainly from our use of changes in variables, rather than the levels. Indeed, if we regress the *level* of default rates on the *level* of distance to default, then the estimated coefficient is negative and significant, consistent with Duffie, Saita and Wang (2007). Given our inability to reject the unit root hypothesis, however, we prefer to estimate the regression in changes. In the next section, we examine why the default rate increases when distance to default increases by identifying the component of distance to default (i.e. the part related to financial innovation) that leads to this puzzling result.

Although the distance-to-default is not significant, the lagged default changes are mostly significant, and these variables together are sufficient to explain 38% of the variation in default rate changes.

Next, we add the macroeconomic variables. The year-ago change in the term spread is negative and highly significant. Since a reduction in the term spread predicts recessions 12-months-ahead (Estrella and Hardouvelis (1991)), this variable captures the business cycle effect on default rates. Changes in consumer expectations are also informative, although the statistical significance is only at the 10% level. A decrease in consumer expectations predicts an increase in default rates. Changes in the unemployment rate also capture the business cycle effect. One of three lags in this variable is significant, and the sign is positive (i.e. higher unemployment rates predict higher default rates) and significant at the 5% level. With the addition of the macroeconomic variables, the adjusted R-squared is 41%.

We now add measures of credit quality and stock returns. As a group, these measures increase the adjusted R-squared by an additional 7%, to 48% in total. The estimated credit quality coefficients are of expected signs, in that 6 of the 10 lags are positive and statistically significant, with 5 of these 6 estimates significant at the 5% level. Therefore, an increase in the difference between high-yield and investment-grade credit spreads (i.e. a decrease in credit quality) predicts an increase in the default rate. Consistent with Duffie, Saita and Wang (2007), an increase in the stock return counter-intuitively predicts an increase in the default rate. Indeed, 3 of the 6 lags of stock returns are positive and significant. Once we account for changes in credit quality and returns, the distance to default becomes significant at the 10% level, and remains positive.

Finally, the growth in aggregate corporate debt predicts an increase in the default rate but the effect is not statistically significant. Since the distance-to-default is also either not significant or marginally positively significant, our results indicate that leverage related variables appear to be poor predictors of aggregate default rates.

INSERT FIGURE 6 HERE

Overall, our prediction model does a good job of explaining the in-sample variation in aggregate default rates, in that close to 50% of the variation in default changes are explained by the model. Figure 6 plots the in-sample prediction errors and they fluctuate randomly around zero for most of the sample period. It is notable, however, that the prediction errors turn consistently negative since 2006. This is consistent with results obtained by economists and ratings agencies.

INSERT FIGURE 7 HERE

The "over-prediction" of default rates in rating agency models is observable in Figure 7. The figure illustrates Moody's 12-months-ahead forecasts of global speculative grade corporate default rates[10] made in December 2006, May 2007 and October 2007, along with the actual global speculative grade default rates for January to September 2008. We observe that Moody's forecasts are consistently above the actual default rates, especially for 2007.

To more formally test the hypothesis of a "structural break" in the estimated relationship of default rates, we investigate the stability of the relationship.

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[10] We use global forecasts since Moody's does not provide US default forecasts.

B. Stability Tests

To ascertain the stability of the results, we perform a factor breakpoint test for structural breaks in various sub-samples.[11] We find evidence of a break in 2003 at a significance of 10%, indicative of a structural break in the relationship between default rates and its determinants at this time. We further perform a CUSUM test and again find evidence of a structural break in 2003 at a significance level of 5%.[12] No further structural breaks are found in the remaining sample. In the remaining sections of the paper, we focus on the period after 2003 whether financial innovation---in particular, the large growth in structured financing at this time--- is a source of the structural break in the default prediction model.

V. Financial Innovation, Distance to Default and Default Rates

We now turn to the task of explicitly tying our analysis of default rates to financial innovation. There are potentially two channels by which new financing may impact default rates. Increases in financing may reduce default rates directly by allowing distressed firms to avoid or postpone default events, at least in the short-term. Second, financial innovation affects default rates indirectly, via its effect on the distance to default. Therefore, we start with an analysis of the effect of new financing on the distance to default. Then, we build on these results to examine the direct and indirect channels by which financial innovation affects default rates.

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[11] The factor breakpoint test splits an estimated equation's sample into several sub-samples and tests for significant differences in equations estimated in each of the sub-samples. The statistical test involves comparing the sum of squared residuals obtained from fitting a single equation to the entire sample with the sum of squared residuals obtained by fitting separate equations to the sub-samples.

[12] The CUSUM test is based on the cumulative sum of recursive residuals. There is evidence of parameter instability if the cumulative sum falls outside the area between the 5% critical lines.

Our maintained hypothesis is that the new financing effectively pushes firms away from their default boundary through changes in the terms of financing (i.e. more flexible or cheaper terms and longer maturities). In the context of structural models in the spirit of Merton (1974), a borrower defaults when its assets V fall below a threshold V*. Financial innovation may affect default rates by changing V or V*, or both. Given V*, new financing increases V and either postpones the time when the firm hits its default threshold or prevents bankruptcy altogether. Alternatively, given V, the new financing lowers V* (by, for example, increasing the time to debt maturity, as in Leland and Toft (1996)). Both channels have the effect of initially reducing the distance to default relative to the period when new financing was not available.[13]

HYPOTHESIS 1. The distance to default and measures of financial innovation are positive related.

Next, we turn to the two channels by which financial innovation impacts default rates. The first channel is the direct effect of new financing on default rates. The second channel is indirect, via the effect of financing on the distance to default, as new financing changes the financing terms and the capital structure and potentially impacts firm performance. The effect on default rates via either channel is ambiguous. At least in the short term, increased financing is likely to decrease measured defaults as firms avoid default events. The longer-run effects are likely to be firm-specific. For some firms, the new financing will not result in improved performance and default is merely delayed. For other firms, the new financing provides a "time out" to improve performance and

[13] The main difference between the two channels is in the effect on recovery rates which are expected to vary inversely with V*.

deny default. The overall effect depends on the relative weight of these two types of firms in the sample.

HYPOTHESIS 2. The direct and indirect (via its effect on distance to default) impact of financial innovation on default rates are ambiguous. If, on average, new financing allows firms only to delay default, then the default rate increases subsequently. However, if new financing allows firms time to improve performance, then the default rate decreases.

Our first measure of financial innovation is the monthly growth in high-yield CLO issuance in the US, which we obtain from Merrill Lynch. As discussed in the introduction, this measure (along with second-lien loans, for which we have no data) is the key channel through which high credit risk firms have been financed. Our second measure of financial innovation is the monthly growth in US aggregate CDO issuance, which we also obtain from Merrill Lynch.

We first examine the effect of financial innovation on distance to default (in Section A) and then consider implications for the aggregate default rates (in Section B).

A. Financial Innovation and Distance to Default

INSERT TABLE 3 HERE

We regress the distance to default on four lags of the growth in CLO issuance. We also include two lags of distance to default to account for persistence in this variable. Results are shown in the first two columns of Table 3. As hypothesized, all four lags are estimated to have positive signs; and three of these are significant. Therefore, past increases in CLO issuance result in increases in the distance to default. Further, these effects are long-lasting, in that they are significant for periods up to four months. The adjusted R-squared is 91%, indicating changes in financial innovation and the own lags of explain most of the variation in distance to default.

We next regress changes in the distance to default on three lags of the growth in CDO issuances. These results are reported in the final two columns of Table 3. As expected, all three lags of the growth in CDO issuance are positive and significant at the 5% level. Similar to growth in CLO issuance, higher CDO issuance increases the distance to default and this effect is long-lasting, up to 3 months. Together, these results establish that financial innovation is a channel through which distance to default, and potentially default rates, is impacted. Given the waves in financial innovation observed in history, the financing channel further implies the possibility of structural breaks in the behavior of distance to default and default rates over time.

B. Financial Innovation and Aggregate Default Rates

INSERT TABLE 4 HERE

We use a variation of the default prediction model (estimated in Table 2) to assess the direct effect of financial innovation, as well as its indirect effect via the distance to default, on aggregate default rates. Initially, we omit the direct effect of financing and focus on the indirect effect. To do so, we decompose the distance to default into its fitted value and the residual, where the fitted value is obtained from the regression of distance to default on financial innovation, estimated in Table 3. The fitted value of distance to default incorporates the effect of financial innovation; the residual is the portion of distance to default that is unexplained by financial innovation.

We regress the default rate on one lag of the fitted and residual values of distance to default. In addition, we include the variables previously found to explain the default rate: macro conditions, credit quality and stock returns. The first two columns of Table 4 show the results. The fitted value of the distance to default has a positive and significant effect on default rates. Hence, the indirect effect of a growth in CLO issuance is to subsequently increase the default rates. In contrast, the residual portion of the distance to default has a negative and significant effect on default rates. This latter result is consistent with standard structural models without financing, such as Merton (1970).

To identify the direct effect, we include in the regression lagged values of measures of financial innovation. The third and fourth columns of Table 4 shows results when we include four lags of growth in CLO issuance. The direct effect is mixed: two of four lags are negative and statistically significant, while the remaining two are positive (one being positive and significant). Although the sum of all the lags is positive, we cannot reject the null hypothesis that the sum of all coefficients is zero. Therefore, while CLO issuance growth predicts the default rate, the direction is ambiguous. As before, the fitted and residual values of the distance to default have significant positive and negative effects, respectively, on default rates. The fifth and sixth columns of Table 4 shows results when we include six lags of CDO issuance. The results are similar to those obtained with CLO issuance, with one difference: the direct effect of CLO issuance on default rates is unambiguously negative. Five of six lags are negative, with four being significant, and the sum of all lags is significantly negative.

In terms of the control variables, a notable result is that, once we add financing variables to the model, the stock return variable has the expected sign: it is negative and significant. In contrast, in the model without financing, stock returns are positively related to default rates. The other variables are generally not significant.

In summary, an increase in measures of financial innovation indirectly increases default rates via its effect on the distance to default. Also, financial innovation directly impacts default rates: the direction is negative when the measure is CDO issuances and ambiguous when the measure is CLO issuances. The portion of distance to default that is unrelated to financial innovation has a negative relation to default rates, consistent with structural default models without financing.

VI. Traditional Financing, Distance to Default and Default Rates

So far, we have considered the effects of structured financing on the distance to default and default rates and have found significant effects. However, during this period, issuances of all kinds were rising, including bank loans, commercial paper and high-yield bond issuances. Do our results reflect the effect of general lending growth on default rates, or is it special to financial innovation? To address this issue, we repeat our previous tests using various measures of traditional financing. These are: growth in commercial banks' commercial and industrial loans, and growth in commercial paper issuances.

The results are shown in Table 5. To compare with our results for financial innovation, we restrict the sample to the years 2005-2007 in Panel A. Considering the results in Panel A, we find that measures of traditional financing have significant effects on the distance to default. However, in contrast to financial innovation measures, the relation is generally negative. In other words, an increase in sources of traditional financing decreases the distance to default. Traditional financing measures also have weak (though still significant) effects on default rates during 2005-2007. Moreover, the component of distance to default explained by financing is positively related to default rates whereas the non-financing component is negatively related to default rates.

We use the full sample for estimation in Panel B. Note that, for CP issuance, the data goes back only till 2001 while for C&I loans the data is available from 1990. The two columns of Panel A in Table 5 show results for non-financial CP issuance that is found to be a significant determinant of distance to default. The two significant lags are both negative, although the sum of all lags is not significantly different from zero. The next two columns show that CP issuance has weak direct effects on default rates: only lag is significant and that too at the 10% level. However, we can easily reject the null that the lags are jointly zero. Further, the part of distance to default explained by CP issuance is positively and significantly related to default rates. The last two columns show results for C&I loans. This variable has a weak negative effect on distance to default: only one of five lags is significant and the null that all lags are jointly zero is only rejected at a p-value of 0.09. Finally, C&I loans have no direct or indirect effects on default rates.

In summary, the effect of traditional financing on distance to default and default rates depends on the sample period. In the sample from 1990, the effect is weak. In the sample from 2005, the effect is relatively strong. For the sample from 2001, the effect is moderate. Consistent with financial innovation, the part of distance to default that is explained by financing is positively related to default rates whereas the residual part is negatively related to default rates. However, unlike financial innovation, increases in traditional sources of financing appear to be decrease the distance to default. This is consistent with better monitoring of borrowers by traditional lenders.

VII. CONCLUSION

Corporate bond default rates have been low in recent years, relative to the predictions of economists and ratings agencies. We examine the hypothesis that structural changes in financing sources have altered the determinants of default. Specifically, financial innovations have opened new financing channels for borrowers, even highly risky borrowers. One implication of this is that companies that might have defaulted otherwise can survive longer, which would produce lower default rates following periods of expanded access to funding.

Using yearly cohorts of speculative-grade bonds outstanding, we first document that aggregate default rates in recent cohorts (i.e. 2004 to 2006) are indeed unusually low in earlier years, even when compared to the rates experienced in prior expansionary periods of 1983-1985 and 1992-1996. Next, we estimate a default prediction model and find that it over-predicts default rates in recent years (from 2004 onwards). We also find evidence of a structural break in the model at this time. Since, structured financing issuances expanded rapidly from 2004 onwards, the results provide circumstantial evidence of a link between the structural breaks and financial innovation.

Using monthly data of high-yield CLO and aggregate CDO issuances from 2005 onwards, we explicitly link financial innovation to default rates. We find that increases in structured financing increase the distance to default. Further, the component of distance to default explained by past financial innovation is positively related to future defaults, whereas the residual part unrelated to leverage financing negatively predicts future default. Therefore, our results demonstrate the endogeneity of the default boundary. Moreover, the results show that the relation between distance to default and default rates depend upon financing. This is in contrast to structural default models of default without financing, which predicts a negative relation in all cases.

In contrast to structured financing, traditional forms of financing (e.g., banks' commercial and industrial loans, and commercial paper issuance) are negatively related to the distance to default. This may be due to superior monitoring incentives of traditional lenders. Moreover, for the most recent sample, incorporating traditional financing into the default model is informative. In particular, it remains true that the component of distance to default that is related to financing has a positively predicts future defaults, whereas the residual component negatively predicts future defaults.

Our results highlight the importance of considering the role of financing in explaining default rate dynamics. Although many structural models have the flexibility to incorporate exogenous changes in financial innovation, the evidence we present suggests a different mechanism. Our findings also have implications regarding the impact of financial innovations on the economy.[14] Our findings indicate a complex relation of financial innovations to default rates. It is likely that the impact of financial innovations on default risk depends on lenders' investment opportunities and on the financial condition of the borrowers. We are currently investigating these questions.

Our work is directly linked to the academic research on the consequences of financial innovations (Frame and White (2002)). While it is generally acknowledged that innovation has both positive and negative impacts on society, the net impact of financial innovation remains an open theoretical question and an empirical challenge as well. For example, Merton (1992) cites the U.S. mortgage market, the development of international

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[14] Recent surveys of this literature include Tufano (2002) and Frame and White (2002), among others.

markets for financial derivatives and the growth of the mutual fund and investment industries as examples where innovation has produced enormous social welfare gains. However, others take opposing viewpoints (see, e.g., Pare (1995), Huang (2000)). A body of theoretical research weighs in on the discussion of the social welfare implication of financial innovations by focusing on the role of innovation in completing or spanning the market.[15] However, even on theoretical level, it is not clear that innovations aimed at completing the market always enhance social welfare (see, e.g., Elul (1995), Allen and Gale (1991)).

Our work is also relevant to the continuing debate on whether specific innovations contribute to high levels of market volatility. Most of the debate centers on derivative markets, with a particular focus on the question of whether derivatives exacerbate emerging market crises. We focus on the relationship between recent innovations in U.S. credit market and corporate default rates. From the perspective of aggregate credit risk, we provide evidence on a specific form of benefit or cost that is associated with recent financial innovations, and also shed light on a potential mechanism through which innovation could affect the aggregate economy.

Lastly, given the extensive discussions on the causes and the costs of the recent credit market turmoil, regulators and researchers face the task of assessing the net impact of financial innovations on the economy, and assessing the possible need for a long-run policy response. We believe that these findings improve our understanding of the costs and benefits of recent innovations in financial markets, and suggest an important target for corresponding policy design. Although our findings suggest a positive role for

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[15] See Allen and Gale (1994) and Duffie and Rahi (1995) which summarize this literature.

financial innovations in lowering default rates over the short run, it remains to be investigated whether this impact is persistent. Furthermore, theories suggest that the impact of financial innovations on default risk is likely to depend on lenders' investment opportunities and on the financial condition of the borrowers. We are currently investigating these questions.

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Table 1
Definition Table

The table presents definitions of variables used in subsequent tables.

Variable name	Definition
ΔD	Changes in Moody's 12-month trailing corporate default rates for speculative-grade or investment grade firms.
ΔDDEF	Changes in distance to default, a volatility-adjusted leverage ratio defined in equation (4) of the text. DDEF is calculated for each firm and then averaged across all speculative-grade or investment-grade firms.
ΔTERM	Changes in the term spread, defined as the difference between constant maturity 10-year and 3-month rates.
ΔCONEXP	Changes in consumer expectations, as reported in the University of Michigan survey.
ΔUEM	Changes in the civilian unemployment rate.
ΔCQ	Changes in credit quality, defined as the difference in high-yield and investment-grade credit spreads.
ΔSRET	Changes in the return on the Wilshire 3000 index.
LEV_GR	Growth in the corporate sector leverage.
LLOAN_GR	Growth in high-yield CLO issuance in the US
CDO_GR	Growth in aggregate CDO issuance in the US
CIL_GR	Growth in commercial and industrial loans of banks
CP_GR	Growth in commercial paper outstanding of non-financial US issuers

Table 2
Predicting Changes in Aggregate Default Rates of Speculative-Grade Issuers

The table shows results from a regression of the monthly change in aggregate default rates of speculative-grade issuers ΔD on the change in the average distance to default $\Delta DDEF$ of these issuers, changes in macroeconomic factors, credit quality ΔCQ and the stock return $\Delta SRET$, and the growth in corporate sector debt *LEV_GR*. Macroeconomic factors are changes in the term spread $\Delta TERM$, change in consumer expectations $\Delta CONEXP$ and the change in the unemployment rate ΔUEM. The variables are defined in Table 1. All regressions include 12 monthly lags of ΔD. For variables with multiple lags, we indicate the number of lags with a positive sign +, *SIG* or negative sign -, *SIG* significant at the 5% or 10% level. All estimates are multiplied by 100. Data is from CRSP, Compustat, Flow of Funds, Haver and Moody's. The sample period is January 1990 to October 2007. The regression uses 203 observations. Standard errors are corrected for autocorrelation and heteroskedasticity using the Newey-West procedure with four lags. ** (*) indicate, at the 5% (10%) level or less, whether the coefficient estimates are significantly different from zero.

	Distance to default		Macroeconomic Conditions		Credit Quality and Stock Returns		Growth in Corporate Leverage	
Explanatory Variable	Estimate	*t*-stats	Estimate	*t*-stats	Estimate	*t*-stats	Estimate	*t*-stats
				Dependent variable: ΔD				
Intercept	-0.02	-0.71	-0.02	-0.86	-0.06**	-2.53	-0.09**	-2.50
ΔDDEF, Lag1	0.36	1.34	0.18	0.57	0.50*	1.86	0.52*	1.81
ΔTERM, Lag12	---	---	-0.17**	-2.10	-0.18**	-2.15	-0.16*	-1.83
ΔCONEXP, Lag1	---	---	-0.01*	-1.88	-0.01*	-1.70	-0.01*	-1.77
LEV_GR, Lag1	---	---	---	---	---	---	0.01	1.06
VARIABLES WITH MULTIPLE LAGS								
ΔUEM, 3 Lags								
+, SIG	---		1		1		2	
-, SIG			0		0		0	
ΔCQ, 10 Lags								
+, SIG	---		---		6		6	
-, SIG					0		0	
ΔSRET, 6 Lags								
+, SIG	---		---		3		2	
-, SIG					0		0	
12 Lags of ΔD included?	YES		YES		YES		YES	
Adj-R^2	0.38		0.41		0.48		0.48	

Table 3

Financial Innovation and the Distance to Default of Speculative Issuers

The table shows results from a regression of changes in the distance to default of speculative issuers Δ*DDEF* on lagged measures of financial innovation. Δ*DDEF* is the average distance to default Δ*DDEF* of these issuers. The measures of financial innovation are growth in high-yield CLO issuance *LL_GR*, and growth in aggregate CDO issuance *CDO_GR*. All variables are defined in Table 1. Estimates have been multiplied by 100. Data is from CRSP, Compustat, Haver and Moody's. The sample period is January 2005 to October 2007 and the data frequency is monthly. The regression uses 30 observations. Standard errors are corrected for autocorrelation and heteroskedasticity using the Newey-West procedure with four lags. ** (*) indicate, at the 5% (10%) level or less, whether the coefficient estimates are significantly different from zero. The *p-value* corresponds to the chi-square statistic for the null hypothesis that all lags of innovation measures are jointly zero.

	Growth in high-yield CLO issuance		Growth in aggregate CDO issuance	
Explanatory Variable	Estimate	*t*-stats	Estimate	*t*-stats
	Dependent variable: Δ*DDEF*			
Intercept	0.53	0.89	0.29	0.84
LL_GR, Lag1	0.37	0.86	---	---
LL_GR, Lag2	0.46**	2.36	---	---
LL_GR, Lag3	0.05**	4.15	---	---
LL_GR, Lag4	0.04**	3.85	---	---
CDO_GR, Lag1	---	---	0.94*	2.03
CDO_GR, Lag2	---	---	0.86**	4.69
CDO_GR, Lag3	---	---	0.67**	2.98
2 Lags of Δ*DDEF* included?	YES		YES	
Wald test: All lags of financial innovation are zero				
Chi-sq p-value	0.00		0.00	
Adj-R^2	0.91		0.93	

Table 4
Financial Innovation and Aggregate Default Rates of Speculative Issuers

The table shows results from a regression of the monthly changes in aggregate default rates of speculative issuers Δ*D* on the change in the average distance to default Δ*DDEF* of these issuers and measures of financial innovation. Δ*DDEF* is decomposed into Δ*DDEF*: *Fitted* and Δ*DDEF*: *Resid*. The fitted value of Δ*DDEF* is obtained from a regression of Δ*DDEF* on measures of financial innovation (reported in Table 3). Δ*DDEF*: *Resid* is the difference between Δ*DDEF* and its fitted value. The measures of financial innovation are growth in high-yield CLO issuance *LL_GR*, and growth in aggregate CDO issuance *CDO_GR*. *SRET* is the stock return. *OTHER CONTROLS* are one lags of changes in the unemployment rate and credit quality, and the 12^{th} lag of term spread and Δ*D*. All variables are defined in Table 1. All estimates have been multiplied by 100. Data is from CRSP, Compustat, Haver and Moody's. The sample period is January 1990 to October 2007. The regression uses 30 observations. Standard errors are corrected for autocorrelation and heteroskedasticity using the Newey-West procedure with three lags. ** (*) indicate, at the 5% (10%) level or less, whether the coefficient estimates are significantly different from zero. The *p-value* corresponds to the chi-square statistic for the null hypothesis that the sum of all lags of innovation measures is jointly zero.

	No financing		Growth in high-yield CLO issuance		Growth in CDO issuance		Growth in structured financing	
Explanatory Variable	Estimate	*t*-stats	Estimate	*t*-stats	Estimate	*t*-stats	Estimate	*t*-stats
Intercept	-0.08**	-2.62	-0.04	-1.60	-0.01	-0.54	---	---
Δ*DDEF*: Fitted, *Lag1*	0.41*	1.75	0.29*	2.03	1.08**	4.73	---	---
Δ*DDEF*: Resid, *Lag1*	-1.60*	-1.93	-1.10*	-1.81	-2.60**	-2.42		
LL_GR, Lag1	---	---	-0.04**	-2.75	---	---	---	---
LL_GR, Lag2	---	---	0.01	1.21	---	---	---	---
LL_GR, Lag3	---	---	0.05**	3.96	---	---	---	---
LL_GR, Lag4	---	---	-0.00**	-2.48	---	---	---	---
CDO_GR, Lag1	---	---	---	---	-0.07**	-3.89	---	---
CDO_GR, Lag2	---	---	---	---	0.02	0.83	---	---
CDO_GR, Lag3	---	---	---	---	-0.01	-0.63	---	---
CDO_GR, Lag4	---	---	---	---	-0.04*	-2.55	---	---
CDO_GR, Lag5	---	---	---	---	-0.08**	-3.93	---	---
CDO_GR, Lag6	---	---	---	---	-0.04**	-2.41	---	---
SRET,Lag1	-0.48	-0.44	-1.95**	-3.32	-1.81**	-2.79	---	---
OTHER CONTROLS INCLUDED?	YES		YES		YES			
Walt test: All lags of financial innovation are jointly zero								
Chi-sq p-value	---		0.00		0.00		---	
Walt test: Sum of all lags of financial innovation is zero								
Chi-sq p-value	---		0.59		0.00		---	
Adj-R^2	0.24		0.65		0.61			

Table 5

Traditional Financing, Distance to Default and Corporate Default Rates

The table shows results from regressions of the monthly changes in the average distance to default $\Delta DDEF$ of speculative-grade issuers on measures of traditional financing (i.e. growth in US non-financial commercial paper issuance *CP_GR*, and growth in commercial and industrial loans of banks *CIL_GR*). The fitted value of $\Delta DDEF$ from this regression is $\Delta DDEF$: *Fitted* and $\Delta DDEF$: *Resid* is the difference between $\Delta DDEF$ and its fitted value. In a second regression, monthly changes in aggregate default rates of speculative-grade issuers ΔD are regressed on $\Delta DDEF$: *Fitted*, $\Delta DDEF$: *Resid* and measures of traditional financing. *OTHER CONTROLS* are one lags of changes in the unemployment rate, credit quality and stock returns, and the 12th lag of term spread and ΔD. All variables are defined in Table 1. All estimates have been multiplied by 100. Data is from CRSP, Compustat, Haver and Moody's. The sample period is 2005-2007 in Panel A and 1990 to 2007 in Panel B. Standard errors are corrected for autocorrelation and heteroskedasticity using the Newey-West procedure with three lags in Panel A and four lags in Panel B. ** (*) indicate, at the 5% (10%) level or less, whether the coefficient estimates are significantly different from zero. The *p-value* corresponds to the chi-square statistic for the null hypothesis that the sum of all lags of innovation measures is zero.

Panel A: 2005-2007 sample

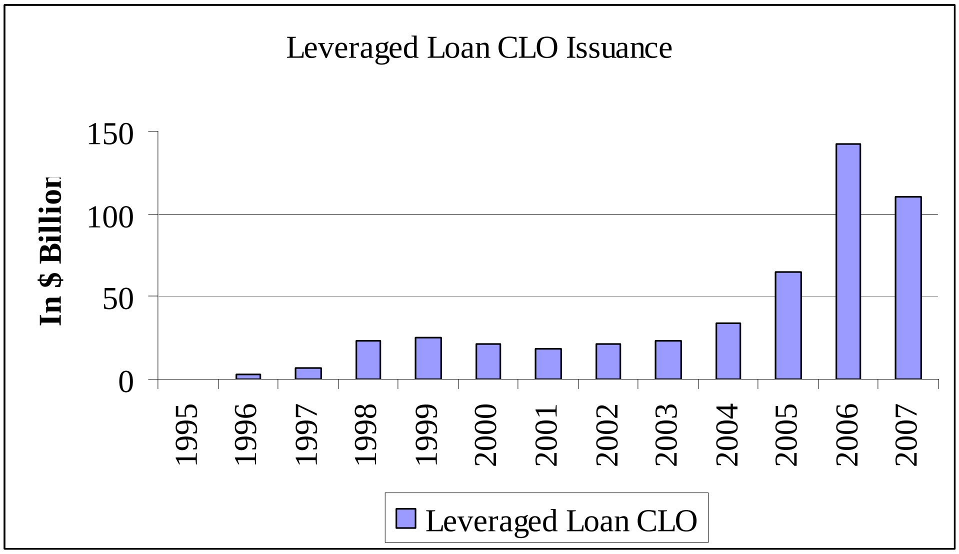
	Non-financial CP issuance				C&I Loans			
	DDEF		DEF		DDEF		DEF	
Explanatory Variable	Estimate	*t*-stats	Estimate	*t*-stats	Estimate	*t*-stats	Estimate	*t*-stats
Intercept	1.61**	3.43	-0.11**	-2.95	2.48**	4.24	-0.08**	-3.12
$\Delta DDEF$: Fitted, *Lag1*	---	---	0.53**	3.79	---	---	0.52**	2.09
$\Delta DDEF$: Resid, *Lag1*	---	---	-1.89**	-2.86	---	---	-1.90*	-2.05
CP_GR, *Lag1*	2.29	0.46	0.16	0.83	---	---	---	---
CP_GR, *Lag2*	3.19	0.55	0.40**	2.18	---	---	---	---
CP_GR, *Lag3*	-0.86	-0.17	0.23	1.47	---	---	---	---
CP_GR, *Lag4*	-4.58	-1.04	0.07	0.37	---	---	---	---
CP_GR, *Lag5*	-7.76**	-2.42	-0.21	-1.27	---	---	---	---
CP_GR, *Lag6*	-5.79*	-1.99	-0.24*	-1.91	---	---	---	---
CIL_GR, *Lag1*	---	---	---	---	-29.00	-0.88	0.43	0.48
CIL_GR, *Lag2*	---	---	---	---	-27.94	-0.77	---	---
CIL_GR, *Lag3*	---	---	---	---	-76.01**	-2.62	---	---
CIL_GR, *Lag4*	---	---	---	---	-30.81	-1.13	---	---
CIL_GR, *Lag5*	---	---	---	---	-45.53*	-1.98	---	---
OTHER CONTROLS INCLUDED?	YES		YES		YES		YES	
Walt test: All lags of financial innovation are jointly zero								
Chi-sq p-value	0.02		0.00		0.03		0.48	
Walt test: Sum of all lags of financial innovation is zero								
Chi-sq p-value	0.38		0.47		0.03		0.48	
Adj-R^2	0.90		0.35		0.91		0.23	

Table 5 (continued): Traditional Financing, Distance to Default and Corporate Default Rates

Panel B: Full sample

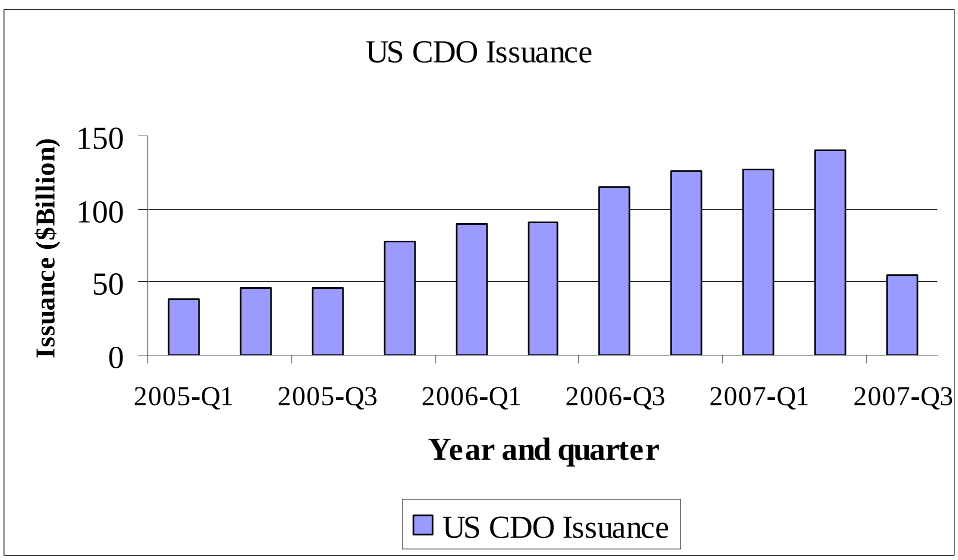
	Non-financial CP issuance, 2001-2007				C&I Loans, 1990-2007			
	DDEF		DEF		DDEF		DEF	
Explanatory Variable	Estimate	*t*-stats	Estimate	*t*-stats	Estimate	*t*-stats	Estimate	*t*-stats
Intercept	1.41**	2.84	-0.14**	-2.37	0.53**	2.35	-0.05**	-2.36
Δ*DDEF*: Fitted, *Lag1*	---	---	0.71*	1.96	---	---	0.47	1.50
Δ*DDEF*: Resid, *Lag1*	---	---	-1.20	-1.20	---	---	0.76	0.90
CP_GR, *Lag1*	-0.24**	-3.18	-0.02	-0.81	---	---	---	---
CP_GR, *Lag2*	-0.13	-1.52	-0.00	-0.33	---	---	---	---
CP_GR, *Lag3*	-0.06	-0.65	0.00	0.01	---	---	---	---
CP_GR, *Lag4*	-0.07	-1.10	-0.01	-0.75	---	---	---	---
CP_GR, *Lag5*	-0.22**	-3.54	-0.01	-0.85	---	---	---	---
CP_GR, *Lag6*	-0.14*	-1.98	-0.03*	-1.88	---	---	---	---
CIL_GR, *Lag1*	---	---	---	---	-12.68	-0.83	1.24	0.99
CIL_GR, *Lag2*	---	---	---	---	-4.58	-0.24	---	---
CIL_GR, *Lag3*	---	---	---	---	-29.05**	-2.18	---	---
CIL_GR, *Lag4*	---	---	---	---	-6.28	-0.37	---	---
CIL_GR, *Lag5*	---	---	---	---	-18.37	-1.15	---	---
OTHER CONTROLS INCLUDED?	YES		YES		YES		YES	
Walt test: All lags of financial innovation are zero								
Chi-sq p-value	0.00		0.00		0.09		0.99	
Walt test: Sum of all lags of financial innovation is zero								
Chi-sq p-value	0.01		0.34		0.02		0.99	
Adj-R^2	0.89		0.13		0.87		0.46	

Figure 1: Global CLO Issuance



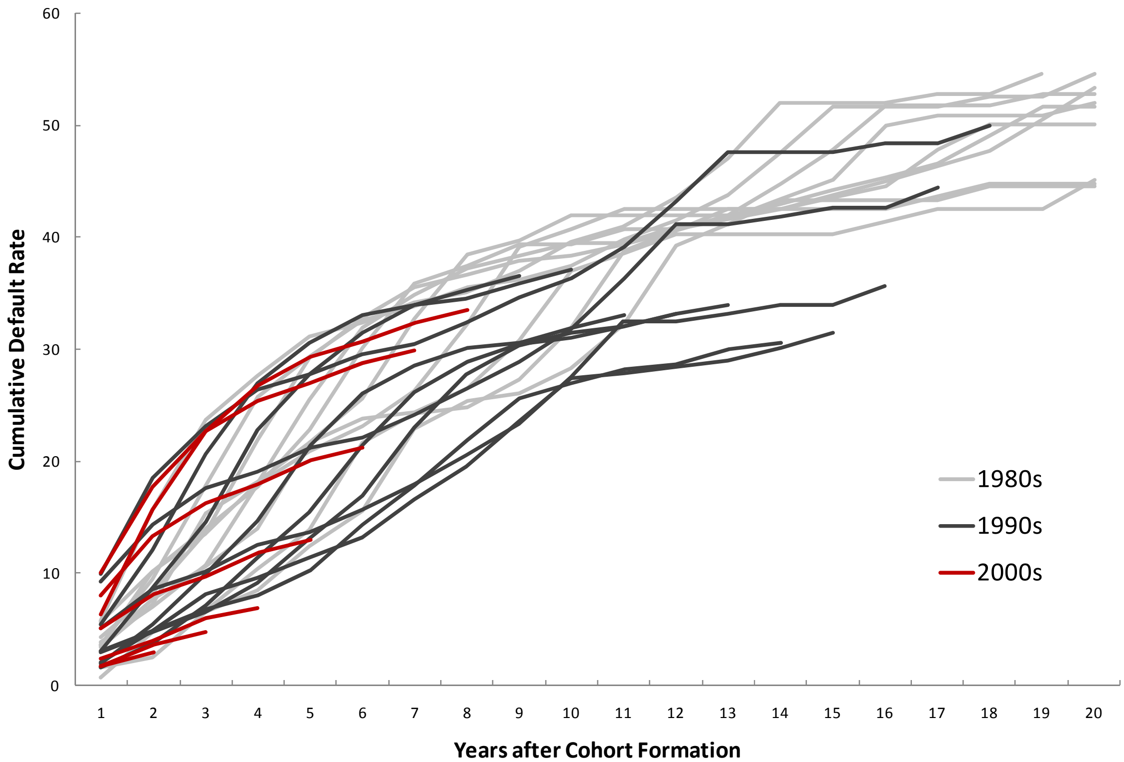
The figure plots the annual global issuance of high-yield collaterized loan obligations (CLO) from 1995 to 2007.

Figure 2: US CDO Issuance



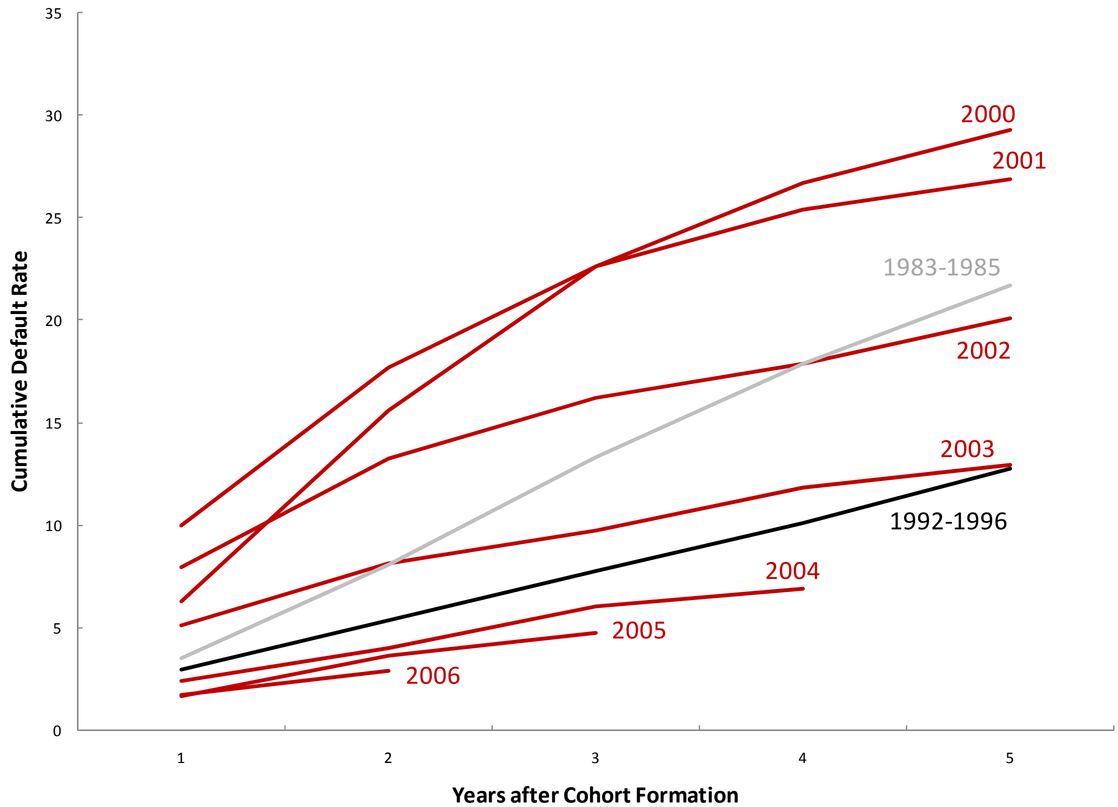
The figure plots the quarterly US collaterized debt obligations (CDO) issuance from 2005 to 2007.

Figure 3: Cumulative Default Rates of Speculative Grade Bonds by Annual Cohort (1980-2007)



This figure shows yearly cumulative default rates for annual cohorts formed by taking the set of speculative-grade bonds outstanding in each year from 1980 through 2006. The cumulative default rate for a given *n* years after cohort formation is defined as the probability that a bond will have defaulted at some point between the year of cohort formation and the end of the n^{th} year after cohort formation. Consequently, the cumulative default rates are monotonically increasing with the number of years after cohort formation.

Figure 4. Cumulative Default Rates of Speculative Grade Bonds for 2000-2007 and for Periods of Economic Expansion



This figure compares the yearly comulative default rates for the 2000-2006 cohorts with two prior expansionary periods: 1983-1985 and 1992-1996. The expansionary periods are defined as years occurring between a business cycle trough and peak as defined by the NBER.

Figure 5. Monthly Aggregate Default Rates of US Speculative-Grade Issuers

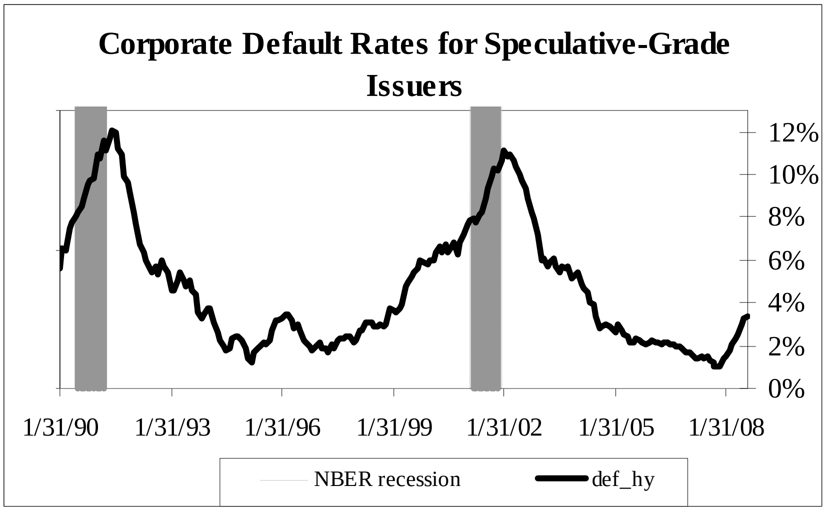
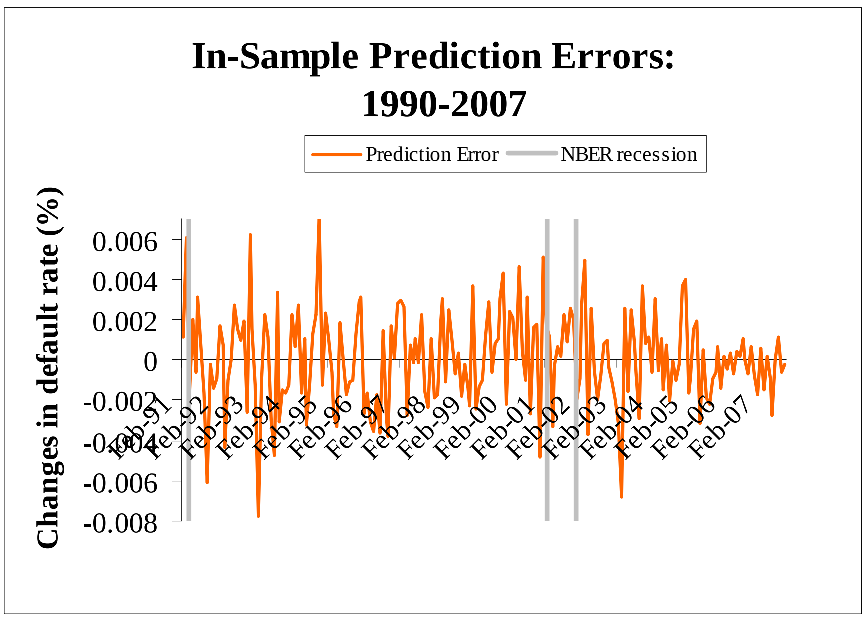
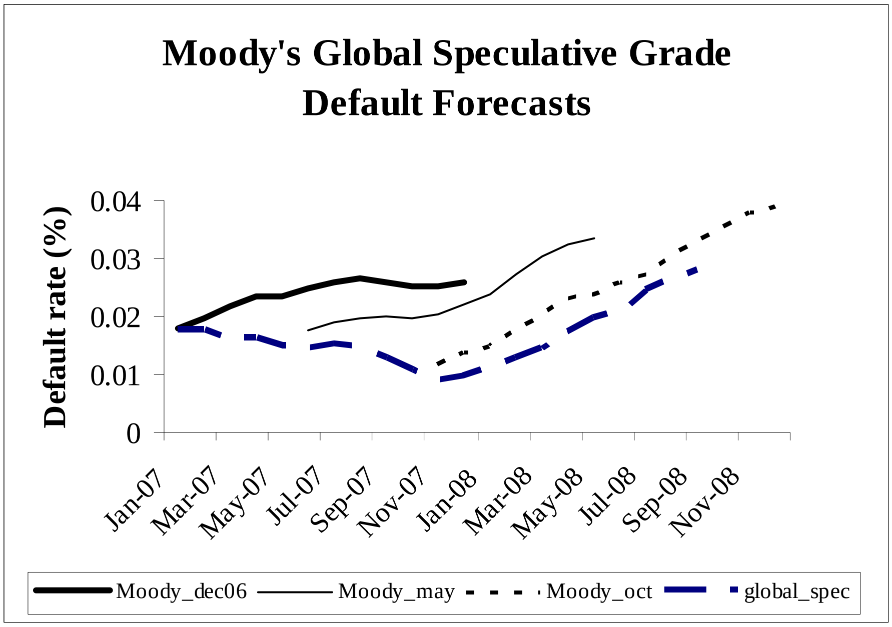


Figure 6. In-Sample Prediction Errors



The figure plots the in-sample prediction errors from the aggregate default prediction model. The model is estimated over the period 1990 to September 2007. The change in default rates are regressed on distance to default, macroeconomic and credit quality variables, stock returns and growth in corporate sector leverage.

Figure 7. Moody's Forecasts of Defaults in Global Speculative Grade Bonds



The figure plots Moody's 12-months-ahead forecasts of global speculative grade corporate default rates made in December 2006, May 2007 and October 2007, along with the actual global speculative grade default rates for January to September 2008.