# Financial innovation and corporate default rates

Samuel Maurer, Luu Nguyen, Asani Sarkar and Chenyang Wei[1]

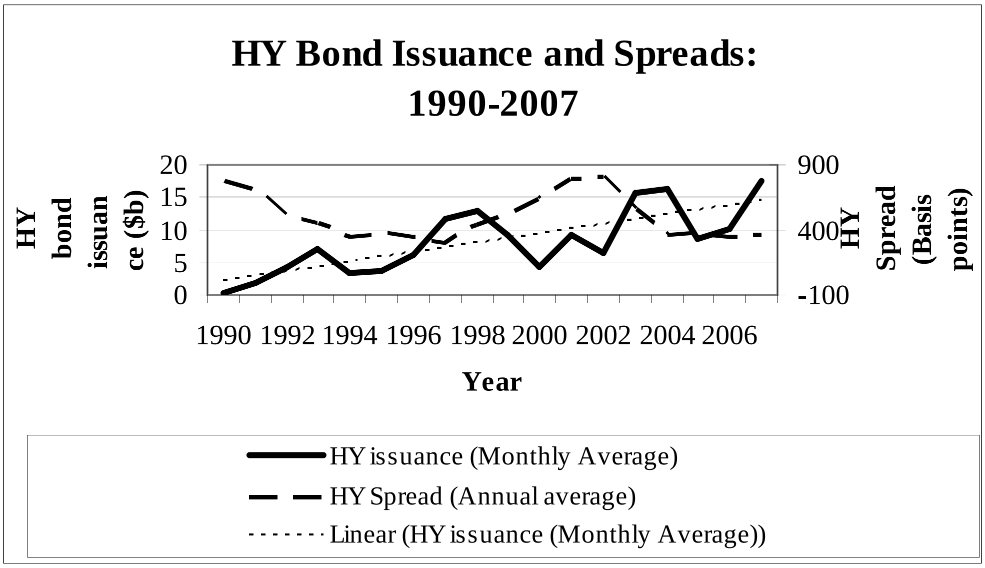
## I. Introduction

Measured default rates are currently at historically low levels. Compared to a historical average of 2%, Moody's 12-month trailing corporate default rate was 0.50% in September 2007. Even more striking, the default rate had fallen since January 2007 whereas some measures of economic fundamentals had worsened over this period of time. For example, the equity implied volatility had more than doubled, and high-yield corporate bond credit spreads had increased more than 100 basis points during this period. In fact, it appears that measured default rates have been lower than predictions by forecasters and ratings agencies at least since 2006.[2]

One reason for over-prediction of default rates may be that the historical relationship between existing model variables has changed. For example, it may be that default rates have become less sensitive to equity volatility and more sensitive to corporate profits which had continued to grow from January to May 2007, according to flow of funds data.

Figure 1

**US high-yield bond issuance and spreads: 1990–2007**




The figure plots monthly averages of US high-yield bond issuance and high-yield corporate credit spreads for 1990 to October 2007. It also shows the linear trend in bond issuance.

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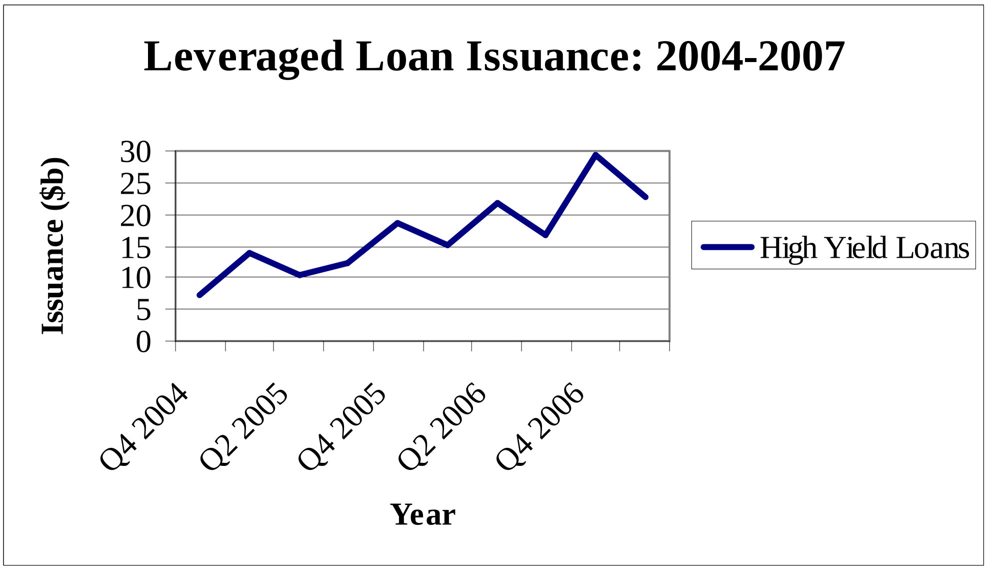
[1] All authors are from the Federal Reserve Bank of New York, 33 Liberty Street, New York, NY 10045. Corresponding author: Asani Sarkar, asani.sarkar@ny.frb.org; 212-720-8943. We thank Anand Srinivasan, seminar participants at the Summer Research Conference, Hyderabad, and the Federal Reserve Bank of New York for helpful comments. The views stated here are those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of New York or the Federal Reserve System.

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

Figure 2

**Leveraged loan issuance**




The figure plots the quarterly issuance of leveraged loans from the fourth quarter of 2004 go the first quarter of 2007.

In this paper, we explore an alternative possibility: that due to financial innovation new variables had been introduced into the default forecast models. Firms with high credit risk have had an expanded menu of financing sources. Issuance of high-yield bonds have been high (even accounting for trend) while high-yield credit spreads have been low by historical standards (see Figure 1). At the same time, financial innovations in the debt markets have resulted in new sources of financing becoming available. In particular, high-yield or leveraged loan volume has grown from essentially zero in 2004 to more than $80 billion in 2006 (see Figure 2). A portion of leveraged loans are used for so-called "rescue financing", or loans to distressed firms who are unable to tap traditional sources of financing.[3] 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.[4]

Structured financing vehicles have helped in the growth of leveraged loans. For example, managers of collateralized loan obligations, or CLOs, are major buyers of such loans. In addition, by repackaging risky bonds or loans into CDO products which re-distribute risk and return of the portfolio through "tranching", investors who traditionally stay away from distress investing can enter the market through investing in the safe tranche of a CDO investment product. As more capital is channeled in and becomes available to even highly risky borrowers companies that might have to default otherwise can survive longer, a phenomenon underlying the observed low default rates accompanying the recent financial innovations.

What are the implications for these new developments for default rates? In theory, the role financial innovations play in corporate default dynamics is unclear. Default rate could be low simply due to cyclical factors which are unrelated to financial innovations. Furthermore, the impact, if any, can be permanent or transitory with opposite directions, depending on factors

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3 See "Rescue finance for troubled firms", by Bernard Wysocki Jr., *The Wall Street Journal*, June 12, 2007.

4 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.

identified in theory. For example, if the marginal firms affected are those in need of funding for available positive-NPV investment opportunities, additional capital channeled through innovation would have permanent positive benefits for the company and possibility the economy as a whole. 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 will ultimately default in later stage with poorer recovery. A even worse possibly 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 be further incentivized to risk shift more, in which case the net effect of innovations might be an increase in the default risk, ceteris paribus.

We hypothesize that one observable effect of financial innovation is the possibility of "delayed default". 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 either by changing V or V* or both. Given V*, new financing increases V and either delays the time when the firm hits its default threshold or avoids 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 reducing the average time to default relative to the period when new financing was not available.[5]

The hypothesis of delayed defaults implies that the percent of early defaults is lower in recent years. We examine the hypothesis by considering bonds outstanding as of June 1 of each year (starting in 1980) and then estimating the percent of bonds that default within a particular horizon (say 2 years). We find that the percent of high-yield bonds defaulting within 2 years or less is unusually low from 2003 to 2005, compared to earlier years as well as compared to the overall default rates of high-yield bonds during those years. The same conclusion applies when considering a horizon of 3 years or less.

As expected, the percent of early defaults is correlated with the business cycle. In particular, the percent of early defaults tends to be high in the year before and during recessions. To account for business cycle effects, we regress the percent of early defaults on a recession dummy, changes in the unemployment rate and the credit spread. We continue to find a large decrease in the percent of early defaults after controlling for business cycle effects.

While the firm level analysis is broadly consistent with firms delaying defaults after accessing new forms of financing, the analysis does not explicitly link default rates and financial innovation. Moreover, the analysis does not allow us to study 2006 and 2007 (due to data constraints) when the impact of financial innovation is presumably maximized. In light of these considerations, we next turn to an analysis of aggregate default rates at the monthly level.

We estimate a prediction model for aggregate corporate default rates using variables identified in earlier studies to have strong predictive power (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 the time series of default levels, we predict *changes* in default rates rather the level. We find that changes in the default rate is significantly predicted by the distance to default and stock returns, growth in corporate debt (as reported in flow of funds data), macroeconomic conditions (ie the term spread and changes in the unemployment rate), measures of credit quality, and bond aging effects. The model has an adjusted R-squared of 53% and it has robust out-of-sample predictive properties.

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

Initially, we estimate the model without using proxies for financial innovation. While the model generally predicts actual default rates reliably, it consistently over-predicts the default rate since 2006. If financial innovation is partly responsible for the low measured default rates as distressed firms avail themselves of new sources of financing, then the prediction error should be partly explained by proxies of financial innovation. Indeed, we find that past increases in leveraged loans predict lower prediction errors. Similarly, past increases in collaterized debt obligations (CDOs) also predict lower prediction errors. In contrast, traditional forms of financing (eg banks' commercial and industrial (C&I) loans, commercial paper issuance, changes in commercial bank loan standards) are unrelated to the prediction errors. These results explicitly link measured default rates to the financial innovation of recent years.

To the best of our knowledge, this is the first systematic evidence that financial innovations are negatively related to aggregate default rate changes. We believe this finding is important. First, existing structural models of default risk have not taken into explicit considerations the role of financial innovations in affecting aggregate default rate dynamics. Although many structural models have the potential flexibility to incorporate the exogenous changes of financial innovation, the current literature does not have clear implications on through which parameter the impact could enter the model. 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 via replacing existing debt with cheaper debt financing. Related to the latter possible channel, several papers have endogenized the default event (eg Leland and Toft (1996) and Anderson, Sundaresan, and Tychon (1996)) by making the default threshold endogenous. However, the evidence in this paper appears to suggest a mechanism of affecting the default threshold differently.

Secondly, as very much discussed and debated in the recent credit market turmoil, regulators face the task of assessing the net impact of financial innovations on the economy. Although our findings suggest a positive role of financial innovations in lowering default rates in the short run, it remains to be investigated whether the impact is persistent. Furthermore, theories suggest that the impact of financial innovations on default risk is likely to be different (even opposite), depending on the investment opportunity set and the financial state of the borrower. We are currently further investigate these questions.

The rest of the paper is organized as follows. In Section II, we describe the data used in this study. In Section III, we present summary statistics and stylized facts on delayed defaults in recent years. We introduce a default prediction model for aggregate default rate changes in Section IV. In Section V, we explicitly link the prediction errors from the default rate changes model to financial innovation. Section VI concludes.

## II. Data

In this section, we discuss the sources of data used in the paper.

### Corporate bond default rate

We use Moody's Default Risk Database, which features comprehensive data on Defaults, Recovery from Default, and Rating Changes (at both the security and issuer level) for all corporate issuers of long-term bonds that have carried a Moody's rating since 1970. Moody's definition of default includes three types of credit events:

- A missed or delayed disbursement of interest and/or principal, including delayed payments made within a grace period;

- 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.

We focus on rated bonds that are domestically outstanding by industrial issuers during the period of 1984–2006. The sample includes only “regular” bonds which excludes bond with non standard features such as convertibility.

Rating cohorts are formed at the end of June in each year, using all outstanding bonds with the cohort rating. We then follow each cohort for 2 years to calculate a forward-looking measure of cohort default rate. Lastly, for aggregate default rate changes, we use data provided by Moody’s Default Research Service.

### Financial innovations

We use two measures to proxy for recent financial innovations in the U.S. credit market. First, we use data on aggregate CDO issuance from the SIFMA web site, based on the observation of the boom in this type of structured finance product.

## III. Early defaults: descriptive statistics

Table Ia

**Annual number and face amount of investment-grade bonds outstanding by rating class**

| | Investment Grade | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Aaa | | Aa | | A | | Baa | |
| Year | # of bonds | Face Amount ($MM) | # of bonds | Face Amount ($MM) | # of bonds | Face Amount ($MM) | # of bonds | Face Amount ($MM) |
| 1984 | 17 | 3,587 | 190 | 29,610 | 228 | 19,976 | 49 | 5,406 |
| 1985 | 18 | 7,232 | 233 | 41,845 | 362 | 32,959 | 74 | 16,327 |
| 1986 | 35 | 12,532 | 343 | 56,136 | 561 | 63,958 | 122 | 17,913 |
| 1987 | 48 | 14,582 | 388 | 65,810 | 696 | 87,150 | 192 | 23,202 |
| 1988 | 111 | 33,786 | 417 | 75,730 | 843 | 105,171 | 248 | 32,940 |
| 1989 | 168 | 44,867 | 412 | 75,450 | 920 | 122,084 | 295 | 48,189 |
| 1990 | 202 | 51,142 | 397 | 77,693 | 935 | 132,141 | 379 | 59,787 |
| 1991 | 209 | 53,172 | 279 | 50,496 | 1,116 | 180,848 | 461 | 72,406 |
| 1992 | 241 | 61,907 | 263 | 52,591 | 1,222 | 212,504 | 573 | 93,787 |
| 1993 | 271 | 66,775 | 260 | 54,204 | 1,304 | 226,879 | 716 | 137,517 |
| 1994 | 247 | 64,386 | 272 | 58,883 | 1,516 | 280,098 | 687 | 132,302 |
| 1995 | 262 | 65,862 | 358 | 77,473 | 1,705 | 320,224 | 674 | 115,120 |
| 1996 | 326 | 63,605 | 457 | 89,071 | 2,252 | 369,967 | 914 | 147,779 |
| 1997 | 435 | 55,013 | 748 | 123,722 | 3,097 | 435,523 | 1,322 | 197,816 |
| 1998 | 487 | 55,651 | 1,186 | 163,638 | 4,361 | 489,860 | 1,776 | 285,200 |
| 1999 | 526 | 64,635 | 1,867 | 245,232 | 4,751 | 530,960 | 2,202 | 366,732 |
| 2000 | 502 | 66,020 | 2,190 | 287,507 | 5,084 | 590,717 | 2,001 | 360,646 |
| 2001 | 410 | 56,630 | 2,264 | 288,151 | 4,714 | 583,086 | 1,751 | 358,061 |
| 2002 | 462 | 58,595 | 2,341 | 285,987 | 4,338 | 515,185 | 1,753 | 381,708 |
| 2003 | 525 | 60,058 | 2,265 | 257,029 | 4,959 | 492,957 | 1,674 | 381,372 |
| 2004 | 953 | 85,894 | 2,506 | 285,803 | 6,335 | 466,242 | 1,707 | 390,379 |
| 2005 | 1,115 | 82,721 | 2,768 | 356,911 | 5,274 | 394,861 | 3,556 | 459,149 |
| 2006 | 1,304 | 89,360 | 5,270 | 471,300 | 3,370 | 394,010 | 1,408 | 368,009 |
| 2007 | 1,572 | 126,513 | 6,147 | 1,667,338 | 2,816 | 454,449 | 1,618 | 397,473 |

Table 1b

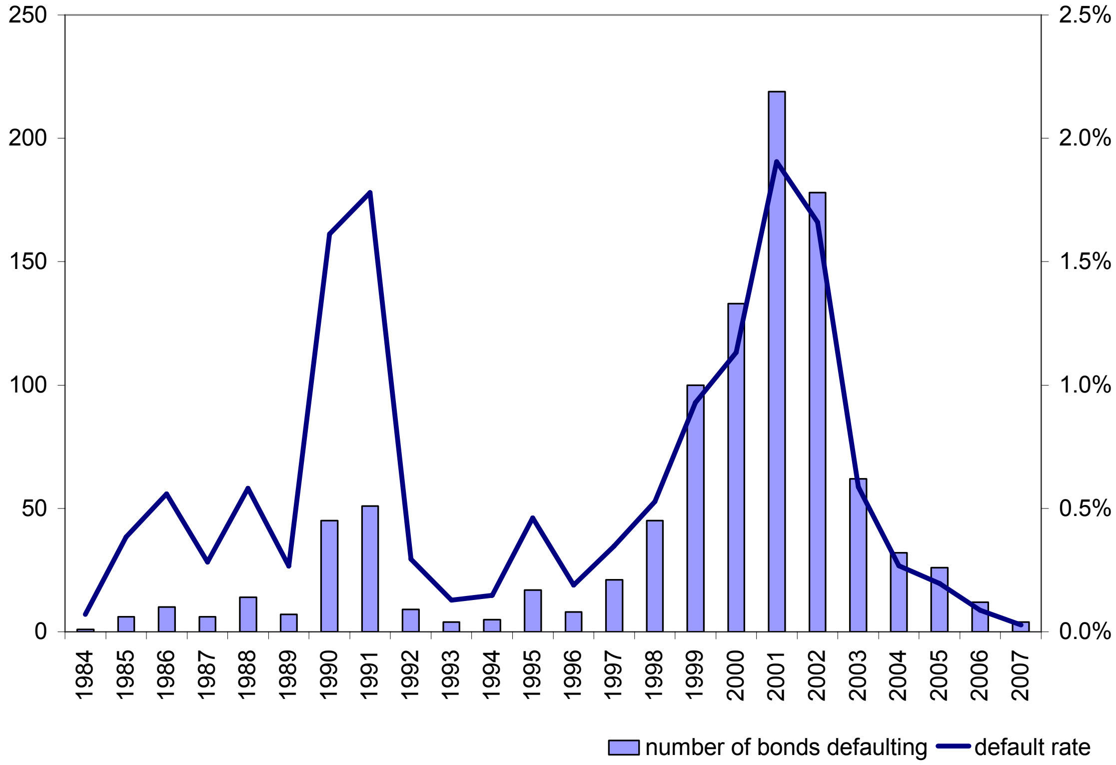
**Annual number and face amount of speculative-grade bonds outstanding by rating class**

| | High Yield Grade | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Ba | | B | | Caa | | Ca | | C | |
| Year | # of bonds | Face Amount ($MM) | # of bonds | Face Amount ($MM) | # of bonds | Face Amount ($MM) | # of bonds | Face Amount ($MM) | # of bonds | Face Amount ($MM) |
| 1984 | 22 | 2,194 | 29 | 2,090 | 1 | 30 | . | . | - | . |
| 1985 | 34 | 4,296 | 49 | 4,721 | 4 | 366 | . | . | - | . |
| 1986 | 54 | 11,861 | 98 | 12,281 | 6 | 430 | 1 | 136 | - | . |
| 1987 | 95 | 20,374 | 160 | 24,518 | 9 | 710 | 9 | 1,171 | - | . |
| 1988 | 99 | 22,142 | 218 | 34,328 | 10 | 1,749 | 11 | 1,371 | - | . |
| 1989 | 109 | 18,299 | 278 | 53,063 | 11 | 1,731 | 17 | 2,224 | 3 | 250 |
| 1990 | 116 | 17,531 | 281 | 55,268 | 26 | 4,489 | 35 | 7,178 | 6 | 695 |
| 1991 | 137 | 31,100 | 235 | 41,859 | 47 | 6,480 | 61 | 10,209 | 6 | 1,035 |
| 1992 | 177 | 33,496 | 209 | 40,204 | 45 | 5,898 | 57 | 9,113 | 5 | 770 |
| 1993 | 217 | 48,441 | 274 | 50,164 | 38 | 6,019 | 24 | 2,965 | 2 | 222 |
| 1994 | 245 | 46,586 | 395 | 68,596 | 32 | 5,490 | 12 | 1,011 | 2 | 222 |
| 1995 | 292 | 57,238 | 465 | 76,853 | 42 | 7,546 | 14 | 1,893 | 1 | 100 |
| 1996 | 350 | 67,294 | 565 | 101,682 | 69 | 11,817 | 22 | 2,558 | 2 | 185 |
| 1997 | 468 | 79,600 | 708 | 125,808 | 79 | 13,187 | 25 | 3,454 | 5 | 931 |
| 1998 | 509 | 103,233 | 1,129 | 189,563 | 157 | 25,939 | 32 | 5,336 | 6 | 1,206 |
| 1999 | 492 | 104,819 | 1,133 | 195,536 | 249 | 42,503 | 60 | 9,395 | 19 | 4,474 |
| 2000 | 498 | 107,130 | 955 | 176,917 | 292 | 50,896 | 78 | 12,441 | 37 | 8,733 |
| 2001 | 527 | 115,428 | 783 | 151,269 | 348 | 57,860 | 122 | 25,982 | 24 | 3,815 |
| 2002 | 543 | 129,100 | 552 | 103,461 | 290 | 58,762 | 107 | 27,353 | 32 | 7,753 |
| 2003 | 487 | 112,706 | 429 | 83,761 | 264 | 50,295 | 75 | 19,998 | 22 | 5,776 |
| 2004 | 435 | 100,231 | 374 | 77,816 | 211 | 40,590 | 43 | 10,467 | 7 | 1,083 |
| 2005 | 418 | 95,977 | 272 | 62,983 | 150 | 27,933 | 32 | 8,837 | 3 | 410 |
| 2006 | 1,983 | 142,568 | 327 | 74,289 | 97 | 18,786 | 20 | 7,456 | 18 | 2,769 |
| 2007 | 1,161 | 106,230 | 656 | 81,824 | 126 | 39,260 | 11 | 2,121 | 2 | 300 |

We start by presenting summary statistics of the rating data. Table 1a and 1b present the annual number and face amount of outstanding bonds by rating for investment-grade and speculative-grade bonds, respectively, in the period of 1984–2007. In the past two decades, there were significant increases in the number and aggregate face amount of bonds in each rating group.

Figure 3

**Historical annual number of defaults and default rates (1984–2007)**




The aggregate defaults tend to exhibit a cyclical pattern (see Figure 3). During the 1980s, less than 0.6% of outstanding bonds in our sample defaulted in a given year. Though the 1990–91 recession was brief, more than 50 bonds defaulted during each calendar year, representing a peak annual default rate of nearly 1.8%. Defaults declined to their previous levels until the late 1990s, gradually rising as economic expansion gave way to the dot-com bubble and recession. The default rate reached nearly 2% in 2001, and did not moderate substantially until 2003. Since 2004, default rates have been below 0.3%, declining to historically low levels in 2006 and 2007.

We further track the default experience of the rating cohorts for 2 years subsequent to the cohort formation. As expected, the 2-year-forward default rates of all investment-grade cohorts are fairly low, and we report the 2-year forward default rates for two high-yield cohorts – “Ba and B” and “Caa and below”.

Figure 4a

**Two-year forward default rates for rating cohort "Ba and B Rated"**

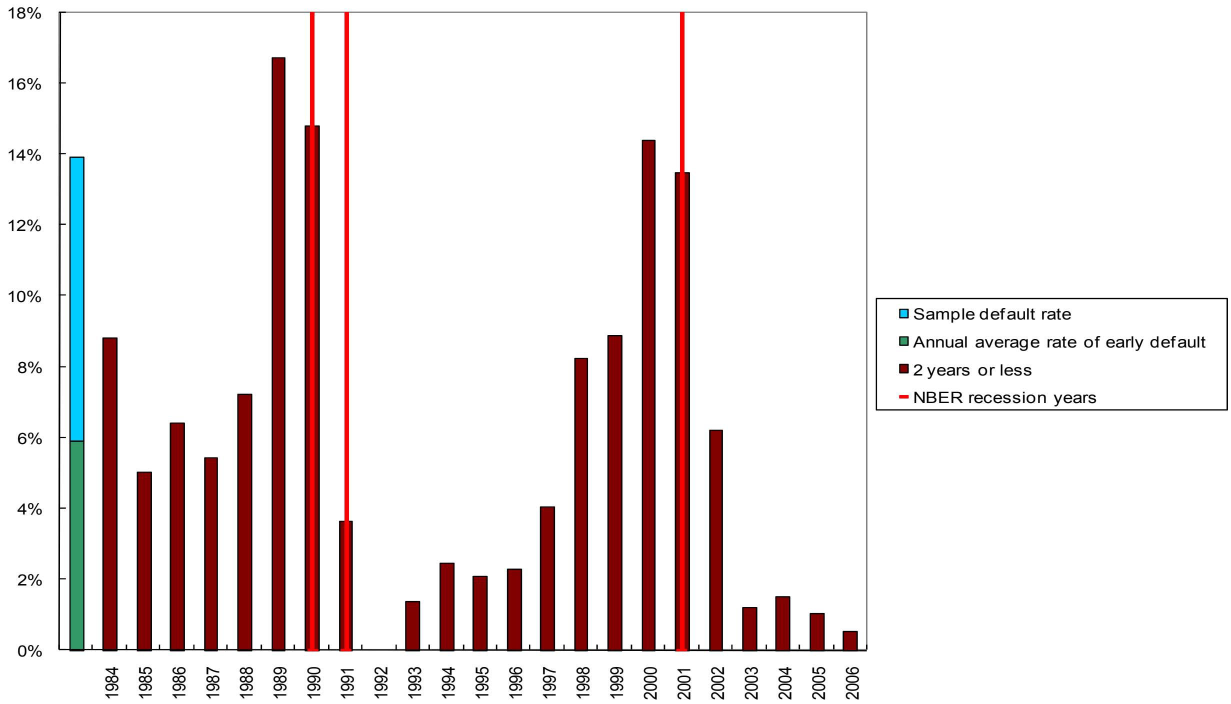



Figure 4b

**Two-year Forward Default Rates for Rating Cohort "Caa and Below"**

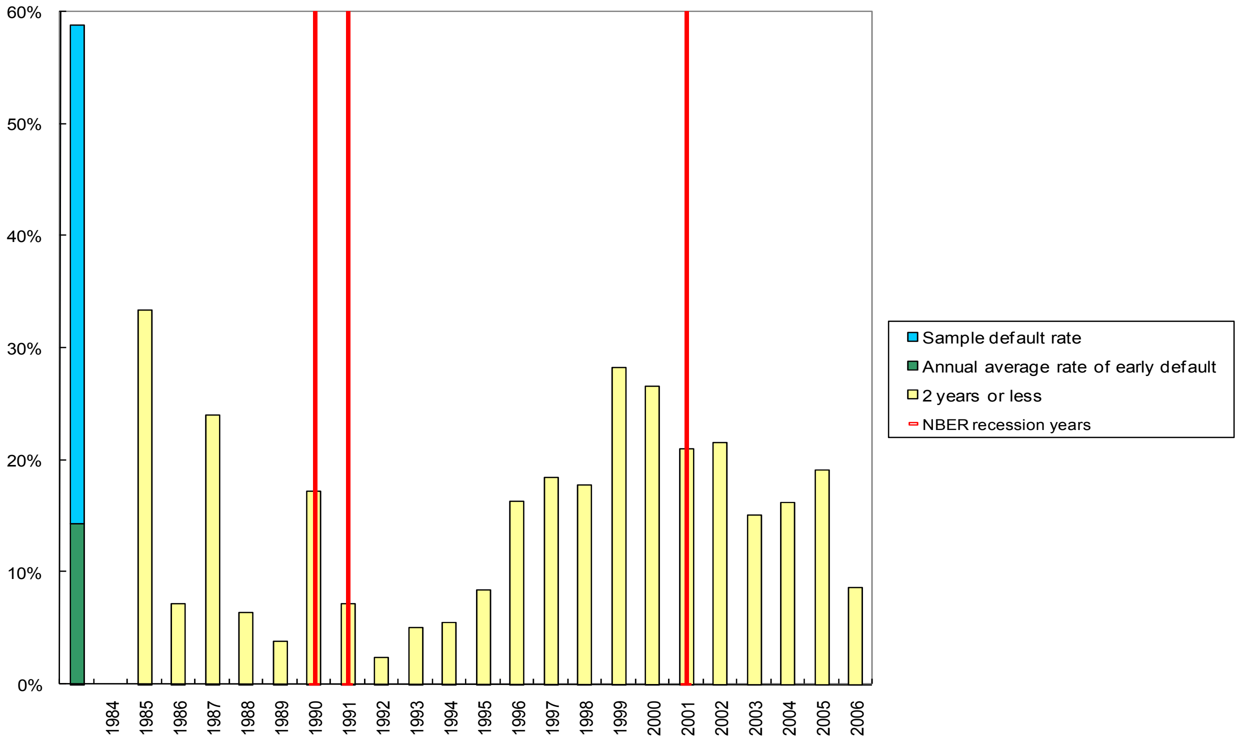
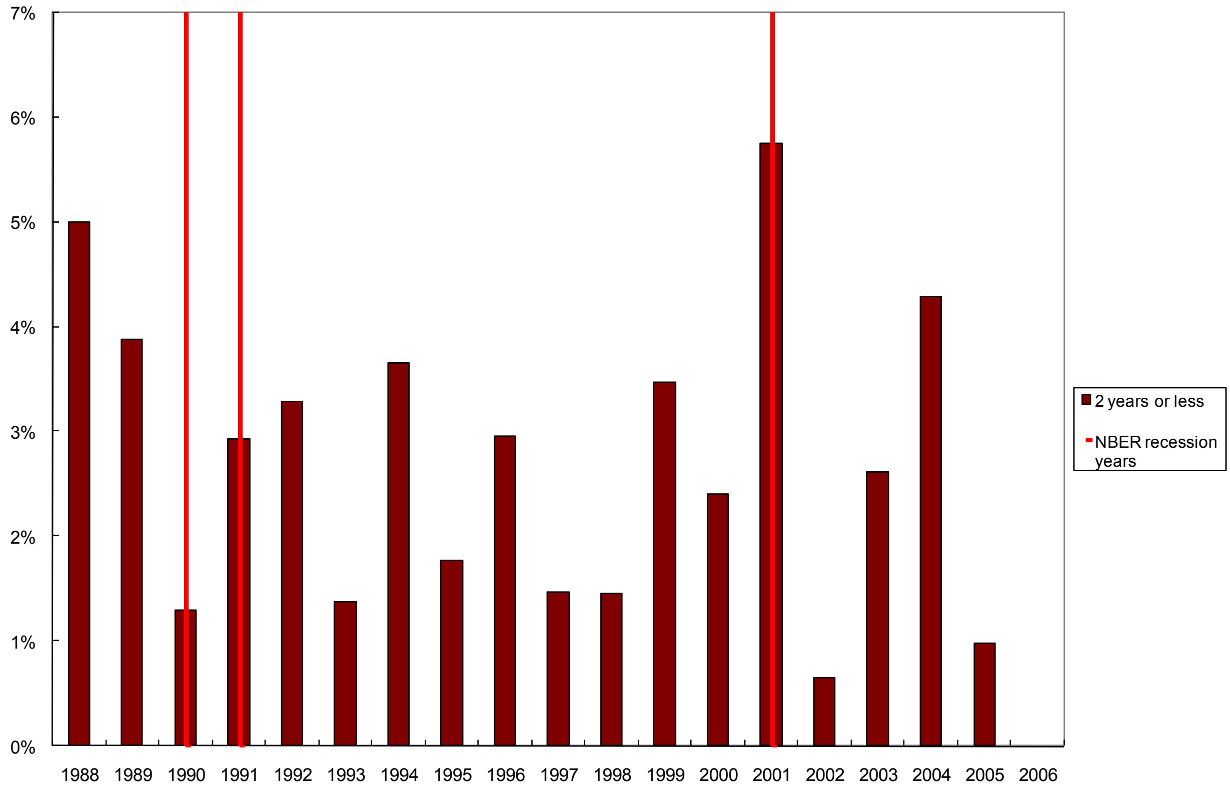


Figure 4a shows the 2-year default experience subsequent to the cohort formation for bonds that are originally rated Ba or B. In the graph, the left-most bar indicates the sample average unconditional default rate and the average default rate conditional on “early default” – default within two years after joining the cohort. The 2-year forward default rates clearly exhibits a cyclical pattern, with defaults peaking before recession periods defined by NBER. Related to the question in this study, the 2-year early defaults in 2003 through 2006 are significantly lower than the sample average. Figure 4b depicts a similar picture for bonds rated Caa or lower. The pattern is much weaker for these lower-rated bonds, though the 2-year early defaults in 2006 are still lower than the sample average. Particularly for bonds rated Ba or B, these stylized facts are consistent with the notion that, controlling for credit risk (rating), early defaults have significantly decreased in recent periods.

Figure 5

**Two-year forward default rates of cohort “Ba and B” – adjusted for business cycle effects**




Since the observation above apparently suffers from the “business cycle” effect, ie the fluctuation in default due to economic conditions, we use a regression model to adjust the 2-year forward default rates by taking out the effect of several macro-economy related variables – the volatility of equity returns, GDP growth (lagged by 1 month), yield spread of investment grade bonds, and NBER’s indication of economic recession. Figure 5 shows the 2-year forward default experience for bonds rated Ba or B after the “business cycle” adjustment. We plot the residuals from the regression model and adjust by adding the absolute value of the most negative value to each bar to make them all non-negative. The overall pattern appears to be different, but continues to show an unusually low forward default rate in 2005 and 2006, the most recent years in our sample for which 2-year subsequent default data is available.

The stylized facts are robust with respect to using a 3-year horizon for calculating the forward default rates, and to using newly issued bonds instead of outstanding new and aged bonds.

Taken together, the picture is consistent with current observations (eg Altman (2007)) of a low aggregate default rate and suggests the decrease in early defaults as a potential interesting angle for further investigation, which we turn to in the next section.

While the firm level analysis is broadly consistent with firms delaying defaults after accessing new forms of financing, the analysis does not explicitly link default rates and financial innovation. Moreover, the analysis does not allow us to study 2007 and 2008 (due to data constraints) when the impact of financial innovation is presumably maximized. In light of these considerations, we now turn to an analysis of aggregate default rates at the monthly level.

## IV. Predicting aggregate default rates

In this section, we develop a model for predicting aggregate defaults while omitting the use of financial innovation measures as explanatory variables. The aim is to show that the prediction errors from this model are significantly related to measures of financial innovation but unrelated to measures of traditional financing.

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. [6] The set of issuers comprises the entire Moody's-rated universe (all-corporate). 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.

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:

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

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:

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

Thus, while in general we expect the explanatory variables to impact $\Delta D_t$ at lags of up to 12 months, it is possible that the longer lags have a bigger impact than shorter lags.

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

We estimate a prediction model for $\Delta D_t$ using variables identified in earlier studies to have strong predictive power. The explanatory variables may be grouped as follows:

*Distance to default* and *Growth in debt of the corporate sector*. 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). The ratio $V_t/L_t$ is obtained at the quarterly level and then interpolated to obtain monthly values. $\mu_A$ is the sample mean and $\sigma_A$ is the sample standard deviation of $V_t$. $DDEF_t$ is obtained for each firm and then averaged. We use the one-month lagged value of $DDEF_t$.

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 $LEVGR_t$.

*Macroeconomic conditions*. A firm's financial health is likely to depend on general macroeconomic conditions. Certainly, 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)). We also use three lags of the change in the unemployment rate which is a strong predictor of the equity risk premium (Sarkar and Zhang, 2007).

We also tried other macroeconomic variables 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 and bond aging effects.* 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 (eg 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 12 monthly lags of this variable.

Helwege and Kleiman (1996) added an "aging" factor to credit quality and were able to explain 81% of the variation. Since defaults are more likely to occur three years after issuance, they use the dollar amount of B3-rated issues lagged three years. We use lagged values of high-yield issuance but only use the four monthly lags since the longer lags were not significant.

*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 positive, indicating higher returns increase default rates). We use 12 monthly lags of returns on the Wilshire 3000 index.

Table II

**Definition table**

The table presents definitions of variables used in subsequent tables

| Variable name | Definition |
|---|---|
| ∆D | Monthly changes in Moody's 12-month trailing corporate default rates. |
| DDEF | Distance to default, a volatility-adjusted leverage ratio defined as described in the text. |
| CH_TERM | Changes in the term spread, defined as the difference between constant maturity 10-year and 3-month rates. |
| CH_UEM | Changes in the unemployment rate. |
| CH_CQ | Changes in credit quality, defined as the difference in high-yield and investment-grade credit spreads |
| HYIS_GR | Growth in high-yield bond issuance |
| SRET | The return on the Wilshire 3000 index. |

## Results

Table III

**Predicting aggregate corporate default rates**

| | Distance to default and debt growth | | Macroeconomic conditions | | Credit quality | | Stock returns | |
|---|---|---|---|---|---|---|---|---|
| **Explanatory variable** | **Estimate** | ***t*-stats** | **Estimate** | ***t*-stats** | **Estimate** | ***t*-stats** | **Estimate** | ***t*-stats** |
| **Dependent variable: ∆D** | | | | | | | | |
| Intercept | –0.01** | –4.08 | –0.01** | –4.57 | –0.00* | –2.22 | –0.00* | –2.37 |
| DDEF, Lag1 | –0.09** | –3.65 | –0.10** | –4.10 | –0.05* | –1.97 | –0.05* | –2.05 |
| LEVGR, Lag1 | 0.01** | 3.94 | 0.01** | 4.44 | 0.01** | 3.51 | 0.01** | 2.63 |
| CH_TERM, Lag12 | – | – | –0.01** | –2.99 | –0.08* | –2.39 | –0.08* | –2.28 |
| **Variables with multiple lags** | | | | | | | | |
| CH_UEM, 3 Lags | | | | | | | | |
| +, N | – | – | 1 | | 1 | | 1 | |
| –, N | | | 0 | | 0 | | 0 | |
| CH_CQ, 12 Lags | | | | | | | | |
| +, N | – | – | – | – | 3 | | 1 | |
| –, N | | | | | 0 | | 0 | |
| HYIS_GR, 4 Lags | | | | | | | | |

Table III (cont)

**Predicting aggregate corporate default rates**

| | Distance to default and debt growth | | Macroeconomic conditions | | Credit quality | | Stock returns | |
|---|---|---|---|---|---|---|---|---|
| **Explanatory variable** | **Estimate** | ***t*-stats** | **Estimate** | ***t*-stats** | **Estimate** | ***t*-stats** | **Estimate** | ***t*-stats** |
| **Variables with multiple lags** | | | | | | | | |
| +, N | – | – | – | – | 0 | | 0 | |
| –, N | | | | | 1 | | 1 | |
| SRET, 12 Lags | | | | | | | | |
| +, N | – | – | – | – | – | – | 0 | |
| –, N | | | | | | | 1 | |
| 12 Lags of ∆D included? | yes | | yes | | yes | | yes | |
| Adj-R2 | 0.41 | | 0.52 | | 0.52 | | 0.53 | |

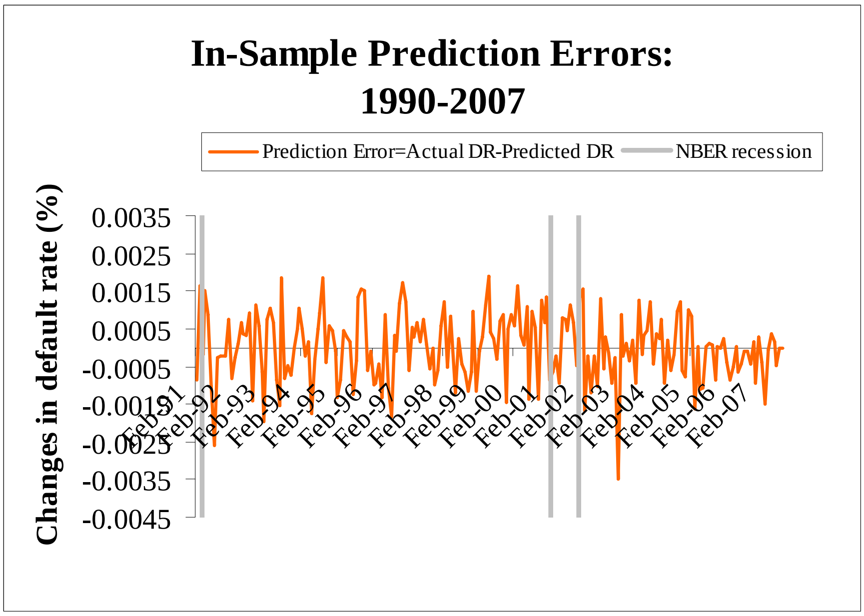
Note: The table shows results from a regression of the monthly change in aggregate default rates ∆D on the distance to default DDEF, growth in corporate debt LEVGR, macroeconomic factors, credit quality, growth in high-yield issuance HYIS_GR and the stock return SRET. Credit quality is the change in the difference in high-yield and investment grade bond credit spreads CH_CQ. Macroeconomic factors are changes in the term spread CH_TERM and the change in the unemployment rate CH_UEM. All variables are defined in the definition table III. The regression also includes 12 monthly lags of ∆D. For variables with multiple lags, we indicate the number of lags N with a positive + or negative – sign significant at the 1% or 5% level. Estimates of DDEF, LEVGR and CH_TERM are multiplied by 100. Data is from Bloomberg, CRSP, Compustat, Haver and Moody's. The sample period is January 1990 to September 2007. The regression uses 200 observations. Standard errors are corrected for autocorrelation ** (*) indicate, at the 1% (5%) level or less, whether the coefficient estimates are significantly different from zero.

Table III shows results from regressing the change in default rates on the various explanatory variables. The estimation is carried out sequentially on the distance to default and debt growth variables, the macroeconomic variables, the credit quality variables, and the stock return. The results are shown in the table following the above pattern. Starting from the first group of results, we find that an increase in the distance to default significantly reduces the probability of default, consistent with Duffie, Saita and Wang (2007). In addition, the growth in aggregate corporate debt predicts an increase in the default rate. The latter result indicates that even though the distance to default is a function of the leverage ratio, nevertheless it may be unable to capture the dynamics of leverage changes. These two variables, along with the 12 lags of default rate changes, are sufficient to explain more than 40% of the variation in default rate changes.

For the second group of estimations, 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 the unemployment rate also capture the business cycle effect, but not as well. Only out of the three lags in this variable is significant, although the sign is as expected: it is positive and significant at the 5% level. The addition of the macroeconomic variables increases the adjusted R-squared to 52%.

The final two groups of variables (credit quality, including high-yield issuance, and stock returns) are less effective in predictive changes in default rates. There are a total of 28 lags of these variables that are included in the regression, yet the adjusted R-squared only increases 1%. However, the signs of the estimated coefficients are of expected signs, even though few of them are statistically significant at the 5% level. For example, an increase in the difference between high-yield and investment-grade credit spreads predicts an increase in the default rate, consistent with a decrease in credit quality overall. An increase in the stock return predicts a decrease in the default rate. Finally, an increase in high-yield issuance predicts a decrease in the default rate. This result likely reflects the fact that high-yield issuance generally increases during good economic times.

Figure 6

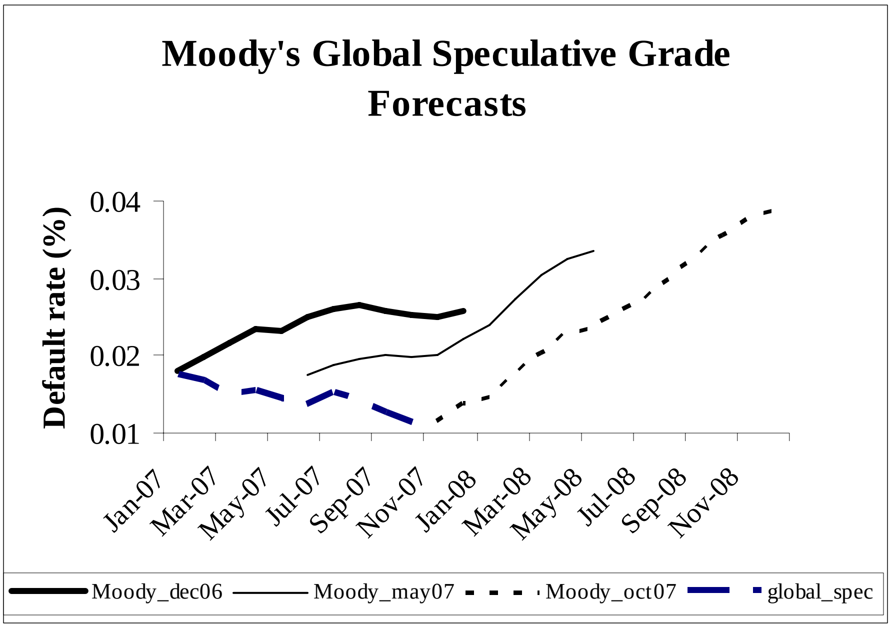



The figure plots the in-sample prediction errors from the aggregate default prediction model. The model is estimated over the period 1990 to September 2007. The change in default rates are regressed on distance to default, growth in corporate leverage, macroeconomic and credit quality variables, high-yield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

Overall, our prediction model does a good job of explaining the in-sample variation in aggregate default rates. Although some previous work has achieved higher R-squared, those results applied to regressions of default rate *levels*. Given the high persistence in default rates, it is expected that levels regressions should achieve higher R-squared. Figure 6 plots the prediction errors and they cluster 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. The "over-prediction" of default rates is apparent in Figure 7 which illustrates Moody's predicted and actual default rates for global high-yield bonds for 2007.

Figure 7

**Moody's forecasts of defaults in global speculative grade bonds**




The figure plots Moody's 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 October 2007.

While in-sample fit is desirable, even more emphasis should be placed on the out-of-sample fit. To that end, we first investigate the stability of the estimated relationships.

### Stability tests

To ascertain the stability of the results, we perform a number of structural break tests, including the Chow Breakpoint test, the Andrews test for an unknown breakpoint and the Ramsey RESET test. While the tests of the different results are not completely consistent (as they generally tend not to be), a conservative conclusion points to a break in 2002. Consequently, we re-estimate the regression from 2003. Stability tests do not indicate any further structural breaks. In the remaining analysis, therefore, we use estimates using only the sample from 2003 onwards. However, we have repeated all of our results using the full sample, and confirmed that the results are robust to the sample period estimated.

## V. Financial innovation and aggregate default rates

So far, we have not explicitly tied our analysis of default rates to financial innovation. We turn to that task in this section. We explore the channel that financial innovation makes new sources of financing available to distressed firms, thus reducing the measured default rates. In terms of the prediction model, financial innovation may be viewed as an omitted variable. If we do not account for it, our predicted default rates will be too high for the recent years. Once we account for financial innovation, we should obtain smaller prediction errors. In other words, the prediction errors and measures of financial innovation should be negatively correlated.

We could introduce the financial innovation measures and re-estimate the original model. Instead, we first obtain the prediction errors from the original model (without introducing financial innovation) and then regress the errors on lagged values of financial innovation measures. Both approaches give similar results, so the choice of method is not germane.

Our first measure of financial innovation is the growth in leveraged loans. 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 growth in aggregate CDO issuance.

Table IV

**Financial innovation and aggregate corporate default rates**

| | **Leverage loan growth** | | **CDO issuance growth** | | **Leveraged loan and CDO issuance growth** | |
|---|---|---|---|---|---|---|
| **Explanatory variable** | **Estimate** | ***t*-stats** | **Estimate** | ***t*-stats** | **Estimate** | ***t*-stats** |
| Intercept | 0.00* | 2.11 | 0.00 | 1.82 | 0.00* | 2.38 |
| *LL_GR, Lag1* | –0.14* | –2.57 | – | – | –0.07 | –0.97 |
| *LL_GR, Lag2* | 0.02 | 0.40 | – | – | 0.02 | 0.63 |
| *LL_GR, Lag3* | –0.07 | –1.06 | – | – | –0.12 | –1.72 |
| *LL_GR, Lag4* | –0.00* | –2.14 | – | – | –0.01* | –2.60 |
| *LL_GR, Lag5* | –0.02** | –10.07 | – | – | –0.02** | –10.44 |
| *CDO_GR, Lag1* | – | – | –0.12** | –3.10 | –0.16 | –1.42 |
| Adj-$R^2$ | 0.28 | | 0.06 | | 0.30 | |

Note: The table shows results from a regression of the residuals from the regressions in Table III on lagged measures of financial innovation. The residuals are prediction errors from predicting monthly change in aggregate default rates while omitting to include measures of financial innovation in the model. The measures of financial innovation are growth in leveraged loans LL_GR and growth in aggregate CDO issuance CDO_GR. Estimates have been multiplied by 1000. Data is from Bloomberg, CRSP, Compustat, Haver and Moody's. The sample period is January 2005 to September 2007. The regression uses 27 observations. Standard errors are corrected for autocorrelation ** (*) indicate, at the 1% (5%) level or less, whether the coefficient estimates are significantly different from zero.

We regress the prediction errors on five lags of the growth in leveraged loans. Results are shown in Table IV. As hypothesized, four of the five lags are estimated to have negative signs; and three of these are significant at the 5% level or less. Therefore, past increases in leveraged loans result in smaller prediction errors: once we incorporate financial innovation variables, the predicted default rates are less likely to over-shoot the measured rates. The adjusted R-squared is 28%, indicating this variable by itself can explain almost one-third of the variation in prediction errors.

Figure 8.

**Aggregate CDO issuance growth**
**and subsequent default rate changes**

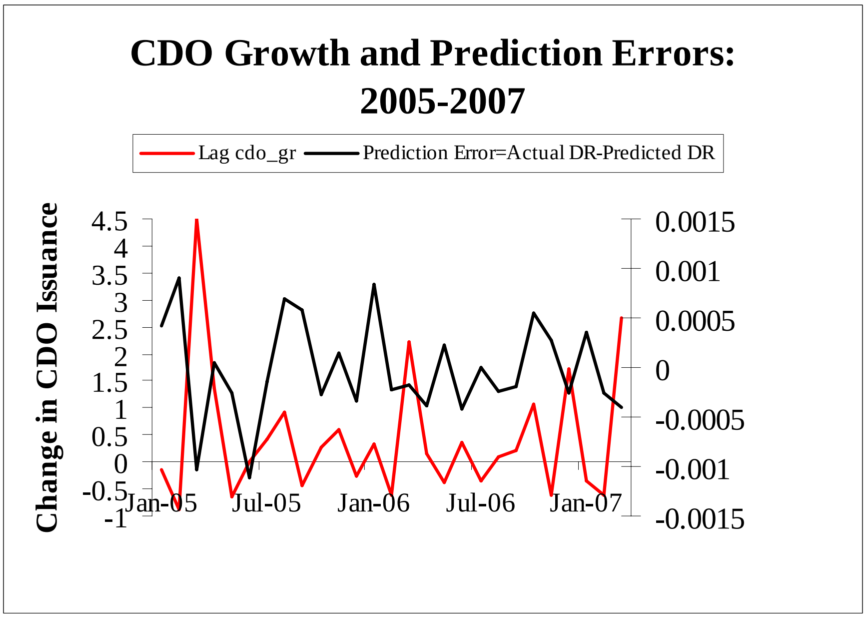
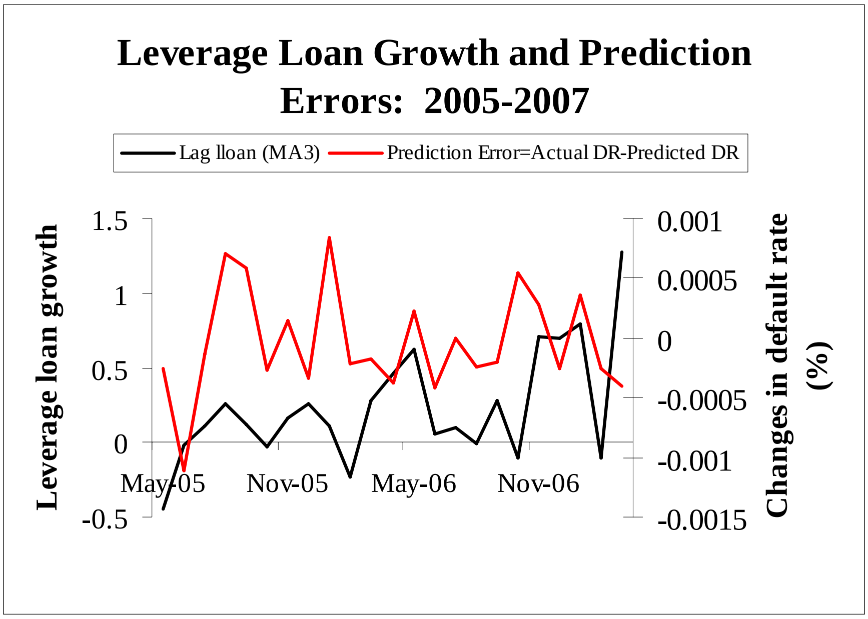



Figure 9

**Aggregate leverage loan growth**
**and subsequent default rate changes**




We next regress the prediction errors on one lag of the growth in CDO issuances and find the same result. The estimated coefficient is negative and significant. Once again, the size of innovations is negatively related to the prediction errors. Together, leveraged loans and CDO issuances can explain 30% of the variation in prediction errors. Figures 8 and 9 illustrate the path of prediction errors and changes in our measures of financial innovations.

Table V

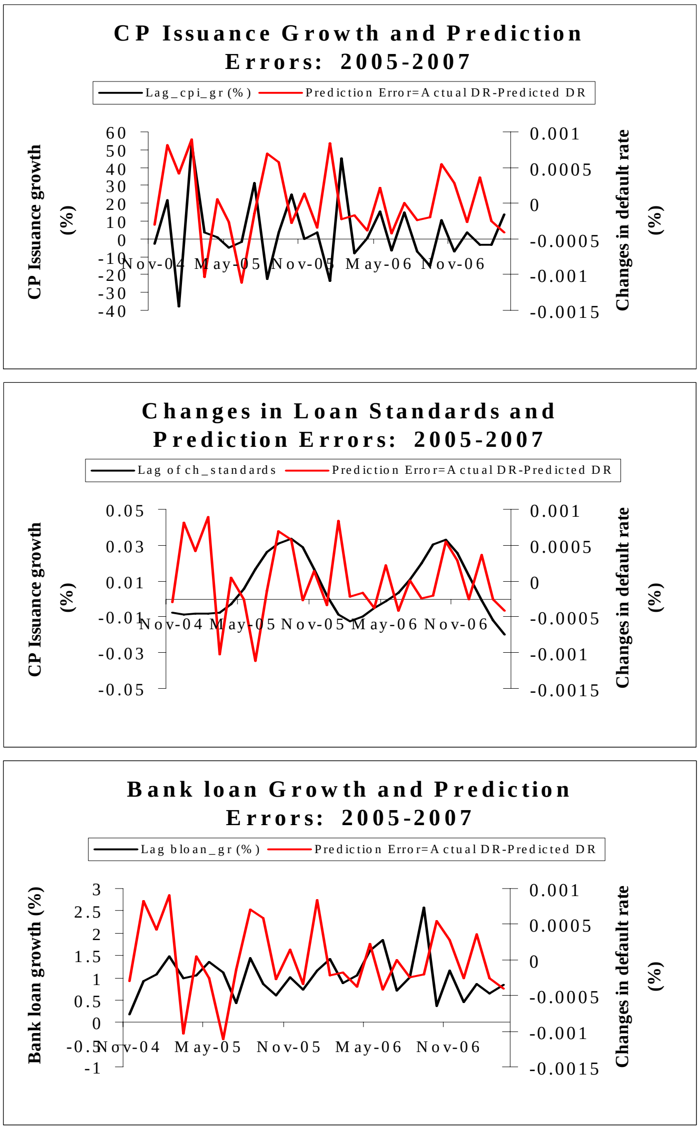
**Traditional financing and aggregate corporate default rates**

| | **Leverage loan growth** | | **CDO issuance growth** | | **Leveraged loan and CDO issuance growth** | |
|---|---|---|---|---|---|---|
| Explanatory variable | **Estimate** | ***t*-stats** | **Estimate** | ***t*-stats** | **Estimate** | ***t*-stats** |
| Intercept | 0.00 | 0.00 | 0.00 | 0.06 | 0.00 | 0.00 |
| *CI_GR, Lag1* | –0.16 | –0.04 | – | – | – | – |
| *CP_GR, Lag1* | – | – | –0.09 | –0.28 | – | – |
| *CP _GR, Lag2* | – | – | –0.07 | –0.24 | – | – |
| *CP _GR, Lag3* | – | – | 0.08 | 0.33 | – | – |
| *CH_STAN, Lag1* | – | – | – | – | –0.16 | –0.10 |
| Adj-$R^2$ | –0.01 | | –0.05 | | –0.06 | |

Note: The table shows results from a regression of the residuals from the regressions in Table III on lagged measures of financial innovation. The residuals are prediction errors from predicting monthly change in aggregate default rates while omitting to include measures of traditional financing in the model. The measures of traditional financing are growth in commercial and industrial loans CI_GR, growth in commercial paper issuance CP_GR and changes in lending standards STAN_CH. Estimates have been multiplied by 1000. Data is from Bloomberg, CRSP, Compustat, Haver and Moody's. The sample period is January 2005 to September 2007. The regression uses 27 observations. Standard errors are corrected for autocorrelation ** (*) indicate, at the 1% (5%) level or less, whether the coefficient estimates are significantly different from zero.

Figure 10.

**Traditional financing and prediction errors**




An objection to our results is that, since during this period, issuances of all kinds were rising, our results reflect the positive effect of general lending growth on default rates, and hence is not 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, growth in commercial paper issuances and changes in commercial banks' lending standards. These results are shown in Table V. We find that no measure of traditional financing has a significant effect on the default prediction errors. The t-statistics are very small, all less than 1. Moreover, in all cases, the adjusted R-squared is negative. These results are a sharp contrast to the significant relation between prediction errors and financial innovations. Figure 10 illustrates the paths of prediction errors and changes in traditional financing measures.

## VI. Conclusion

In recent years, two trends emerged in U.S. credit market – the boom in structured finance activities manifested a strong trend in financial innovations, and a very low default rate among U.S. borrowers (Altman (2007)). Increasingly, anecdotes and media discussions suggest a link between the two – development of financial innovations in credit market have both opened new channels of credit financing for borrowers, and created new investment opportunities for investors (capital suppliers) with different risk preference and risk-return tradeoff. For example, by repackaging risky bonds or loans into CDO products which re-distribute risk and return of the portfolio through "tranching", investors who traditionally stay away from distress investing can enter the market through investing in the safe tranche of a CDO investment product. As more capital is channeled in and becomes available to even highly risky borrowers companies that might have to default otherwise can survive longer, a phenomenon underlying the observed low default rates accompanying the recent financial innovations.

In theory, the role financial innovations play in corporate default dynamics is unclear. Default rate could be low simply due to cyclical factors which are unrelated to financial innovations. Furthermore, the impact, if any, can be permanent or transitory with opposite directions, depending on factors identified in theory. For example, if the marginal firms affected are those in need of funding for available positive-NPV investment opportunities, additional capital channeled through innovation would have permanent positive benefits for the company and possibility the economy as a whole. 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 will ultimately default in later stage with poorer recovery. A even worse possibly 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 be further incentivized to risk shift more, in which case the net effect of innovations might be an increase the default risk, ceteris paribus.

In this paper, we empirically investigate the relationship between financial innovations and U.S. corporate default rates. Using rating cohort-level evidence and a regression analysis to better control for business cycle effect, we first document that aggregate default rates in recent years (2006–2007) are indeed unusually low. More importantly, we find strong evidence that past growth in financial innovations is associated with subsequent default rates that are unusually low as suggested by a default prediction model.

Specifically, we first form annual rating cohorts and investigate the two-year forward default rates of each cohort through time. The "Ba and B" and "Caa and below" cohorts formed in 2004 and 2005 both exhibit default percentages in two years after cohort formation that are significantly lower than the 20-year sample average. After we remove the business cycle effect embedded in the time variation of the forward default measure, we continue to observe the 2005 "Ba and B" cohort carrying the third lowest 2-year forward default rate in the sample.

If financial innovations indeed drive default rates lower, we would expect to observe a negative relation between changes in innovation activities and subsequent changes in default rates. To test this hypothesis, we first build a default prediction model which explains more than 50% of the time variation in monthly changes of the U.S. historical aggregated default rates. The prediction errors for aggregate monthly default rate in 2006 and 2007 are regressed on proxies for financial innovations, namely the aggregate CDO issuance and leverage financing volume. Our results show that higher aggregate CDO issuance or leverage financing volume is negatively associated with subsequent changes in aggregate default rates.

To the best of our knowledge, this is the first systematic evidence that financial innovations are negatively related to aggregate default rate changes. We believe this finding is important. First, existing structural models of default risk have not taken into account explicit considerations the role of financial innovations in affecting aggregate default rate dynamics. Although many structural models have the potential flexibility to incorporate the exogenous changes of financial innovation, the current literature does not have clear implications on through which parameter the impact could enter the model. 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 via replacing existing debt with cheaper debt financing. Related to the latter possible channel, several papers have endogenized the default event (eg Leland and Toft (1996) and Anderson, Sundaresan, and Tychon (1996)) by making the default threshold endogenous. However, the evidence in this paper suggests a mechanism of affecting the default threshold differently.

Secondly, as very much discussed and debated in the recent credit market turmoil, regulators face the task of assessing the net impact of financial innovations on the economy. Although our findings suggest a positive role of financial innovations in lowering default rates in the short run, it remained to be investigated whether the impact is persistent. Furthermore, theories suggest that the impact of financial innovations on default risk is likely to be different (even opposite), depending on the investment opportunity set and the financial state of the borrower. We are currently further investigating these questions.

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