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Understanding Changes in Corporate Credit Spreads

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New evidence is reported on the empirical success of structural models in explaining changes in corporate credit risk. A parsimonious set of common factors and company-level fundamentals, inspired by structural models, was found to explain more than 54 percent (67 percent) of the variation in credit-spread changes for medium-grade (low-grade) bonds. No dominant latent factor was present in the unexplained variation. Although this set of factors had lower explanatory power among high-grade bonds, it did capture most of the systematic variation in credit-spread changes in that category. It also subsumed the explanatory power of the Fama and French factors among all grade classes.

We report our assessment of the empirical success of structural models in explaining changes in corporate credit spreads. We focus on the change in the credit spread, not its level.[1] The difference between studying spread levels and studying spread changes is equivalent to the difference between studying equity prices and studying equity excess returns. A one-to-one correspondence exists between the spread level and the bond price, whereas changes in credit spreads are directly associated with bond excess returns.[2] Therefore, credit-spread changes are the focus in bond pricing and, like expected equity returns in equity analysis, are the key to characterizing the risk–return trade-off in corporate bond markets, fixed-income portfolio allocation, credit-risk management, and credit-derivatives pricing.

So, what drives credit-spread changes? Early studies by Black and Scholes (1973) and Merton (1974) introduced "structural" models to explain corporate default risk and inspired the search for company-level and macro variables, such as stock volatility, company leverage, and interest rates, that could drive the changes in corporate credit spreads.

From among the various approaches to evaluating structural models (e.g., Eom, Helwege, and Huang 2004; Schaefer and Strebulaev 2004), we adopted the view that structural models are empirically successful in corporate bond pricing if they use variables that capture the variation in credit-spread changes. Using this approach, Collin-Dufresne, Goldstein, and Martin (2001; hereafter, CDGM) found that structural model variables explain less than 25 percent of the variation in credit-spread changes. The remaining unexplained variation, they found, is dominated by a strong latent factor. These findings pose a serious challenge to the empirical validity of structural models in explaining corporate credit-spread changes. Should we dismiss, or at least discount, the importance of structural models in empirical studies of credit-spread changes? As we will show, not necessarily.

Potential Determinants of Credit-Spread Changes

Our determinants of credit-spread changes were inspired by structural default-risk models, which view equity and debt as options on the company's value. In this contingent-claims framework, default occurs when the value of the company falls below a default threshold. Hence, variables governing company value affect default probabilities and recovery rates and, ultimately, drive credit spreads.

Whether structural models are empirically successful has long been an open question. One of the most popular and commercially successful systems for evaluating default risk, the Moody's KMV expected default frequency (EDF) methodology, as well as Moody's RiskCalc credit-scoring system, is based on the Merton (1974) model.[3] Yet, the academic literature is inconclusive regarding the performance of structural models. On the one hand,

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Jones, Mason, and Rosenfeld (1984) and Kim, Ramaswamy, and Sundaresan (1993) found that structural model variables explain only a small fraction of credit risk. Similarly, CDGM did not find structural models to be promising in identifying variables that adequately explain credit-spread changes. On the other hand, Campbell and Taksler (2003) documented strong comovement between aggregate bond spreads and aggregate idiosyncratic equity volatility. This evidence provides support for structural models because such models distinguish volatility as a key determinant of default probability.

We do not formally implement a structural model to evaluate a model's ability to fit prices or spreads. Instead, using a linear time-series regression, we assess how well structural model variables explain the variation in changes of corporate credit spreads. The model variables typically include interest rates, the slope of the term structure, equity market return and volatility, and company leverage and volatility. As well as previously studied variables, we incorporate company-level and aggregate idiosyncratic equity volatility and growth prospects and stock return momentum. The entire set of selected variables and how they relate to the probability of default and the recovery rate conditional on default are described in the following subsections.

■ *Idiosyncratic equity volatility*. The contingent-claims approach views debt as a combination of a risk-free loan and a short put option on the company. Higher volatility increases the option value, thereby decreasing bond prices and increasing spreads. Intuitively, higher volatility increases the likelihood of hitting the default threshold. Structural models posit that a company's value is driven by the company's total volatility, which has previously been proxied by equity market volatility. Following Campbell and Taksler (2003), we focus on idiosyncratic equity volatility. Campbell and Taksler documented a synchronous upward move in aggregate spreads and aggregate idiosyncratic volatility from 1990 to 2000. Furthermore, Campbell, Lettau, Malkiel, and Xu (2001) documented that both idiosyncratic and total volatility moved strongly upward in the past decade while market volatility remained constant.

Campbell and Taksler's (2003) findings link idiosyncratic equity volatility and credit-spread levels. Little is known, however, about how changes in idiosyncratic volatility affect credit-spread changes, which is why we explore it here.

■ *Stock return momentum*. Empirical research has extensively documented that the cross-section of equity returns is predictable from past returns over some horizons. Jegadeesh and Titman (1993) found momentum in stock prices; they showed that past "winners" continue to outperform past "losers" over the short-to-medium term. Thus, higher momentum in equity returns implies higher future company valuation and could imply lower probability of default and lower spreads.

The impact of momentum on credit-spread changes has not previously been documented, but Avramov, Chordia, Jostova, and Philipov (forthcoming 2007) establish a strong link between credit rating and momentum in equity returns. Given this new evidence, as well as the rich literature on the effect of momentum on future stock returns and its potential effect on the unobservable valuation process, momentum is a good candidate for inclusion in our analysis of credit-spread changes.

■ *Growth opportunities*. Improving prospects of company growth and profitability decrease the likelihood that the company's value will reach the default threshold. Our use of the price-to-book ratio (P/B) to proxy for future profitability was motivated by Pastor and Veronesi (2003), who offered a theoretical framework and empirical evidence that a company's P/B is linked to the level and volatility of expected profitability. Within the context of structural models, the new variables—momentum and P/B—affect underlying company value and, hence, the probability of default.

■ *Spot rate*. Longstaff and Schwartz (1995) argued that an increase in the spot rate increases company value (i.e., a higher reinvestment rate increases future value). This effect, in turn, lowers the probability that the value of the company's assets will fall below the default threshold. So, an increase in the spot rate reduces the credit-risk component in credit spreads and leads to tighter spreads. Longstaff and Schwartz empirically confirmed the negative relationship between spot rates and credit spreads.

■ *Term-structure slope*. We consider two competing hypotheses on the directional impact of changes in the term-structure slope on credit-spread changes. On the one hand, a steepening of the slope implies an increase in expected future spot rates, thereby reducing credit spreads. In addition, Fama and French (1989) argued that an increase in the yield-curve slope leads to an improving economy, improving recovery rates, and decreasing credit risk. On the other hand, the increase in expected future interest rates, which is implied by a steepening yield curve, may reduce the number of projects with positive net present value (NPV) available to the company. This reduction would, in turn, lower the company's valuation and increase spreads.

The realized impact of changes in the term-structure slope on credit-spread changes is an empirical question.

■ *Leverage*. Merton (1974) implied that high leverage increases the probability of default because it raises the default threshold. As in CDGM, we used the company's equity return as a measure of change in the company's leverage. The use of this proxy is also justified by Welch (2004), who found that many proxies used in the literature play much less of a role than stock returns do in capturing changes in leverage.

■ *Market conditions*. Changes in credit spreads are affected by changes in expected recovery rates, which affect payoffs to bondholders. Because the expected recovery rate is a function of the overall business climate (see, e.g., Altman and Kishore 1996), an improving economy should drive credit spreads down. We used equity market returns to proxy for changes in business climate, as was done by CDGM.

■ *Fama–French factors*. Elton, Gruber, Agrawal, and Mann (2001) showed that the credit spread compensates for exposure to aggregate risk factors, namely, the Fama and French (1993) factors. For robustness and comparison, we studied the predictive power of the Fama–French factors in the presence of our proposed set of structural model variables.

Data

Our goal was to show that a parsimonious set of structural model variables can capture the time-series variation in individual bond credit-spread changes. We obtained bond and stock data from Datastream. Our sample includes all U.S. corporate bonds listed in Datastream that satisfied a set of selection criteria commonly used in the corporate bond literature. Extracting all U.S. corporate bonds from Datastream between September 1990 (the first available date for corporate bond spreads) and January 2003 yielded 8,892 bond issues. The bond and equity datasets were then matched by using each bond's unique identifier.

This initial sample was subjected to a number of filtering criteria. We excluded bonds with no corresponding equity data in Datastream. We removed all bonds with equity or derivative features (such as callable, puttable, and convertible bonds), bonds with warrants, and bonds with floating interest rates. We also excluded bonds with fewer than 25 consecutive monthly observations, as did CDGM. We removed all bonds for which the credit-spread data appeared to be problematic. For example, a bond record might have indicated a negative credit spread because of an incorrect U.S. Treasury yield-curve assignment. Finally, because extreme spreads can arise from data errors or credit-spread blowups, we removed individual credit-spread observations exceeding 13 percent (five standard deviations from the mean).[4]

The filtered sample contains 2,375 fixed-rate, straight U.S. corporate bonds issued by 678 companies. The average number of monthly credit-spread observations per bond is 47. Note that our dataset addresses potential survivorship bias issues because we have not excluded bonds that went bankrupt or expired.

Our data are similar in quality to data from Bloomberg and the Lehman Brothers database. Analysis of a subset of bonds from the three data sources revealed a close match in their prices. This similarity is not surprising because these databases have the same data providers (i.e., the large institutional dealers in the bond market). Datastream, however, covers a much larger cross-section of bonds. We verified that the size and liquidity (as measured by trading volume) of the part of our sample covered by other sources were similar to that of the part not covered by other databases.

For all selected bonds, we extracted all end-of-month credit spreads available in Datastream for the period September 1990 to January 2003. Datastream computes credit spreads as the yield differential between the bond and the Treasury curve, with maturity and compounding frequency taken into account:

$$Spread_{i,t} = Yield_{i,t} - Yield_{CURVE,t}, \tag{1}$$

where $Yield_{i,t}$ is the t-period yield on corporate bond i and $Yield_{CURVE,t}$ is the yield on a t-period T-bond.

Bond Sample. **Table 1** provides descriptive statistics for the entire sample of 2,375 corporate bonds and for low-, medium-, and high-credit-risk groups.[5] Table 1 reports that the average rating across the credit-risk groups declined from A (numeric average of 5.92) for the highest-grade group to a non-investment-grade BB– (numeric of 12.99) for the lowest-grade group.[6] Our high-credit-risk group contained mostly high-yield bonds, which have not been considered in previous studies of credit-spread changes.

Both credit spreads and their changes differ substantially among the credit-risk groups. As Table 1 shows, the volatility of spread levels (and changes) rises sharply with rising credit risk—from 0.33 percent (0.17 percent) to 2.02 percent (0.77 percent) a month. The mean credit-spread change also

Table 1. Descriptive Statistics: Corporate Bond Sample, September 1990–January 2003

		Groups Based on Credit-Risk Level		
Statistic	All Bonds	Low	Medium	High
Credit spread (%)				
Mean (median)	2.46 (1.84)	0.80 (0.82)	1.88 (1.84)	4.69 (4.05)
Standard deviation	2.03	0.33	0.37	2.02
Range	0.00 to 12.99	0.00 to 1.32	1.32 to 2.63	2.63 to 12.99
Credit-spread change (%)				
Mean (median)	0.03 (0.01)	0.00 (0.00)	0.01 (0.01)	0.06 (0.05)
Standard deviation	0.52	0.17	0.23	0.77
Range	–10.02 to 11.81	–1.09 to 1.22	–1.25 to 1.20	–8.76 to 9.67
Duration (years)	5.16	4.90	5.95	4.35
Time to maturity (years)	8.69	8.20	10.44	7.19
Issue size ($ millions)	300	296	307	297
Trading volume ($ millions per month)	5.48	4.96	6.66	5.59
S&P average rating	8.58 (BBB)	5.92 (A)	8.29 (BBB+)	12.99 (BB-)

Notes: Trading volume was not available for all bonds; the figures represent trading volume per bond per month when data were available. Credit ratings were available for only some of the bonds. The last row reports the average letter S&P (Standard & Poor's) rating in parentheses. S&P ratings convert to numeric ratings as follows: AAA = 1, AA+ = 2, AA = 3, AA– = 4, . . ., D = 22. An S&P rating below BBB– is considered to be noninvestment grade.

differs substantially among the credit-risk groups. Duration, time to maturity, size, and trading volume are comparable across the credit-risk groups.

Aggregate Variables. Descriptive statistics for our marketwide measures for aggregate idiosyncratic equity volatility, aggregate P/B, and equity market return are reported in Panel A of **Table 2**. The marketwide measures were calculated as equally weighted averages across all 678 stocks in the sample.

Government rates in the study were represented by the monthly series of 2-, 5-, 10-, and 30-year Merrill Lynch government bond yield

Table 2. Descriptive Statistics: Independent Variables, September 1990–January 2003

Statistic	Mean	Median	Minimum	Maximum	Standard Deviation
A. Common factors					
Equity market return (%)	1.28	1.57	–17.09	11.07	4.34
Change in P/B (× 100)	0.50	2.21	–64.12	62.49	14.16
Change in idiosyncratic equity volatility (× 10; 000)	0.08	0.08	–19.75	20.42	3.97
Change in 5-year government rate (%)	–0.03	–0.05	–0.82	0.82	0.31
Change in term-structure slope (%)	0.00	0.00	–0.27	0.40	0.10
MKT factor (%)	0.55	1.10	–15.99	10.82	4.34
SMB factor (%)	0.12	–0.10	–11.60	14.62	3.43
HML factor (%)	0.08	0.05	–20.79	14.92	3.99
Fed cycle dummy (1 = expansion)	0.63	1.00	0.00	1.00	0.48
B. Company-level variables					
Stock return (%)	1.04	0.71	–28.01	33.10	9.73
Stock momentum (%)	1.97	1.68	–35.05	40.87	13.32
Change in idiosyncratic equity volatility (× 10; 000)	–0.01	–0.02	–28.72	27.77	5.76
Change in P/B (× 100)	0.16	0.50	–94.00	79.00	23.49

Note: Company-level numbers are cross-sectional medians for all companies.

indices. We used one index at a time in our regressions because changes in these indices are highly correlated; correlations range between 0.73 and 0.95. We selected the yield on the 5-year note as the spot rate because its maturity was close to the sample average.[7]

The term-structure slope is the yield differential between any two of the 2-, 5-, 10-, and 30-year Merrill Lynch indices. Except for equity market returns, we used changes, rather than levels, in the aggregate variables.

The factors from the Fama–French three-factor model are as follows: The MKT factor is the return on the market minus the return on the risk-free rate, the SMB factor is the return on the small-capitalization portfolio minus the return of the large-cap ("big") portfolio, and HML is the return on the portfolio of high book-to-market stocks minus the return on the portfolio of low book-to-market stocks.[8] (The row in Table 2 titled "Fed cycle dummy" is explained in the "Additional Robustness Tests" section.)

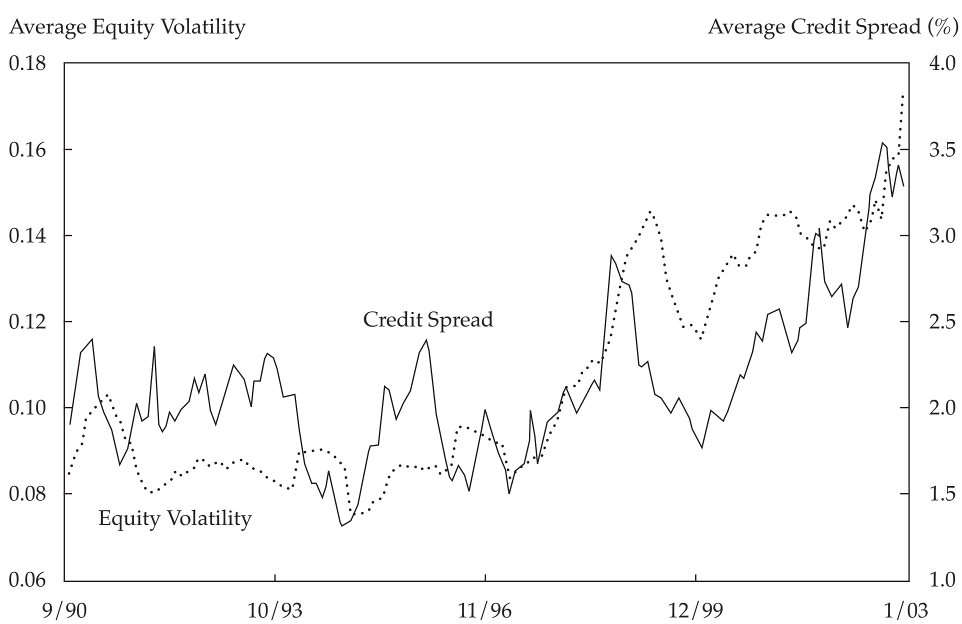
Company-Level Variables. Descriptive statistics for the company-level variables are presented in Panel B of Table 2. The company-level variables were based on each issuer's equity data. Monthly stock returns and P/Bs were obtained from Datastream. Following Brennan, Chordia, and Subrahmanyam (1998), we calculated stock return momentum as the cumulative return over the two months ending at the beginning of the previous month. This variable excludes the preceding month's return to avoid spurious association between prior and current returns because of thin trading or effects of the bid–ask spread.[9] Monthly volatilities were calculated as the sum of squared daily returns over the trading days of the month. Company-level idiosyncratic equity volatility was computed as the difference between monthly market volatility and monthly total company-level volatility, as in Campbell et al. (2001).

Because our analysis focuses on the determinants of changes in corporate credit spreads, we used changes in volatility and P/Bs. We considered the possibility that, because book values remain relatively unchanged from month to month, the change in the individual P/B would be highly collinear with the company stock return. We found, however, that the two variables have an average correlation coefficient of 0.18, which indicates that much of the information in the P/B is not captured by the stock return.

Results

We begin with an overview of credit spreads in the period 1990–2003. **Figure 1** displays the evolution of aggregate idiosyncratic equity volatility and average corporate credit spread in the 1990–2003 period. Figure 1 indicates that the synchronous upward trend previously documented by Campbell and Taksler (2003) for the late 1990s extended beyond their

Figure 1. Credit Spreads of U.S. Corporate Bonds and Idiosyncratic Equity Volatility, September 1990–January 2003



sample period. A prominent spike in the spread levels is visible in 1998 during the major credit events of the Russian crisis and the follow-up collapse of Long-Term Capital Management. Another spike in 2002–2003 marks the record defaults of the burst in the telecom bubble. Similarly, the upward trend in idiosyncratic volatility peaks around the fall of 1998 and the end of 2002. This strong comovement supports Campbell and Taksler's suggestion that increasing corporate spreads may be driven by the increase in idiosyncratic volatility.

Figure 2 shows a strong negative comovement between the average credit spread and the five-year Treasury yield that is consistent with the theoretical predictions of structural default-risk models. The two series have a correlation of –0.83. The correlation between the changes in these series is about the same (–0.86), which suggests that increases in interest rates significantly reduce the default probability of a typical company.

Time-Series Determinants of Credit-Spread Changes. We first examined the time-series explanatory power of common factors and company-level attributes for all 2,375 corporate bonds in our sample. In the time-series analyses, we ran individual-bond regressions, then averaged the estimated coefficients across all bonds. The average values are reported. The *t*-statistics were computed from the cross-section of the individual regression coefficients.

To indicate the relative importance of each variable, we present in **Table 3** results of univariate regressions of credit-spread changes on individual common factors (in Panel A) and company-level variables (in Panel B). Panel A shows that credit-spread changes in our sample were significantly affected by all these structural model factors. Factor sensitivities are strongly significant and have the theoretically expected sign. Specifically, changes in government rates had the strongest impact on credit-spread changes in terms of both significance and explanatory power. Changes in the five-year spot rate alone explained 28.63 percent of the variation in individual credit-spread changes. Consistent with the theoretical implications of risk-neutral contingent-claims pricing, increasing spot rates led to decreasing credit spreads.

Equity market returns were the second-strongest (after the government rate) determinant of credit-risk changes. This factor explained 18.25 percent of the variation.

Changes in the term-structure slope were also important determinants of changes in corporate credit spreads. Changes in the long-term slope (30Y – 2Y; that is, changes between 30-year and 2-year yields) had a strong positive impact on credit-spread changes, which is consistent with the hypothesis that an increasing slope decreases the expected NPV of available projects and thus reduces company value and increases credit spreads. Changes between 30- and 10-year yields (30Y – 10Y) explained 17.7 percent (with the highest explanatory power of the slope factors) of individual spread changes. The high explanatory power of this slope

Figure 2. Treasury Yields vs. Corporate Credit Spreads, September 1990–January 2003

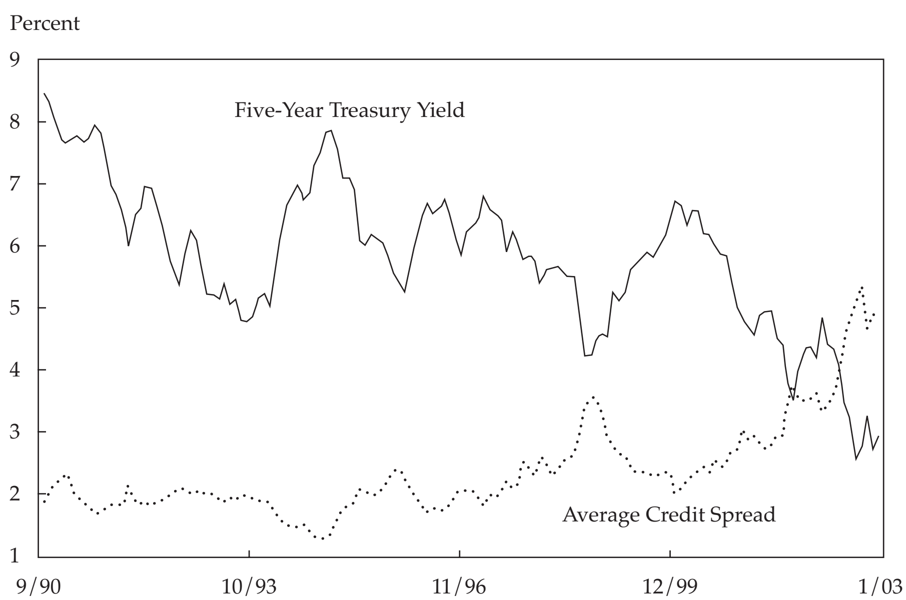


Table 3. Explanatory Power of Common Factors and Company-Level Characteristics, Data for September 1990–January 2003 (t-statistics in parentheses)

Factor	β_{ik}	Adjusted R^2
A. Common factors		
Equity market return	–3.22	18.25%
	(–36.26)	
Change in aggregate P/B	–0.89	3.21
	(–34.88)	
Change in aggregate idiosyncratic equity volatility	123.73	6.47
	(32.25)	
Spot rate		
2-Year (2Y)	–0.56	26.79
	(–45.30)	
5-Year (5Y)	–0.54	28.63
	(–49.29)	
10-Year (10Y)	–0.60	25.73
	(–50.52)	
30-Year (30Y)	–0.52	15.82
	(–45.95)	
Term-structure slope		
5Y – 2Y	–0.26	1.74
	(–14.96)	
10Y – 2Y	0.30	4.15
	(17.58)	
30Y – 2Y	0.48	11.49
	(31.96)	
30Y – 10Y	1.22	17.70
	(42.60)	
B. Company-level characteristics		
	β_i	Adjusted R^2
Stock return	–1.35	15.45%
	(–22.17)	
Stock momentum	–1.45	6.37
	(–1.70)	
Change in idiosyncratic equity volatility	263.52	13.20
	(26.44)	
Change in P/B	–0.52	7.29
	(–14.46)	

Note: Boldface indicates t-statistics that are significant at the 5 percent level.

could be a result of its correspondence to the period when refinancing needs (the average bond maturity is 8.69 years) of a typical company occur. In contrast, an increase in the short end of the term-structure slope (5Y – 2Y) reduced credit spreads, which is consistent with the hypothesis that an increasing slope implies an improving economy, which leads to a credit-risk decline.

In line with the findings of Campbell and Taksler (2003), changes in aggregate idiosyncratic volatility had a strong positive impact on credit-spread changes at the individual-bond level. Finally, an increase in the aggregate P/B, indicating improving growth opportunities, reduced credit spreads.

Panel B in Table 3 shows the relative importance of each company-level characteristic. These variables are all significant and have the theoretically expected sign. As posited by structural models, changes in company leverage (proxied by stock returns) and company-level idiosyncratic volatility are the most important drivers of credit-spread changes. Positive stock returns (a decrease in leverage) tend to decrease spreads significantly, whereas increases in stock volatility tend to increase them significantly. Bond spreads also responded to momentum in stock returns, but the t-statistic of –1.70 is significant only at the 10 percent level.[10] Finally, changes in the company's growth opportunities (measured by the P/B) reduced spreads and explained about 7.29 percent of the variation in credit-risk changes.

Next, we analyzed the joint explanatory power of all suggested variables in a series of regressions of the following type:

$$\Delta Spread_{it} = \alpha_i + \beta_{1i} F_t + \beta_{2i} C_{it} + e_{it}, \tag{2}$$

where F_t is the vector of common factors realized at time t, C_{it} is the vector of company-level characteristics at time t, and β_{1i} and β_{2i} are the vectors of sensitivities.

Table 4 presents the results of five specifications of regression Equation 2 and provides a clear picture of the relative power of the common and company-level variables in explaining credit-spread changes. In addition to the common factors previously explored, we added the Fama–French factors. Column M1 (for Model 1) shows only the combined explanatory power of five common factors: equity market return, changes in the aggregate P/B, aggregate idiosyncratic volatility, the (5-year) spot rate, and the term-structure slope measured by the yield differential between 30-year and 10-year Treasuries.[11] The R^2 indicates that these five factors captured as much as 43.78 percent of the time-series variation in credit-spread changes. Changes in the 5-year spot rate had the strongest impact on credit-spread changes, followed by changes in idiosyncratic volatility. All the aggregate variables except changes in the term-structure slope are significant.

Column M2 presents only the combined explanatory power of company-level variables plus lagged credit-spread changes to control for potential autocorrelation. The company-level

Table 4. Total Explained Variation in Credit-Spread Changes, Data for September 1990–January 2003
(*t*-statistics in parentheses)

Variable	M1	M2	M3	M4	M5
A. Common factors					
Equity market return	–0.66	—	–0.05	—	—
	(–6.98)		(–0.59)		
Change in aggregate P/B	–0.10	—	–0.07	—	–0.11
	(–4.63)		**(–3.23)**		**(–4.30)**
Change in aggregate idiosyncratic equity volatility	58.13	—	27.46	—	15.11
	(14.36)		**(6.24)**		**(3.30)**
5-Year spot rate	–0.46	—	–0.45	—	–0.43
	(–34.18)	—	**(–33.70)**		**(–29.75)**
Term-structure slope (30Y – 10Y)	0.02	—	–0.07	—	0.07
	(0.70)	—	**(–2.19)**		(1.86)
MKT factor	—	—	—	–0.02	0.00
				(–27.62)	(1.27)
SMB factor	—	—	—	–0.01	0.00
				(–19.77)	**(4.14)**
HML factor	—	—	—	–0.03	0.00
				(–22.00)	(1.93)
B. Company-level characteristics					
$\Delta Spread_{i,t-1}$	—	–0.11	–0.06	—	–0.04
		(–12.51)	**(–7.95)**		**(–4.80)**
$\Delta Spread_{i,t-2}$	—	–0.06	–0.03	—	–0.05
		(–8.68)	**(–4.85)**		**(–7.27)**
Stock return	—	–0.77	–0.30	—	–0.25
		(–17.69)	**(–8.49)**		**(–6.20)**
Stock momentum	—	–0.28	–0.26	—	–0.18
		(–10.36)	**(–9.70)**		**(–5.60)**
Change in idiosyncratic equity volatility	—	129.15	49.83	—	84.05
		(17.05)	**(6.35)**		**(9.51)**
Change in P/B	—	–0.18	–0.01	—	–0.07
		(–7.72)	(–0.27)		**(–2.24)**
Adjusted R^2	43.78%	26.35%	53.44%	25.93%	54.72%

Note: Boldface indicates *t*-statistics that are significant at the 5 percent level.

attributes explained as much as 26.35 percent of the time-series variation of credit-spread changes. All the company characteristics are significant and have the expected sign. Changes in idiosyncratic volatility and stock returns are the most significant variables. These results attest to the importance of company fundamentals in explaining variations in corporate credit-spread changes.

Next, we combined the aggregate and company-level variables to assess their joint explanatory power. Column M3 shows that such variables captured as much as 53.44 percent of the variation in credit-spread changes. The company characteristic P/B lost significance when the aggregate P/B was included in the regression. Similarly, when the company stock return was included, the market return lost significance. All the remaining variables remained strongly significant in the all-inclusive regression. This evidence suggests that the credit-spread variation has both a systematic component captured by common factors and an idiosyncratic one captured by company-level variables.

Next, we added the three Fama–French factors to the parsimonious set of structural model determinants. The Fama–French factors have traditionally been used in equity pricing, but Elton et al. (2001) documented that these factors also capture systematic variation in credit spreads. Indeed, Column M4 shows that the Fama–French factors have a negative and significant impact on credit-spread changes, explaining, as a group, 25.93 percent of spread changes.

As Column M5 shows, including the Fama–French factors with our common and company-level variables (excluding equity market return because it is highly correlated with the MKT factor) increased the explanatory power only from 53.44 percent to 54.72 percent. Note in Column M5 that both MKT and HML lost significance in the presence of our suggested variables and that the SMB factor flipped signs.

Overall, the evidence suggests that our structural model factors capture essentially all the systematic variation in credit-spread changes and subsume the explanatory power of the Fama–French factors.

To summarize, the time-series regression results provide strong empirical support for structural models. Common factors alone explained about 44 percent of the time variation in individual credit-spread changes, and company-level attributes alone explained 26 percent. Common factors and company-level variables combined explained more than 53 percent of the variation in credit-spread changes, a substantial improvement over previous findings.

Credit-Spread Variation by Credit-Risk Group. The evidence thus far suggesting that aggregate variables and company-level variables explain a substantial part of the variation in individual credit-spread changes contradicts previous research. We show here that much of the sharp difference is attributable to the composition of bonds in our sample. Specifically, our sample has extensive coverage of high-yield bonds.

For further analysis, we divided our sample into three credit-risk groups and reestimated the M5 specification of Equation 2 for each group separately. For a bond to be included in a credit-risk group, all its credit-spread observations had to fall within the group bounds. This grouping procedure placed 405, 370, and 475 bonds in, respectively, the low-, medium-, and high-credit-risk groups. The results, reported in **Table 5**, show that the explained variation of credit-spread changes increases substantially with rising credit risk, from 35.89 percent for high-grade bonds to 67.51 percent for low-grade bonds. Common factors, with the exception of the Fama–French factors, increase in significance as credit risk increases. All the company-level variables except the change in P/B also increase in significance with increased credit risk. Consistent with the evidence in Avramov et al. (forthcoming 2007), Table 5 shows that momentum is most important in explaining the variation in credit-spread changes in the highest-credit-risk group.

We also estimated specifications M1–M4 within the three credit-risk groups (results available upon request). The explanatory power was always larger in the high-credit-risk group. Specifically, the adjusted R^2 for the low-credit-risk group (high-credit-risk group) was 28.51 percent (53.67 percent) for the M1 specification, 18.56 percent (28.37 percent) for the M2 specification, 34.96 percent (67.14 percent) for the M3 specification, and 14.67 percent (30.26 percent) for the M4 specification. Company characteristics were always significant in the high-credit-risk group.

Additional Robustness Tests. To further assess the robustness of our results, we investigated the impact of marketwide liquidity, as affected by Federal Reserve Board expansionary or contractionary policy, on credit-spread changes.[12] Our sample period was characterized by several Fed actions, such as raising and reducing the federal funds rate, that could have affected corporate bond liquidity. To incorporate the potential impact of Fed actions on credit spreads, we constructed a dummy variable indicating Fed expansionary cycles (dummy = 1 following a decrease of the federal funds rate) and contractionary cycles (dummy = 0 following an increase of the federal funds rate). The decision to change the federal funds rate is published in press releases summarizing the transcripts of the Federal Open Market Committee meetings, which are available on the Federal Reserve Board website (http://federalreserve.gov/fomc/). The press releases or transcripts do not explicitly state that the Fed is involved in a expansionary or contractionary policy, but the policy can be interpreted from the decisions to increase (or decrease) the federal funds target rate.

The results of adding the Fed cycle information to the regressions are reported in **Table 6**. Our previous results are unchanged except that the Fama–French factors have lost significance now even in the high-grade segment. The adjusted R^2s are also unchanged, which indicates that our results are robust to changes in liquidity induced by Fed intervention. More importantly, the Fed cycle dummy is significant only in the highest-grade group, where expansionary (contractionary) Fed policy reduces (increases) credit spreads.

We also used out-of-sample regressions to assess the robustness of our results. **Table 7** shows results from the regression reported in Table 5 reestimated to extend the sample period to August 2006. The explained variation has decreased slightly for the low- and medium-credit-risk groups and increased for the high-credit-risk group (R^2 of 70.16 percent), which widens the differences in explanatory power among the credit-risk

Table 5. Common Factors, Company-Level Characteristics, and the Fama–French Factors (Regression M5) by Credit-Risk Group, Data for September 1990–January 2003
(*t*-statistics in parentheses)

Variable	Low Credit Risk	Medium Credit Risk	High Credit Risk
A. Common factors			
Change in aggregate P/B	–0.05	–0.08	–0.25
	(–2.69)	**(–2.56)**	**(–2.52)**
Change in aggregate idiosyncratic equity volatility	10.75	8.36	34.61
	(2.35)	(0.95)	**(2.24)**
5-Year government rates (5Y)	–0.23	–0.44	–0.74
	(–14.66)	**(–13.23)**	**(–16.51)**
Term-structure slope (30Y – 10Y)	–0.06	–0.13	0.10
	(–1.65)	(–1.93)	(0.81)
MKT factor	–0.00	0.00	–0.01
	(–0.03)	(0.60)	**(–2.14)**
SMB factor	–0.00	0.00	0.00
	(–2.31)	(0.22)	(0.51)
HML factor	–0.00	0.00	0.00
	(–2.42)	**(3.02)**	(0.61)
B. Company-level characteristics			
$\Delta Spread_{i,t-1}$	–0.21	–0.06	–0.04
	(–13.21)	**(–3.22)**	**(–2.42)**
$\Delta Spread_{i,t-2}$	–0.11	–0.10	–0.04
	(–7.98)	**(–6.69)**	**(–2.57)**
Stock return	0.00	–0.10	–0.44
	(0.00)	(–1.94)	**(–4.09)**
Stock momentum	–0.01	–0.12	–0.23
	(–0.32)	**(–3.15)**	**(–3.05)**
Change in idiosyncratic equity volatility	8.37	34.81	35.06
	(0.90)	(1.81)	(1.75)
Change in P/B	–0.04	–0.08	–0.13
	(–2.71)	**(–2.30)**	(–1.62)
Adjusted R^2	35.89%	54.83%	67.51%

Notes: Sample sizes were 405 bonds for the low-credit-risk group, 370 for the medium-credit-risk group, and 475 for the high-credit-risk group. Boldface indicates *t*-statistics that are significant at the 5 percent level.

groups. Aggregate idiosyncratic volatility has become more significant, especially for the middle- and high-credit-risk groups. The effects of spot rates and the term structure are also more pronounced, especially for the high-credit-risk group. The Fama–French factors are less important—the HML factor losing its statistical significance for all credit-risk groups. Company idiosyncratic volatility is now strongly significant. The company P/B, momentum, and stock returns have also markedly increased in significance.

Overall, extending the data out-of-sample reinforced our main results and conclusions, namely, that the structural model factors explain the variation of credit-spread changes, especially in the high-credit-risk group, and that common factors and company fundamentals play different roles in different credit-risk groups.

Table 6. M5 Regression Factors plus Federal Reserve Cycle Dummy by Credit-Risk Group, Data for September 1990–January 2003
(t-statistics in parentheses)

Variable	Low Credit Risk	Medium Credit Risk	High Credit Risk
A. Common factors			
Change in aggregate P/B	–0.05	–0.07	–0.24
	(–2.66)	**(–2.24)**	**(–2.42)**
Change in aggregate idiosyncratic equity volatility	10.35	12.68	38.76
	(2.28)	(1.47)	**(2.46)**
5-Year spot rate (5Y)	–0.23	–0.46	–0.73
	(–14.17)	**(–13.35)**	**(–16.19)**
Term-structure slope (30Y – 10Y)	–0.04	–0.17	0.13
	(–1.24)	**(–2.64)**	(1.05)
MKT factor	0.00	0.00	–0.01
	(0.17)	(0.30)	**(–2.41)**
SMB factor	–0.00	0.00	0.00
	(–1.93)	(0.07)	(0.65)
HML factor	–0.00	0.00	0.00
	(–1.83)	**(3.26)**	(0.50)
Fed cycle dummy (1 = expansion)	–0.01	–0.01	0.01
	(–4.70)	(–1.80)	(1.60)
B. Company-level characteristics			
$\Delta Spread_{i,t-1}$	–0.22	–0.07	–0.04
	(–13.67)	**(–3.65)**	**(–2.52)**
$\Delta Spread_{i,t-2}$	–0.12	–0.10	–0.04
	(–8.12)	**(–6.76)**	**(–3.01)**
Stock return	0.00	–0.10	–0.41
	(0.01)	(–1.73)	**(–3.75)**
Stock momentum	–0.02	–0.13	–0.23
	(–0.67)	**(–3.24)**	**(–2.98)**
Change in idiosyncratic equity volatility	1.11	27.81	35.01
	(0.12)	(1.40)	(1.76)
Change in P/B	–0.04	–0.08	–0.10
	(–2.34)	**(–2.15)**	(–1.26)
Adjusted R^2	35.28%	55.00%	66.56%

Notes: Sample sizes were 405 bonds for the low-credit-risk group, 370 for the medium-credit-risk group, and 475 for the high-credit-risk group. Boldface indicates t-statistics that are significant at the 5 percent level.

Our findings so far indicate that structural models capture a substantial amount of the time-series variation in individual bonds' credit-spread changes, especially among middle- and low-grade bonds. Still, the strongest evidence against structural models, provided by CDGM, is the possible existence of a latent factor that is unrelated to structural models and equity markets and that captures 75 percent of the residual variation of credit-spread changes. Therefore, we next investigate whether such a large latent factor is present in the residual variation of any credit-risk segment of our bond sample.

Unexplained Credit-Spread Variation. We implemented principal-components (PC) analysis of (1) credit-spread changes and (2) the residuals of the time-series regressions. These residuals reflect

Table 7. Explained Variation in Credit-Spread Changes in Regression M5 by Credit-Risk Group, Data for September 1990–August 2006
(*t*-statistics in parentheses)

Variable	Low Credit Risk	Medium Credit Risk	High Credit Risk
A. Common factors			
Change in aggregate P/B	–0.02	–0.10	–0.24
	(**–2.11**)	(**–2.16**)	(**–2.24**)
Change in aggregate idiosyncratic equity volatility	11.24	12.61	13.27
	(**2.51**)	(**3.02**)	(**3.13**)
5-Year spot rate (5Y)	–0.19	–0.36	–0.68
	(**–2.39**)	(**–18.63**)	(**–32.88**)
Term-structure slope (30Y – 10Y)	–0.39	–0.03	0.27
	(–1.85)	(–0.92)	(**3.41**)
MKT factor	–0.00	–0.00	–0.01
	(–0.32)	(–1.91)	
SMB factor	–0.01	–0.00	
	(**–3.14**)	(–0.85)	
HML factor	–0.03	–0.00	
	(–1.55)	(–0.52)	
B. Company-level characteristics			
$\Delta Spread_{i,t-1}$	0.10	–0.06	
	(1.03)	(**–5.94**)	
$\Delta Spread_{i,t-2}$	–0.35	–0.07	0.01
	(**–2.69**)	(**–8.21**)	(1.04)
Stock return	0.68	–0.38	–0.54
	(0.59)	(**–2.47**)	(**–8.32**)
Stock momentum	–0.41	–0.11	–0.22
	(–1.86)	(**–4.84**)	(**–6.77**)
Change in idiosyncratic equity volatility	–13.80	42.31	35.59
	(–0.98)	(**3.72**)	(**3.85**)
Change in P/B	–0.42	–0.19	–0.15
	(–0.84)	(–0.91)	(**–1.98**)
Adjusted R^2	30.48%	49.95%	70.16%

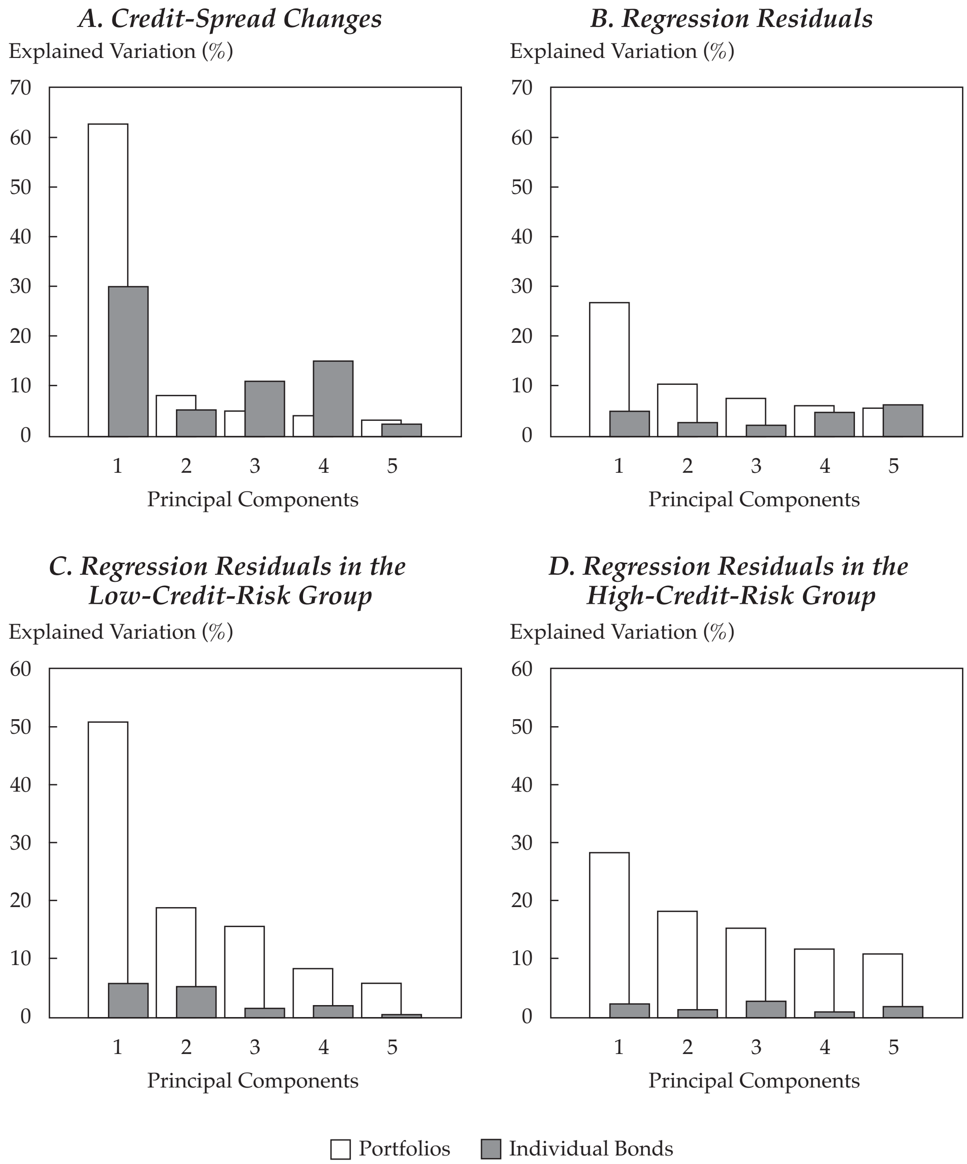
Notes: Sample sizes are the same as in Table 6. Boldface indicates *t*-statistics that are significant at the 5 percent level.

variation unexplained by structural models. Comparing the two illustrates how well our variables capture the common variation in credit-spread changes. The purpose of this PC analysis was to detect whether significant unexplained systematic variation remains in the residuals, rather than to establish the number of driving factors. For this reason, we looked only at the first five components and focused on the strength of the first latent factor.

The 2,375 corporate bond credit spreads and regression residuals were each assigned to one of 35 portfolios formed as the interaction of five credit-spread and seven time-to-maturity categories. PC analysis was applied to portfolios rather than individual bonds because bonds expire or default and were thus not available for the entire sample period.

Chart A of **Figure 3** summarizes the PC analysis based on the *total* variation in spread changes; Chart B summarizes the *unexplained* variation reflected by the regression residuals. The white bars in Chart A point to a strong common factor in the *portfolio-aggregated* credit-spread changes that captures 63 percent of their variation. The explanatory power of

Figure 3. Principal-Components Analyses: Average R^2s



each subsequent principal component is significantly smaller. When we focus on the portfolios of residuals in Chart B (from model M3), however, the white bars show that the first principal component accounts for less than 28 percent of the residuals' variation. This evidence is apparently at odds with previous findings (i.e., CDGM) of a much stronger latent factor in the regression residuals. Portfolio-grouping procedures may help explain the difference. For example, when we decreased the number of regression residual portfolios from 35 to 15, the latent first factor captured a much larger percentage, 45 percent, of the unexplained variation.

To investigate this aspect further, we regressed the *individual* credit-spread changes on each of the first five portfolio-based latent factors. We report the average R^2s in the dark bars overlaying the white bars in Chart A of Figure 3.[13] We did the same for the individual residuals and the corresponding portfolio-based residual latent factors in Chart B. The dark bars in Chart A reveal a prominent systematic factor that captures 30 percent of the common variation in individual bonds. Moreover, each of the third and fourth portfolio-based latent factors also captures more than 10 percent of the individual spread variation, which suggests that there is indeed substantial systematic variation in individual credit-spread changes.[14] However, our structural model variables capture most of this systematic variation. Indeed, the dark bars in Chart B show no significant latent factor in the individual residuals. Each of the first five latent factors captures less than 6 percent of the variation in individual bond residuals.

Because the variation explained by structural models is much smaller in high-grade bonds, we applied PC analysis to the high- and low-grade groups separately to discover whether systematic variation remained in them. (The PC analysis was performed on the basis of 15 portfolios because of the reduced number of bonds within each credit-risk group.) Charts C and D in Figure 3 summarize this analysis. The white bars in both plots demonstrate that there is a stronger latent factor in the unexplained variation of the portfolio-aggregated residuals of high-grade bonds (more than 50 percent of their common variation captured) than in low-grade bonds (less than 30 percent captured). Repeating the previous analysis with individual-bond residuals (thus, a much larger sample) revealed that most of the common variation is spurious and driven by portfolio grouping. Indeed, regressing the individual bond residuals on the latent factors showed that each factor explained less than 7 percent of the common variation in individual high-grade bond residuals and less than 4 percent in individual low-grade bond residuals.

These findings suggest that our parsimonious set of structural model variables successfully captures essentially all of the systematic variation in individual bonds' credit-spread changes for bonds of all credit-risk levels. Although the explained variation is smaller in high-grade bonds than in lower-grade bonds, structural models are still successful in the high-grade credit group; the models leave little systematic variation unexplained.

Conclusion

Using 2,375 corporate bonds from the period 1990–2003, we documented that structural model variables successfully explain credit-spread dynamics. A parsimonious set of aggregate and company-level variables explained about 68 percent, 55 percent, and 36 percent of the total variation in credit-spread changes of, respectively, low-, middle-, and high-grade individual bonds. Principal-components analysis of the individual-bond regression residuals revealed that for all bond grades, structural models successfully capture the systematic variation in credit-spread changes.

We also demonstrated that the Fama–French factors capture some of the systematic risk in credit-spread changes. The explanatory power of the Fama–French factors increased with increasing credit risk. When the Fama–French factors were combined with our proposed set of determinants, however, the Fama–French factors lost significance for each credit-risk category, which suggests that structural model factors capture the systematic risk in credit-spread changes better than do the Fama–French factors.

We developed further evidence on the viability of structural models in empirical corporate bond pricing. Building on recent innovations in asset pricing, we conclude that idiosyncratic volatility and the price-to-book ratio have a strong basis in a structural model framework. We found both variables to be economically and statistically significant in explaining the time-series variation in corporate credit-spread changes. Hence, these variables should be considered together with the more traditional ones in studies of bond-level credit risk.

These findings are robust to liquidity considerations. In particular, we showed that changes in the overall bond market liquidity because of Fed tightening and easing cycles do not affect the documented support for structural models.

Why are our findings so different from the closely related work of CDGM? The findings differ because CDGM focused on investment-grade bonds but we included all grades, and high-yield bonds behave substantially differently from investment-grade bonds. Company-level fundamentals and common factors are important determinants of credit-risk changes among high-yield bonds but not among investment-grade bonds. When we focused on low-credit-risk bonds, our results were qualitatively similar to those of CDGM.

In addition, CDGM documented a strong latent factor in the unexplained variation of credit-risk changes, from which they concluded that structural model variables do not explain credit-spread changes but are driven by supply/demand shocks. We showed that the presence of a dominant latent factor can arise from bundling the individual regression residuals into portfolios. In particular, focusing on individual regressions yielded no dominant latent factor in the unexplained variation.

Finally, we explored more variables than CDGM explored. In particular, we found idiosyncratic volatility and the book-to-market ratio to be significant determinants of changes in corporate credit risk.

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This article qualifies for 1 PD credit.

Notes

1. Eom, Helwege, and Huang (2004) and Huang and Huang (2003) linked the success of structural models to the relative size of the credit-risk component in spread levels (that is, the size had to be large for success of the model). Even a small such component can account for most of the spread changes, however, if the non-credit-risk component shows little variation over time.
2. Focusing on changes in credit spreads rather than levels is also justified from a statistical standpoint. The level tends to be nonstationary, but the spread change is well behaved. In particular, using the augmented Dickey–Fuller test, we found that 99 percent of our series of credit-spread changes were stationary at the 5 percent significance level, although the vast majority of the level series were not.
3. See Crosbie and Bohn (2003).
4. Credit blowups usually result from defaulted investment-grade credits, which are then relegated to junk bond status. In this situation, the credit spread can jump from a few hundred to tens of thousands of basis points. The distressed high-grade companies are usually referred to as "fallen angels."
5. For much of the analysis, the bond sample was divided into three credit-risk groups on the basis of the bonds' credit-spread levels. The tercile bounds were calculated as the 33 1/3 and 66 2/3 credit-spread percentiles on the basis of all credit-spread observations in the full sample of bonds. We did not use bond ratings to form groups because many bonds were not rated by any agency. Using the bonds with an S&P rating in Datastream, however, we did verify a monotonic relationship between spread level and credit rating for all rating groups (results not reported).
6. To compute the average rating, we first converted the alphabetic S&P ratings into numeric equivalents, as shown in the Table 1 notes.
7. We replicated all of the analysis but with alternative maturities, and the results were virtually identical (results available upon request).
8. See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.
9. For robustness, we also calculated 6- and 12-month momentum variables as, respectively, the cumulative return for months 4–6 and months 7–12 (as in Brennan et al. 1998).
10. Testing the momentum variable for longer lags (not reported) did not improve significance.
11. We also ran regressions using alternative term-structure variables, but the results (available upon request) remained unchanged.
12. On the bond level, liquidity has been studied mainly as a component of credit-spread *level* (see Ericsson and Renault 2006). Because individual-bond liquidity is stable through time (see Hotchkiss, Jostova, and Warga 2003), liquidity is less of a consideration in studying credit-spread *changes*.
13. Comparing the average R^2s from individual regressions on each factor is equivalent to comparing the weights of the eigenvalues from the PC analysis.
14. Note that because the 35 portfolios span a different space from that spanned by the 2,375 individual series, the first five principal components constructed on the basis of the portfolios are not necessarily monotonically decreasing in their explanatory power of the individual series.

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