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Abstract

Variables that in theory determine credit spreads have limited explanatory power in existing empirical work on corporate bond data. We investigate the linear relationship between theoretical determinants of default risk and default swap spreads. We find that estimated coefficients for a minimal set of theoretical determinants of default risk are consistent with theory and are significant statistically and economically. Volatility and leverage have substantial explanatory power in univariate and multivariate regressions. A principal component analysis of residuals and spreads indicates limited evidence for a residual common factor, confirming that the theoretical variables explain a significant amount of the variation in the data.

I. Introduction

A credit derivative is a contingent claim that allows the trading of default risk separately from other sources of uncertainty. From being a fledgling market in the mid nineties, credit derivative markets have grown tremendously over the last few years. The market exceeded 20 trillion dollars in outstanding notional principal in 2006. The most common credit derivative contract is the single-name credit default swap, which accounts for roughly a third of the trading activity. This instrument is essentially an insurance contract against the default of an underlying

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entity. Compensation is paid if a credit event occurs while in return the buyer of protection makes regular payments based on the credit default swap premium, often referred to as the spread.

In the last decade, a substantial body of empirical work has developed on credit-sensitive instruments, with an emphasis on corporate bonds. This work can be categorized according to the theoretical framework it relies on. One popular approach is to use what are known as reduced-form models. These models exogenously postulate the dynamics of default probabilities and use market data to recover the parameters needed to value credit-sensitive claims.[1] While these models have been shown to be versatile in practical applications, they remain relatively silent on the theoretical determinants of the prices of defaultable securities.

An alternative approach, commonly referred to as the structural approach, is to rely on models that have evolved following Black and Scholes (1973) and Merton (1974). This approach links the prices of credit-risky instruments directly to the economic determinants of financial distress and loss given default. In particular, these models imply that the main determinants of the likelihood and severity of default are financial leverage, volatility, and the risk-free term structure. These models have been plagued by poor performance in empirical studies.[2] Perhaps as a result of the difficulty of implementing structural models in practice, a more direct approach was taken by Collin-Dufresne, Goldstein, and Martin (2001), who use the structural approach to identify the theoretical determinants of corporate bond credit spreads. These variables are then used as explanatory variables in regressions for changes in corporate credit spreads, rather than inputs to a particular structural model. Collin-Dufresne et al. (2001) conclude that the explanatory power of the theoretical variables is modest, and that a significant part of the residuals is driven by a common systematic factor that is not captured by the theoretical variables. Campbell and Taksler (2003) perform a related analysis but use regressions for levels of the corporate bond spread. They conclude that firm-specific equity volatility is an important determinant of the bond spread, and that the economic effects of volatility are large. Cremers, Driessen, Maenhout, and Weinbaum (2004) confirm this result and argue that option-based volatility contains useful information for this type of analysis that is different from historical volatility.

Our study is intimately related to these papers. Although our focus is also on credit risk, an important distinction is that we study very different data—swap spreads rather than corporate bond yield spreads. Using swaps rather than bonds has a number of important advantages. Default swap spreads, while economically comparable to bond yield spreads, do not require the specification of a benchmark risk-free yield curve—they are already "spreads." Thus we avoid any added noise arising from a misspecified model of the risk-free yield curve. The choice of the risk-free yield curve includes the choice of a reference risk-free asset, which

[1] Useful surveys can be found in Lando (1997) and Duffie and Singleton (2003). Empirical papers using reduced-form models to value credit-risky bonds include Duffee (1999) and Duffie, Pedersen, and Singleton (2003).

[2] See, in particular, Jones, Mason, and Rosenfeld (1984). More recently Eom, Helwege, and Huang (2004) have documented the poor empirical performance of these models.

can be problematic (see Houweling and Vorst (2005)), but also the choice of a framework to remove coupon effects.

Another advantage is that default swap spreads may reflect changes in credit risk more accurately and quickly than corporate bond yield spreads. Blanco, Brennan, and Marsh (2003) provide evidence that changes in the credit quality of the underlying name are likely to be reflected more quickly in the default swap spread than in the bond yield spread. This may be due to important non-default components in bond spreads that obscure the impact of changes in credit quality.[3]

Related to this, trading in default swap markets has increased, while many corporate bonds are rarely traded. Partly as a result, swap data are collected at a daily frequency, whereas many studies that use corporate bonds typically use observations at a monthly frequency. Early in our sample the trading volume is relatively low, leading to frequent unavailability of quotes at the daily frequency. However, trading volume grew dramatically over our sample period, leading to more daily quotes and a more liquid market, which should allow for cleaner tests.

Relatively little empirical work has been done on default swap markets.[4] Notable exceptions include Berndt, Douglas, Duffie, Ferguson, and Schranz (2004), Houweling and Vorst (2005), Hull, Predescu, and White (2004), Longstaff et al. (2005), Blanco et al. (2003), and Zhang, Zhou, and Zhu (2006). Berndt et al. (2004) use default swap data to study default risk premia. Houweling and Vorst (2005) implement a set of simple reduced-form models on market swap quotes and corporate bond quotes. Their paper focuses on the pricing performance of the model and the choice of benchmark yield curve. Hull et al. (2004) analyze the impact of rating announcements on the pricing of swaps. Blanco et al. (2003) study the relative pricing of corporate bonds and default swaps. Longstaff et al. (2005) document the differences between default swap spreads and corporate bond yield spreads, using various risk-free benchmarks. Under the assumption that default swap spreads do not contain a liquidity component, the differences between the spreads highlight the relative importance of default risk and liquidity for corporate bonds. Zhang et al. (2006) use regressions to determine how much of the variation in default swap spreads can be explained by volatility risk and jump risk.

Like Collin-Dufresne et al. (2001), Campbell and Taksler (2003), Cremers et al. (2004), and Zhang et al. (2006), we carry out linear regression analysis on the relationship between spreads and key variables suggested by economic theory. Our benchmark results focus on a minimal set of determinants of default risk, including financial leverage, firm-specific volatility and the risk-free rate. We run regressions for changes in spreads as well as for the levels of the spreads. We find that the estimated coefficients for the three variables are consistent with theory, and that the estimates are highly significant both statistically and economically. Levels regressions and difference regressions result in very similar point estimates, while the size of the effects is intuitively plausible. The explanatory power of these theoretical variables for spread levels is approximately 60%, and the explanatory power for spread differences is approximately 23%. Interestingly,

[3]Fisher (1959) and Longstaff, Mithal, and Neis (2005) document the existence of an illiquidity component in bond yield spreads.

[4]Theoretical work includes Das (1995), Hull and White (2000), and Das and Sundaram (1998).

we find a negative correlation between spreads and the risk-free rate. A similar correlation has been documented for bond yield spreads by Longstaff and Schwartz (1995) and Duffee (1998). Presently, no consensus prevails as to the economic reasoning behind this stylized fact. Our results are consistent with the implication of structural models that an increase in the risk-free rate will decrease risk-adjusted default probabilities. Subsequently, we use a more extensive set of theoretical variables determining default and recovery risk. The variation in spreads explained by the difference regressions is higher than in existing work on corporate bond spreads.

We advocate a cautious interpretation of the differences between our results and those available for corporate bond spreads. Some studies, such as Campbell and Taksler (2003), focus more narrowly on the relationship between volatility and credit risk. Also, the particular maturity structure of the swap data may influence our conclusions on the explanatory power of the results. Collin-Dufresne et al. (2001) exclusively rely on difference regressions. While the R^2s for our difference regressions are higher than those in Collin-Dufresne et al. (2001), a large fraction of the variation in spread differences remains unexplained. We obtain high R^2s for levels regressions, but it could be argued that this finding obtains because spreads are very persistent (see Pedrosa and Roll (1998)). On the other hand, given the presence of noise in the data, the maximum attainable R^2 for the difference regressions under the null hypothesis is surely less than 100%.

Our conclusion is therefore mixed: whereas a substantial amount of variation in default swap spreads cannot be explained by changes in leverage, volatility, or the risk-free rate, these variables suggested by economic theory are clearly important determinants of the spreads. Their explanatory power is overall somewhat higher than in the work of Collin-Dufresne et al. (2001) on corporate bond data. This finding is reinforced by an analysis of the regression residuals, which shows that the evidence for a remaining common component is weaker than in Collin-Dufresne et al. (2001). These findings may be due to the recent increase in liquidity in default swap markets.

This paper proceeds as follows. In Section II, we lay out our analytical framework. In particular, we discuss the determinants of spreads suggested by existing theory and then present our regression equations. In Section III, we present and discuss our empirical results. Section IV concludes.

II. Analytical Framework

A. The Theoretical Determinants of Spreads

This paper analyzes spreads from the perspective of structural form models. Following Merton's (1974) pathbreaking work, the basic structural model has been extended in different ways.[5] While these models typically focus on the importance of additional theoretical variables or change the precise functional

[5]A non-exhaustive list of recent contributions would include Longstaff and Schwartz (1995), Anderson and Sundaresan (1996), Leland and Toft (1996), Duffie and Lando (2000), Collin-Dufresne and Goldstein (2001), and François and Morellec (2004).

dependence of default on existing theoretical variables, they all have in common that default and, therefore, the value of the default-sensitive security depends on a number of determinants that are central to the Merton (1974) approach. First, leverage is central to all these models: ceteris paribus, the more levered the firm, the higher the probability of default. Second, the volatility of the underlying assets is an essential determinant of the value of the default-sensitive security because the latter is equivalent to a credit risk-free security combined with a short put. Volatility influences the value of the put option. Third, the level of the riskless rate also impacts the value of the option. Merton's model and recent extensions predict a negative relationship between the risk-free rate and the bond spread.[6] The risk-free rate determines the risk-adjusted drift of firm value, and thus an increase in this variable will tend to decrease risk-adjusted default probabilities and also spreads.

Rather than carrying out a full structural estimation of any given model, we rely on what these models together suggest are the main determinants of credit risk. We use these variables in simple linear regressions of spreads on the suggested factors. Note that although structural models have almost exclusively been used to value corporate bonds, the implied relationship between the theoretical variables and default swap spreads is the same. In terms of the sequence of cash flows and the impact of default, bonds and swaps are very similar, and structural variables will have the same impact on the values of both securities.[7]

B. Regressions

According to theory, spreads should be determined by the amount of leverage incurred by the underlying firm, the volatility of the underlying assets, and the riskless spot rate. We denote the leverage of firm i at time t as $\mathrm{LEV}_{i,t}$ and the volatility as $\mathrm{VOL}_{i,t}$. For our base case regression results, we define the risk-free rate variable to be the 10-year yield, denoted as r_t^{10}. While theoretical models are based on the dynamics of the instantaneous risk-free rate, which is unobservable, this unobservable short rate can be thought of as being determined by a number of factors, one of which is the yield on long-maturity bonds. We investigate the robustness of our results with respect to the choice of these factors in more detail in Section III.C.

The regression suggested by theory consists therefore of regressing the spread, denoted by $S_{i,t}$, on these three variables. Including an intercept, the regression for the spread $S_{i,t}$ suggested by theory is therefore

$$S_{i,t} = \alpha_i^l + \beta_i^l \mathrm{LEV}_{i,t} + \beta_i^v \mathrm{VOL}_{i,t} + \beta_i^r r_t^{10} + \varepsilon_{i,t}. \tag{1}$$

Some authors have studied spread differences. The choice between levels regressions and difference regressions can be motivated both economically and

[6]See e.g., Longstaff and Schwartz (1995) and Collin-Dufresne and Goldstein (2001).

[7]In fact, in the absence of counterparty risk and market frictions, it can be shown that a swap on a floating rate bond originally issued at par can be synthesized by an offsetting portfolio of this floater and an otherwise identical credit risk-free floater. The net cash flows of this portfolio must equal those of the swap in the absence of arbitrage. See Duffie and Singleton (2003) for a detailed discussion of this and more complex cases.

statistically. From an economic perspective, one may be interested in explaining either the variation in differences or levels. From a statistical perspective, first differencing is appropriate if the dependent variable and regressors are integrated, but this is difficult to determine for our sample.[8] Given that there is some uncertainty about the statistical specification, we believe that it is appropriate to test the theory both in differences and levels. It must be noted that because of the presence of noise in the data, differences are harder to explain than levels, and a regression in differences therefore should provide a more stringent test. The difference regressions are given by

$$\Delta S_{i,t} = \alpha_i^d + \beta_i^l \Delta \mathrm{LEV}_{i,t} + \beta_i^v \Delta \mathrm{VOL}_{i,t} + \beta_i^r \Delta r_t^{10} + \varepsilon_{i,t}. \tag{2}$$

We also regress the spread on each of these regressors separately to get a better idea of the explanatory power of each regressor. We report on these regressions in differences

$$\Delta S_{i,t} = \alpha_i^d + \beta_i^l \Delta \mathrm{LEV}_{i,t} + \varepsilon_{i,t}, \tag{3}$$

$$\Delta S_{i,t} = \alpha_i^d + \beta_i^v \Delta \mathrm{VOL}_{i,t} + \varepsilon_{i,t}, \quad \text{and} \tag{4}$$

$$\Delta S_{i,t} = \alpha_i^d + \beta_i^r \Delta r_t^{10} + \varepsilon_{i,t}. \tag{5}$$

Campbell and Taksler (2003), Cremers et al. (2004), and Collin-Dufresne et al. (2001) also use univariate regressions to investigate the importance of certain theoretically determined variables for the determination of credit spreads on corporate bonds. Collin-Dufresne et al. (2001) report on difference regressions, and Campbell and Taksler (2003) and Cremers et al. (2004) on levels regressions.

III. Empirical Analysis

A. Data

To investigate the regressions suggested by theory, we require data on default swap spreads, firm leverage, volatility, and riskless yields. We obtain these data from the following sources:

Default Swap Spreads. We use quotes from the CreditTrade Market Prices database for 1999–2002 corresponding to swaps on senior debt. The swap market has experienced considerable growth over this period. Graph A of Figure 1 depicts the evolution of the number of daily available quotes.

Only the contracts on companies for which we have data in CRSP and COMPUSTAT are used in our study. Utilities and financial companies are excluded. Since there are very few quotes on junior debt, these quotes are excluded. The

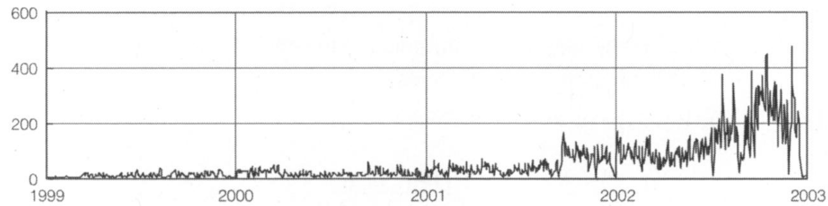
[8]It is difficult to construct unit root tests due to the irregularly spaced data in our sample. Also, these tests are subject to power problems in short samples. Note also that if one accepts the unit root hypothesis, differencing of the data may improve the efficiency of the resulting estimates, but the levels regressions yield consistent point estimates.

FIGURE 1

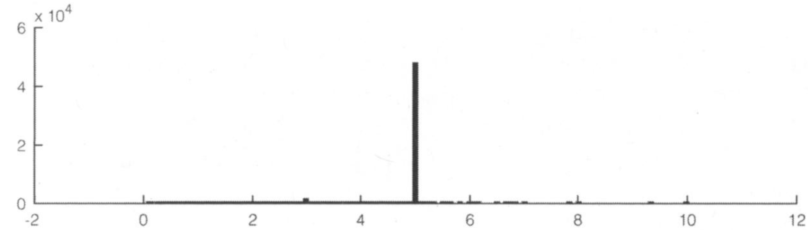
Key Aspects of the Default Swap Data

Graph A of Figure 1 depicts the daily frequency of bid and offer quotes for the default swap spreads during the period January 1999 to December 2002. Graph B reports a histogram of the maturities of the credit default swaps in our dataset. The five-year maturity segment represents the bulk of the market.

Graph A. Time Series of Quote Frequency



Graph B. Distribution of Contract Maturities



number of quotes satisfying the above criteria is 53,625. At least 92% of these quotes are firm, in that they represent a commitment to trade a given notional principal ranging from \$2 million to \$10 million.[9] Graph B of Figure 1 depicts the number of quotes as a function of the tenor. The market is clearly concentrated on maturities around five years. We therefore only retain 48,626 quotes that have tenors between 4.5 and 5.5 years. This sample represents 90.7% of all quotes.

Even though the swap market is a worldwide market, the majority of the quotes fall within New York trading hours. This finding is to a large extent due to our selection criteria, because CRSP and COMPUSTAT mainly contain data on U.S. companies. From the 48,626 quotes, we selected, for each day and reference entity, the quote closest to 4PM ET.[10]

[9]The remaining 8% of the quotes are recorded with a zero notional amount. However, according to personal communication with CreditTrade staff, a zero notional simply indicates that it was not recorded.

[10]More precisely, we filter the quotes as follows: either the time stamp is after 3PM; or the time stamp is between 12 noon and 3PM, and the time stamp on the previous available quote is more than two trading days old; or the time stamp is between 9AM and 12 noon, and the time stamp on the previous available quote is more than three trading days old; or the time stamp is between 6AM and 9AM, and the time stamp on the previous available quote is more than four trading days old; or the time stamp is between 3AM and 6AM, and the time stamp on the previous available quote is more than five trading days old. This rule is motivated by consideration for the difference regressions. To compute the differences in the premia, we ideally want quotes at the exact same time of the day. This is not possible and because of sample size considerations, it is also not possible to limit ourselves to time stamps after 3PM. By including quotes with time stamps further removed from 4PM, the potential for biases in the computed spread differences increases. However, by only selecting quotes farther

Bid and offer quotes are treated separately.[11] As a final filter, we only retain firms with at least 25 quotes or changes in quotes, depending on the regression specification. It should be noted that the number of observations in any given regression will depend on whether it is run on levels or differences and on whether bids or offers are used. This leaves us with 4,813 bid and 5,436 offer quotes over the whole sample period, with slightly fewer observations for regressions in differences.[12]

The data for the theoretical determinants of the spreads (the explanatory variables in the regressions) are constructed as follows:

Leverage. The leverage ratio is defined as

$$\frac{\text{Book Value of Debt} + \text{Book Value of Preferred Equity}}{\begin{bmatrix}\text{Market Value of Equity} + \text{Book Value of Debt} \\ + \text{Book Value of Preferred Equity}\end{bmatrix}}. \tag{6}$$

The Market Value of Equity was obtained from CRSP, and the Book Value of Debt and the Book Value of Preferred Equity from COMPUSTAT. Since book values are only available at the quarterly level, we linearly interpolate in order to obtain daily figures. Because the market value of equity is taken into account in the denominator, this measure of leverage varies substantially at a daily frequency.

Volatility. A time series of equity volatility was computed for each company using an exponentially weighted moving average model on daily returns obtained from CRSP.[13] In the empirical literature on the determinants of corporate bond spreads, our approach is closest to that of Campbell and Taksler (2003), who construct historical volatility based on 180 days of returns in their base case regressions. Collin-Dufresne et al. (2001) use the VIX data, which represents option-implied volatility based on S&P 100 index options. Cremers et al. (2004) use both volatility implied by individual equity options as well as historical volatility.

Treasury Bond Yields. Daily data on 10-year Treasury bond yields were collected from DataStream. We use the appropriate constant maturity index constructed by the U.S. Treasury based on the most actively traded issues in that maturity segment.

Table 1 and Figure 2 provide descriptive statistics and visual summaries of the spreads and the explanatory variables used in the main regressions. The spread

removed from 4PM if the previous quote is further removed in time, we reduce the potential bias from time stamps at different parts of the day.

[11]We obtain very similar results when including bids and offers in the same regression. However, in that case, the bid-ask bounce affects the explanatory power of the regression. When including a dummy to correct for this, the R^2s increase as the variation in the bid-ask spread is captured by the dummy. We therefore prefer to report results on separate regressions for bids and offers. Note that we cannot use the midpoint of the bid-offer spread in the regression because bid and offer quotes are not necessarily available on the same day.

[12]Lists of the companies that are included in the sample for the different regressions are available on request.

[13]For each reference entity, volatility h_t was generated according to $h_t = r_t^2\,(1 - \lambda) + h_{t-1}\lambda$, with r_t denoting daily returns. In order to obtain a more precise estimate of λ, we constrain this parameter to be the same across firms in the estimation.

TABLE 1

Summary Statistics

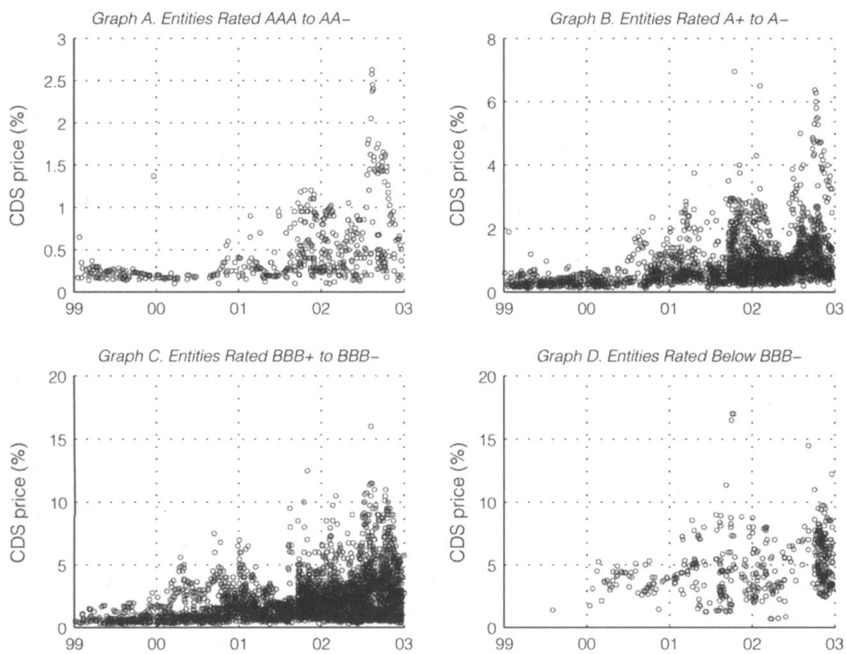
Table 1 presents descriptive statistics. It also includes numerical S&P and Moody's credit ratings. Numerical ratings in the sample range from 1 (Aaa) to 20 (Ca) for Moody's and from 1 (AAA) to 25 (in default) for S&P.

					Correlation with Default Swap Spreads	
	Mean	Stdev	5th Pctl	95th Pctl	Time Series	Cross-Sectional
Default swap spread (%)	1.80	1.73	0.28	5.30		
Leverage (%)	51.57	17.71	22.75	79.85	0.28	0.23
Volatility (%)	48.80	20.39	25.46	84.09	0.65	0.70
10-year yield (%)	4.92	0.66	3.85	6.11	−0.69	
S&P rating	7.9	2.1	4	11		
Moody's rating	8.1	2.2	4	11		
Slope (%)	1.45	0.82	−0.51	2.37	0.59	
2-year yield (%)	3.47	1.39	1.80	6.33	−0.68	
S&P 500	1,111.84	180.87	847.76	1,436.51	−0.70	
Smirk slope (%)	0.59	0.07	0.49	0.70	−0.20	
VIX (%)	29.60	7.19	21.11	43.86	0.52	

FIGURE 2

Default Swap Spreads over Time Categorized by Rating

Graphs A–D of Figure 2 depict the levels of default swap spreads over time and according to rating categories. Data includes bid and offer quotes for all maturities.



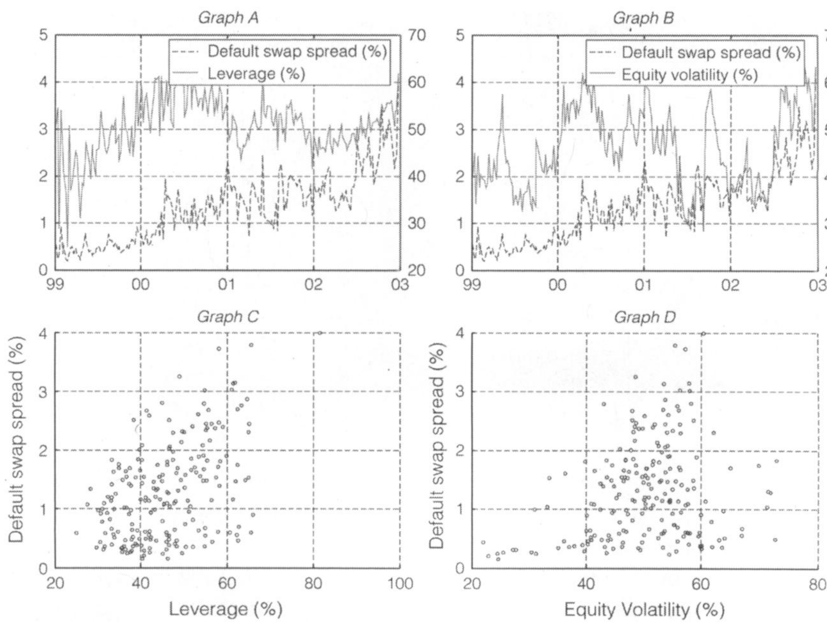
is 180 basis points (bps) on average with a large standard deviation. The explanatory variables seem to be less variable than the spread, and especially the 10-year yield is tightly centered around the mean. From Figure 2, it would seem that the high variability of the spread is partly due to the fact that the spread has been increasing over time, regardless of the rating of the reference obligation, and that the spread differs considerably across reference obligations with different ratings. Figure 2 also clearly indicates that the number of available data points is very different for different rating categories.

The data set has a cross-sectional as well as a time-series dimension. Cross-sectional correlations indicate how credit spreads differ between companies because of differences in leverage and volatility. Time-series correlations indicate how credit spreads change for a given company as the company's leverage ratio and equity volatility change. Table 1 indicates that time-series as well as cross-sectional correlations between the spreads and the three theoretical variables have the expected sign. Interestingly, for both volatility and leverage, the cross-sectional correlation is not very different from the time-series correlation. Figure 3 provides additional insight into this issue. Graphs A and B are obtained by averaging the variables across firms at a point in time and clearly suggest a positive time-series relationship between the spreads and leverage and volatility, respectively. Because our data are unevenly spaced, we use weekly averages. Graphs C and D are obtained by averaging the data across time for a given firm, and while they suggest a positive relationship for volatility as well as leverage, they clearly confirm the result in Table 1 that the correlation is higher for volatility.

FIGURE 3

Default Swap Spreads, Leverage, and Volatility

Graph A of Figure 3 plots default swap spreads and firm leverage, both averaged across reference entities on a weekly basis. Graph B plots spreads and equity volatilities, both averaged across reference entities on a weekly basis. Graph C plots the firm-specific (time-series) average of the spreads versus average leverage. Graph D plots the firm-specific (time-series) average of the default swap spreads versus average equity volatility.



B. Regression Results

We follow Collin-Dufresne et al. (2001) and present results on average regression coefficients obtained by running a series of time-series regressions, one for each company. These regressions emphasize the time-series correlations between spreads and theoretical variables. From a managerial perspective, these regressions are of most interest because they indicate how credit spreads change for a given company as the company's leverage ratio and equity volatility change.

Table 2 presents the results of the levels regression (1) and the difference regression (2). For both regressions, we report results obtained with bid quotes as well as results obtained with offer quotes. In each case, we report results obtained from all data, and we also report results for samples split up by rating. For each analysis, the three last rows indicate the number of companies included, the average number of observations included in the time-series regressions, and how much time elapses on average between different quotes for the same underlying. The top four rows list the average regression coefficients obtained from the time-series regressions, and rows 5–8 present the t-statistics, computed in the same way as in Collin-Dufresne et al. (2001). These t-statistics capture cross-sectional variation in the time-series regression coefficient estimates.

A number of important conclusions obtain. First, the estimated sign for the coefficient on leverage is always positive, as expected a priori. Second, the estimated sign for the coefficient on volatility is also always positive, as expected. Third, the coefficient on the 10-year yield also conforms to theoretical expectations because it is estimated with a negative sign. What is even more encouraging is that the t-statistics almost uniformly indicate statistical significance at conventional significance levels. Interestingly, the few exceptions occur for the levels regressions, not for the (more challenging) difference regressions.

The point estimates for the coefficients are remarkably similar across the levels and difference regressions, least so for the coefficients on the 10-year yield. Not surprisingly, there are some differences in the point estimates across ratings. For lower-rated firms, the point estimates for leverage and volatility are bigger than for higher-rated firms. These effects are perfectly intuitive and consistent with the predictions of any structural credit risk model. We also find that spreads for lower-rated firms are more sensitive to interest rates. Again, this is consistent with the theory. It is also consistent with the empirical findings of Duffee (1998) on corporate bond yield spreads.

A final statistic of interest is the adjusted R^2. First and foremost, the explanatory power of the levels regressions is of course much higher than that of the difference regressions. For the levels regressions, the theoretical variables explain approximately 60% of the variation in the spread. For the difference regressions, the theoretical variables explain approximately 23%. The R^2s for the lower ratings are always a bit higher than those for the higher ratings, as expected. It may also be of interest that in the levels regressions the R^2s for the bid quotes are a bit higher than the R^2s for the offer quotes, even though this pattern does not show up in the difference regressions.

While the effects of a change in the yield curve somewhat depend on whether one estimates in levels or differences, the results for volatility and leverage are

TABLE 2

Multivariate Regression Using Variables Suggested by Theory

Table 2 presents descriptive statistics and regression results for linear regressions using the three explanatory variables suggested by theory: leverage, volatility, and the riskless interest rate. Reported coefficients are averages for regression coefficients from time-series regressions using all observations on a given underlying company. The t-statistics are computed based on the time-series regression coefficients as in Collin-Dufresne, Goldstein, and Martin (2001).

	Regressions in Differences						Regressions in Levels					
	Bid Quotes			Offer Quotes			Bid Quotes			Offer Quotes		
	Low Rating	High Rating	All	Low Rating	High Rating	All	Low Rating	High Rating	All	Low Rating	High Rating	All
Coefficients												
Constant	0.007	0.003	0.005	0.019	0.000	0.010	0.104	−1.072	−0.492	−2.242	−0.783	−1.513
Leverage	0.072	0.041	0.056	0.060	0.035	0.048	0.076	0.051	0.063	0.100	0.046	0.073
Equity volatility	0.011	0.004	0.008	0.023	0.006	0.014	0.017	0.004	0.010	0.023	0.007	0.015
10-year yield	−0.307	−0.118	−0.212	−0.387	−0.169	−0.278	−0.596	−0.100	−0.345	−0.342	−0.057	−0.200
t-Statistics												
Constant	0.87	0.64	1.09	1.56	0.04	1.47	0.09	−1.81	−0.78	−1.66	−1.62	−2.11
Leverage	6.00	4.82	7.52	4.97	4.85	6.66	5.48	5.86	7.72	6.30	5.69	7.87
Equity volatility	4.58	2.97	5.24	5.19	3.61	5.72	3.64	1.97	3.99	3.56	3.39	4.34
10-year yield	−4.49	−2.49	−4.97	−3.13	−2.35	−3.86	−4.27	−1.29	−4.13	−2.28	−0.74	−2.35
R^2	23.3%	21.3%	22.3%	24.2%	23.3%	23.7%	65.5%	57.3%	61.4%	59.6%	52.6%	56.1%
No. of companies	39	39	78	45	45	90	40	41	81	47	47	94
Avg. no. of obs.	60.0	59.5	59.7	55.6	61.0	58.3	58.3	60.5	59.4	55.2	60.4	57.8
Avg. day between quotes	19.7	19.6	19.7	20.1	19.1	19.6	20.9	19.3	20.1	20.5	19.6	20.1

robust across specifications. This renders the economic interpretation of the point estimates of significant interest. Using the estimation results for all companies, a 1% increase in (annualized) equity volatility raises the spread on average by approximately 0.8–1.5 bps. For companies with lower ratings, the effect is estimated to be between 1.1 and 2.3 bps. The leverage effect is also stronger for lowly rated companies: a 1% change in the leverage ratio increases their spread by approximately 6–10 bps, whereas this effect is between 4.8 and 7.3 bps when considering all companies.

The average number of observations per firm is between 55 and 60, and the average number of days between quotes is approximately 20. This suggests that for some of the included contracts, liquidity may be an issue. To investigate if liquidity impacts the results, we repeat the analysis in quintiles along i) the average time since the last quote, and ii) the average number of quotes per firm. The analysis reveals no clear and robust pattern.

Table 3 further explores these results by providing results for the univariate regressions (3)–(5).[14] The point estimates have the same signs as in Table 2, and the t-statistics for the time-varying regressors are significant at conventional significance levels. The univariate point estimates for leverage and volatility are larger than in Table 2, but the effects are roughly of the same order of magnitude. The R^2s in Table 3 indicate that each of the three variables in isolation has some explanatory power, even though the leverage variable clearly dominates the other two regressors.[15]

Note that the negative correlation between spreads and the risk-free rate discussed above has also been documented for bond yield spreads by Longstaff and Schwartz (1995) and Duffee (1998). Presently, no consensus prevails as to the economic reasoning behind this stylized fact. Duffie and Singleton (2003) state that one possible explanation for the negative correlation is the existence of stale corporate bond prices. The spreads are measured by taking the difference between the corporate and the Treasury yield curves; therefore, an increase in Treasury yields might be associated with a decrease in spreads until the recorded corporate bond price accounts for the change. Our results rule out the latter explanation because swap spreads are not given by the difference of two yields as bond spreads are. However, our results are consistent with the implication of structural models that an increase in the risk-free rate will decrease risk-adjusted default probabilities.[16]

C. Additional Regression Results

Here we further investigate the robustness of the regression results presented in Section III.B. In a first step, we estimate the regression proposed by Collin-

[14]Note that the regression in Table 2 is the one suggested by theory, and it is possible that the univariate regression coefficients are biased because of an omitted variable argument.

[15]Point estimates for levels regressions (not reported) are similar to those of the difference regressions, and the R^2s are considerably higher. The leverage variable alone explains between 37.1% and 45.7% of the variation in spreads, the volatility variable between 23.9% and 29.7%, and the 10-year yield variable between 28.2% and 40.1%.

[16]See Longstaff and Schwartz (1995) for a discussion.

TABLE 3

Univariate Regressions

Table 3 presents descriptive statistics and regression results for univariate linear difference regressions using one of the explanatory variables suggested by theory at a time (equations (3)–(5)). Reported coefficients are averages for regression coefficients from time-series regressions using all observations on a given underlying company. The t-statistics are computed based on the time-series regression coefficients as in Collin-Dufresne, Goldstein, and Martin (2001).

	Bid Quotes			Offer Quotes		
	Low Rating	High Rating	All	Low Rating	High Rating	All
Panel A. Regression Using Leverage Only						
Coefficients						
Constant	0.017	0.006	0.012	0.024	0.002	0.013
Leverage	0.087	0.045	0.066	0.103	0.045	0.074
t-Statistics						
Constant	2.40	1.22	2.65	1.70	0.40	1.73
Leverage	7.63	5.92	9.14	7.07	7.56	8.82
R^2	14.2%	13.7%	14.0%	12.4%	13.7%	13.0%
Panel B. Regression Using Equity Volatility Only						
Coefficients						
Constant	0.041	0.018	0.030	0.052	0.015	0.033
Equity volatility	0.016	0.007	0.011	0.027	0.010	0.018
t-Statistics						
Constant	5.59	2.47	5.57	3.63	1.92	4.01
Equity volatility	6.25	5.25	7.62	6.00	4.94	7.00
R^2	10.1%	6.9%	8.5%	14.4%	11.0%	12.7%
Panel C. Regression Using 10-Year U.S. Treasury Bond Yields Only						
Coefficients						
Constant	0.030	0.014	0.022	0.036	0.010	0.023
10-year yield	−0.486	−0.285	−0.386	−0.661	−0.356	−0.509
t-Statistics						
Constant	5.20	1.99	4.77	2.60	1.35	2.90
10-year yield	−5.53	−5.79	−7.51	−5.03	−4.63	−6.57
R^2	6.3%	7.5%	6.9%	4.7%	7.9%	6.3%

Dufresne et al. (2001). Their base case regression includes the explanatory variables $\mathrm{LEV}_{i,t}$, $\mathrm{VOL}_{i,t}$, and r_t^{10} included in (1) but adds a number of other determinants of default risk and recovery risk, including

Treasury Bond Yields. We collected daily series of two- and 10-year bond yields from DataStream.

The Slope of the Yield Curve. This is defined as the difference between the 10-year Treasury bond yield used in regression (1) and two-year Treasury bond yields also obtained from DataStream. We use the two-year Treasury bond yield as the level of the yield curve in order to make the interpretation of the slope more straightforward.

The Square of the Two-Year Yield.

The Return on the S&P 500. Daily data on the S&P 500 return were obtained from DataStream.

The Slope of the Smirk. We estimate the slope of the smirk on equity options using out-of-the-money S&P 500 American futures put options from the Chicago Mercantile Exchange Futures and Options Database. A number of choices have to be made as regards these calculations. First, implied volatilities are computed using the American options analytical approximation technique proposed by Whaley (1986). Second, we cannot simply compute the smirk using one particular maturity because the same maturity is not available on every trading day. To take into account the dependence of the smirk on maturity, we define moneyness as $\ln(K/F)/\sqrt{T}$, were K is the strike price, F is the futures price, and T is the time to expiration. Standardizing moneyness by $\sqrt{T}$ makes the slope of the smirk (on a given trading day) remarkably similar across expirations. Third, we estimate a linear relation between moneyness and implied volatility.[17] Robustness tests demonstrate that adding a quadratic term does not change the results. Fourth, we arbitrarily choose 45 days as a benchmark maturity. The slope of the 45-day smirk is then obtained from linearly interpolating the coefficients corresponding to the nearest available expirations.

The inclusion of these regressors can be motivated as follows. Both the yield on short maturity bonds and the slope of the yield curve are factors that determine the instantaneous short rate. The square of the two-year yield attempts to capture nonlinearities in the relationship between term structure variables and spreads. Collin-Dufresne et al. (2001) motivate the use of the return on the S&P 500 to proxy for the overall state of the economy and the slope of the smirk to proxy for jumps in firm value. The following regression in differences results:

$$
\begin{aligned}
(7) \qquad \Delta S_{i,t} &= \alpha_i^d + \beta_i^l \Delta \mathrm{LEV}_{i,t} + \beta_i^v \Delta \mathrm{VOL}_{i,t} + \beta_i^r \Delta r_t^2 + \beta_i^{r2} (\Delta r_t^2)^2 \\
&\quad + \beta_i^{r3} \Delta \mathrm{TSSLOP}_t + \beta_i^{sp} \Delta \mathrm{S\&P}_t + \beta_i^{sm} \Delta \mathrm{SMSLOP}_t + \varepsilon_{i,t}.
\end{aligned}
$$

Table 4, which presents the results of these regressions, has the same format as Table 3, and the t-statistics were computed in the same fashion. Compared to Table 2, the extra variables increase the R^2 by roughly 7.5%. For the corresponding levels regressions (not reported) the increase in the R^2 is approximately 14%. Interestingly, the increase in R^2 is larger for the regressions that use offer quotes. The term structure variables are often insignificantly estimated, perhaps suggesting some multicollinearity between them, or high correlation with another explanatory variable. The return on the S&P 500 has a significantly estimated negative impact on the spread, indicating that in times with high returns (good times), the spread narrows. This finding is consistent with the findings in Collin-Dufresne et al. (2001) for spreads on corporate bonds. The slope of the smirk seems to have a minor impact on the spread. Finally and perhaps most importantly, the point estimates for leverage and volatility are very similar to the ones in Table 2. We therefore conclude that the magnitude of the effects discussed before is robust to the inclusion of a number of other variables, which inspires confidence in our estimates.

We also repeated our regression analysis using panel data techniques. Because of space constraints, we do not report these estimation results but instead briefly summarize our findings. When including fixed effects for the reference entities, parameter estimates are similar to those in Tables 2 and 3. By comparing regression results with and without time dummies and with and without fixed effects, we conclude that the theoretical variables included in the regressions have

[17]To circumvent the noise in very deep out-of-the-money options, we ignore options whose moneyness was lower than the median across time of the lowest moneyness of each trading day.

TABLE 4

Regression Using the Regressors from Collin-Dufresne, Goldstein, and Martin (2001)

Table 4 presents descriptive statistics and regression results for linear difference regressions using the benchmark specification in Collin-Dufresne et al. (2001). Reported coefficients are averages for regression coefficients from time-series regressions (equation (7)) using all observations on a given underlying company. The *t*-statistics are computed based on the time-series regression coefficients as in Collin-Dufresne et al. (2001).

	Bid Quotes			Offer Quotes		
	Low Rating	High Rating	All	Low Rating	High Rating	All
Coefficients						
Constant	0.014	0.010	0.012	−0.002	−0.007	−0.004
Leverage	0.063	0.033	0.048	0.059	0.033	0.046
Equity volatility	0.010	0.004	0.007	0.020	0.006	0.013
2-year yield	−0.115	−0.121	−0.118	−0.256	−0.143	−0.200
Yield curve slope	0.005	−0.116	−0.055	0.003	−0.104	−0.050
S&P 500	−1.924	−0.284	−1.104	−1.301	−0.034	−0.667
Smirk slope	0.144	−0.150	−0.003	−0.524	0.148	−0.188
Sq. 10-year yield	−0.115	−0.117	−0.116	0.009	0.076	0.042
t-Statistics						
Constant	1.12	1.61	1.74	−0.18	−2.23	−0.74
Leverage	5.28	3.48	6.18	4.22	4.87	5.88
Equity volatility	4.28	2.48	4.81	4.79	3.54	5.48
2-year yield	−0.99	−2.88	−1.93	−1.79	−3.35	−2.67
Yield curve slope	0.03	−1.57	−0.61	0.02	−1.21	−0.49
S&P 500	−2.72	−0.90	−2.79	−1.34	−0.15	−1.33
Smirk slope	0.26	−0.97	−0.01	−1.04	0.66	−0.68
Sq. 10-year yield	−0.66	−1.48	−1.23	0.04	1.47	0.39
R^2	31.1%	27.9%	29.5%	34.1%	30.5%	32.3%
No. of companies	39	39	78	45	45	90
Avg. no. of obs.	60.0	59.4	59.7	55.6	61.0	58.3
Avg. days btw. quotes	19.7	19.6	19.7	20.1	19.1	19.6

more explanatory power in a time series than a cross-sectional sense. However, leverage has relatively more explanatory power in the time dimension, whereas volatility is relatively better at explaining the cross-section. This finding is consistent with the cross-sectional and time-series correlations reported in Table 1. For leverage, the cross-sectional correlation is lower than the time-series correlation, while it is the opposite for volatility.

Finally, we also ran separate regressions for 1999, 2000, 2001, and 2002 in order to investigate the robustness of the results over time (not reported). Estimated coefficients are robust over time for volatility and leverage. However, for 1999, the economic significance of these variables is smaller. In addition, an interesting result is that the R^2 increases noticeably over time, which may be due to increasing market liquidity.

D. Out-of-Sample Results

Table 5 reports on the out-of-sample performance of the difference regression (2). For each spread in this sample, we first obtain regression coefficients using the sixty preceding observations and subsequently compute an out-of-sample error. We then compute root mean squared errors (RMSEs). We use 60 observations in the regressions because this is approximately the average number of observations included in the time-series regressions in Tables 2–4. The resulting sample is of course much smaller than the one used in Tables 2–4, because we need at least 60 changes in quotes to include a company in the analysis, whereas

TABLE 5

Out-of-Sample RMSEs

Table 5 presents results of an out-of-sample forecasting exercise using regression (2). Out-of-sample forecasts are obtained using the past 60 available observations. The RW forecast refers to the forecast obtained using the random walk model.

	Bid Differences				Offer Differences			
Company	In-Sample	Out-of-Sample	RW Forecast	No. of Forecasts	In-Sample	Out-of-Sample	RW Forecast	No. of Forecasts
AOL Time Warner Inc	0.368	0.511	0.599	52	0.456	0.710	0.702	42
AT&T Wireless Services Inc	0.633	0.183	0.199	5	0.649	0.381	0.200	2
Boeing Co	0.099	0.165	0.190	9	0.100	0.178	0.195	23
Carnival Corp	0.170	0.107	0.118	42	0.209	0.159	0.147	63
Caterpillar Inc	0.079	0.120	0.133	3	0.141	0.117	0.117	32
Cendant Corp	0.360	0.208	0.211	22	0.443	0.266	0.256	20
Clear Channel Communications Inc	0.609	0.089	0.100	5	NA	NA	NA	NA
Cox Communications Inc	0.549	0.152	0.167	9	0.542	0.118	0.125	4
Deere and Co	0.140	0.123	0.117	24	0.111	0.138	0.146	38
Delphi Automotive Systems Corp	0.137	0.205	0.251	49	0.197	0.245	0.264	67
Walt Disney Co	0.105	0.114	0.129	80	0.109	0.129	0.142	86
Eastman Kodak Co	0.202	0.137	0.143	50	0.319	0.189	0.149	54
Enron Corp	0.169	0.226	0.227	31	0.165	0.355	0.370	25
Federated Department Stores Inc	0.117	0.147	0.161	14	0.120	0.172	0.203	20
Goodyear Tire and Rubber Co	0.425	1.191	1.339	17	0.539	1.548	1.858	29
Hewlett-Packard Co	0.100	0.117	0.140	17	0.115	0.158	0.165	32
Hilton Hotels Corp	0.378	0.531	0.561	90	0.391	0.489	0.494	103
International Business Machines Corp	0.092	0.090	0.091	61	0.080	0.095	0.097	62
International Paper Co	0.123	0.166	0.166	29	0.123	0.154	0.154	49
Lockheed Martin Corp	0.134	0.105	0.100	1	0.139	0.009	0.020	1
MGM Mirage Inc	0.234	0.202	0.188	54	0.516	0.443	0.427	60
Motorola Inc	0.335	0.330	0.435	35	0.389	0.540	0.505	56
Omnicom Group	0.281	0.173	0.172	16	0.363	0.187	0.188	18
Park Place Entertainment Corp	0.433	0.307	0.280	37	0.348	0.408	0.424	15
JC Penney Co Inc	0.474	0.774	0.875	34	0.702	0.697	0.592	28
SBC Communications Inc	0.162	0.199	0.211	40	0.192	0.192	0.177	34
Sprint Corp	0.496	0.644	0.671	84	1.196	1.527	1.447	83
Sun Microsystems Inc	0.265	0.375	0.387	18	0.331	0.331	0.326	19
TRW Inc	0.220	0.369	0.276	4	0.311	0.144	0.330	4
Toys R Us Inc	0.396	0.932	0.961	5	0.820	0.440	0.369	2
Tyco International Ltd	0.741	0.312	0.323	9	1.081	0.147	0.257	2
Viacom Inc	0.099	0.102	0.115	67	0.094	0.106	0.117	82
Visteon Corp	0.237	0.476	0.509	11	NA	NA	NA	NA
Aggregate	0.301	0.384	0.418	1,024	0.440	0.572	0.575	1,155

a company is included in the analysis in Tables 2–4, provided that 25 changes in quotes are available. In the case of the bid quotes, the sample contains 33 companies, and in the case of the offer quotes, the sample contains 31 companies. For some companies, the RMSE is computed based on a very small number of observations.

A number of interesting conclusions obtain. First, the (in-sample) RMSEs are comparable to those available in the literature.[18] Second, the RMSEs for the bid quotes are mostly smaller than the RMSEs for the offer quotes, and on average the difference is rather large. This is somewhat surprising, because the differences in explanatory power between the bid and offer quotes in Table 2 are small, especially in the difference regressions that we report on in the out-of-sample experiment. Third, the out-of-sample performance of the regression is quite good when compared to the in-sample RMSE. In the case of the bid quotes,

[18]Campbell and Taksler (2003) find RMSE levels just above 30 bps in-sample. Cao, Yu, and Zhong (2006) study the explanatory power of implied volatility on default swap spreads. They find basis point RMSE levels around 60 bps.

the aggregate out-of-sample RMSE is 27% higher than the in-sample RMSE. For the offer quotes, the difference is 30%. To provide additional perspective on the model's out-of-sample perspective, we also provide the random walk forecast, based on the assumption that the spread level follows a random walk. For the bid quotes as well as for the offer quotes, the regression-based forecast outperforms the random walk forecast. This result is of interest, because Duffee (2002) finds that affine term structure models fail to outperform the random walk model when forecasting Treasury yields.

E. Coefficient Stability

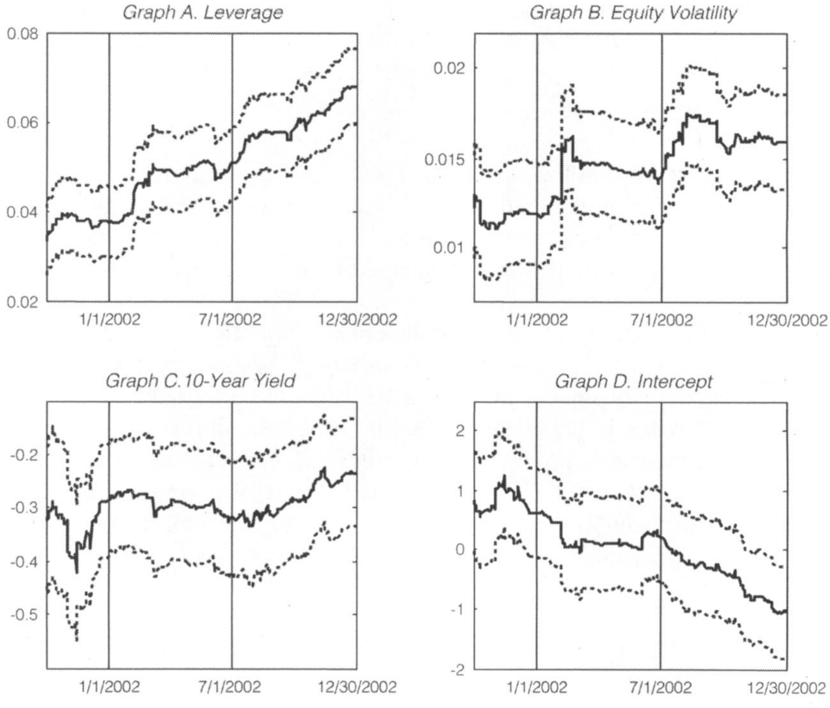
Figure 4 further explores the robustness of the results by investigating the stability of the regression coefficients over time. We report results obtained using rolling regressions. These results are obtained using panel data techniques, because the unbalanced nature of the dataset makes it difficult to summarize the results of rolling time-series regressions.

Unfortunately our sample is rather short for the purpose of this exercise. Although the regression results in Tables 2–4 are typically obtained using about 1,200 days (60 observations and 20 days between quotes, on average), we therefore

FIGURE 4

Rolling Panel Regression Coefficients on Default Swap Spread Determinants

Graphs A–D of Figure 4 report the estimates for the leverage, volatility, and interest rate coefficients as well as the intercept using rolling panel regressions with a 1,000-day window. The period covered is October 2, 2001 to December 31, 2002. The solid line represents the point estimate and the dotted lines show 95% confidence bands.



use a slightly shorter window of 1,000 days in order to obtain a larger sample. Figure 4 reports the results of this exercise for the period between October 2, 2001 and December 31, 2002. These results indicate that the parameter estimates are robustly positive for leverage and volatility, and robustly negative for the 10-year yields. However, each of the time series of coefficients displays a clear trend over time, and this trend is most pronounced for the coefficient on leverage. While coefficient estimates have the sign predicted by theory, their economic significance varies over time.

F. Discussion

It is interesting to compare these results with the findings by Campbell and Taksler (2003), Collin-Dufresne et al. (2001), and Cremers et al. (2004) for corporate bond spreads. Our results confirm the findings in these papers that the theoretical determinants of credit risk are empirically relevant and estimated with the sign predicted by theory. However, there are some differences with respect to explanatory power and economic significance. Collin-Dufresne et al. (2001) estimate difference regressions, and their base-case regressions are the ones in Table 4. The R^2s in Collin-Dufresne et al. (2001) are lower, also, when studying the effects of leverage in isolation. Our point estimates for the effects of leverage and volatility are larger than theirs, but it must of course be noted that our measure of volatility is very different because they use a market-wide measure of volatility. Campbell and Taksler (2003) investigate level regressions and focus mainly on the effect of volatility, using a historical measure of volatility. They use panel regressions and obtain higher R^2s than we do in our panel regressions, but this finding must be interpreted with caution, because they include a number of control variables that explain approximately 25% of all variation. The most interesting difference is that the estimate of a 1% change in annualized volatility in Campbell and Taksler (2003) is 14 bps, considerably higher than our estimate.

Some of the empirical results in Cremers et al. (2004) are closely related to the ones in this paper because they investigate the explanatory power of volatility in the absence of other explanatory variables. However, they do not consider the impact of leverage. Cremers et al. (2004) use panel regressions. It is noteworthy that their point estimates for the firm-implied volatility are very similar to the ones we obtain using historical volatility. This is likely due to the fact that we compute volatility as an exponentially weighted moving average, which, like implied volatility, is more variable than a 180 day historical average.

In summary, the explanatory power of the theoretical variables in our analysis differs from the results in the literature on corporate bond spreads, which itself contains some divergent results. However, one important caveat is that the explanatory power of these regressions depends on maturity (see Campbell and Taksler (2003), Collin-Dufresne et al. (2001), and Cremers et al. (2004)), and the maturity of the swaps in our sample (roughly five years) may be very different from the average maturity for corporate bonds.

Zhang et al. (2006) use regressions to investigate the explanatory power of realized volatility measures for default swap spreads. They also investigate the importance of jump risk. Some of their results on historical volatility can be directly compared to some of our findings. In particular, while they find that a 1% change in annualized volatility increases credit spreads by 3–9 bps, our estimates are between 0.8 and 1.5 bps. Their R^2 for a regression of default swap spreads levels on historical volatility is 45%, while our R^2s for this regression (in levels) are between 23.9% and 29.7%. However, our explanatory power is substantially higher when we use panel data techniques with fixed effects.

G. Analyzing the Regression Residuals

To understand the structure of the remaining variation in the data, we analyze the regression residuals from the difference regression (2) using principal components analysis. By analyzing the correlation matrix of the errors of the time-series regressions, we investigate whether there exists an unidentified common factor that explains a significant portion of the variation of the errors. The structure of the data somewhat complicates the analysis. There are three types of complications in the data. First, the data are nonsynchronous. This causes some difficulties at a technical level. Second, the number of observations differs considerably by company, which forces us to make some choices regarding the use of the data. We use the 15 companies with the highest number of observations to obtain results that are based on as much time-series information as possible. Third, because we work with difference regressions, there is more than one time index, and each element of the correlation matrix has to be estimated individually. We do so by using the procedure of de Jong and Nijman (1997).[19]

Table 6 reports our results. To investigate the implications of improved liquidity, we split up the sample.[20] For the first half of the sample, the first principal component is fairly important for bid (offer) quotes, explaining 59.0% (64.8%) of the variation. The first eigenvector has many positive elements of similar magnitude. The first principal component of the errors has more diverse weights, and it explains only 36.0% (35.6%) of the variation of the errors. The results for the second half of the sample are qualitatively similar. However, the first principal component is relatively less important for the spreads as well as for the errors. One potential explanation is that the first component captures, among other things, a common illiquidity-related component, which has been reduced over time because of the growth of the swap market.

Our third principal components analysis is closer in spirit to the one in Collin-Dufresne et al. (2001), although it differs because of data constraints. Collin-Dufresne et al. (2001) perform a principal components analysis by

[19]Martens (2003) reviews and compares different methods for computing covariance matrices for non-synchronous data. His simulations show that the de Jong and Nijman (1997) method is the most reliable in the absence of a bid-offer spread. Given that we work with either bids or offers, we choose this method. Since the estimated correlation matrix is not generally positive semidefinite, we compute the positive semidefinite matrix closest to the estimated correlation matrix according to the Frobenius-norm using a numerical algorithm due to Sharapov (1997) and also used by Ledoit, Santa-Clara, and Wolf (2003).

[20]Because we need a large number of quotes per company to conduct a meaningful principal component analysis, and because the number of quotes increases with time, we define the first half of the sample as the first 50% of all quotes. The first half of the sample therefore covers more than half of the total sample period.

TABLE 6

Principal Components Analysis using Data on 15 Companies

Table 6 presents results of a principal components (PC) analysis using data on the 15 most quoted companies. PCs are applied either to the differences of the default swap spreads or the errors from regression (2) explaining the differences of spreads. For each exercise, the first two vectors and the percentage of the variance explained by each factor are reported.

Bid Differences				Offer Differences			
Regression Errors		Spreads		Regression Errors		Spreads	
First Component	Second Component	First Component	Second Component	First Component	Second Component	First Component	Second Component
Panel A. First Half of Data							
−0.06	0.16	−0.02	−0.58	−0.40	−0.09	0.31	0.13
0.30	−0.10	0.29	−0.12	0.41	−0.01	0.31	0.12
0.17	0.49	0.29	0.06	0.41	−0.05	0.31	0.14
−0.07	0.12	−0.06	0.48	0.00	−0.51	0.25	−0.41
0.41	−0.15	0.33	−0.07	0.11	−0.07	0.12	−0.26
0.14	0.15	0.29	−0.09	0.17	−0.30	0.27	0.31
−0.26	0.33	0.31	−0.11	0.01	0.06	0.00	0.24
0.29	0.33	0.31	0.07	0.38	−0.16	0.32	−0.06
0.14	0.44	0.31	0.11	−0.21	−0.32	0.31	0.15
0.39	−0.21	0.31	−0.04	−0.08	−0.31	0.31	−0.11
0.40	−0.21	0.32	−0.05	0.06	−0.29	0.19	−0.20
0.36	0.19	0.31	−0.10	0.40	0.09	0.31	0.14
0.20	0.25	0.20	0.44	0.21	−0.44	0.28	−0.26
−0.15	0.22	0.03	0.18	−0.22	−0.27	0.18	−0.39
0.08	0.11	0.08	0.36	0.12	0.22	0.14	0.49
Explained by PC							
36.0%	22.3%	59.0%	19.3%	35.6%	24.9%	64.8%	13.9%
Panel B. Second Half of Data							
0.39	−0.18	0.30	−0.18	0.42	0.12	0.31	0.31
0.39	−0.08	0.35	0.12	0.26	−0.29	0.30	−0.02
0.32	−0.08	0.35	−0.09	−0.06	−0.28	0.31	0.04
0.11	−0.13	0.17	−0.41	0.46	0.04	0.25	0.38
0.23	0.22	0.24	−0.35	0.45	0.14	0.27	0.40
−0.22	−0.32	0.14	0.21	0.28	0.14	0.13	0.40
0.24	−0.12	0.20	0.23	0.17	−0.26	0.30	−0.32
0.35	0.16	0.28	0.22	0.30	0.32	0.31	0.12
0.27	0.13	0.23	0.22	0.16	−0.23	0.20	−0.14
0.05	0.34	0.30	−0.06	0.12	−0.35	0.27	−0.22
0.09	0.53	0.26	0.01	0.06	−0.48	0.25	−0.30
0.29	−0.47	0.33	0.16	0.19	−0.03	0.27	−0.26
0.34	−0.01	0.26	−0.09	−0.03	−0.05	0.01	0.02
0.03	−0.11	0.16	0.44	0.13	−0.45	0.30	−0.28
0.12	0.31	0.17	−0.47	0.22	0.02	0.20	0.09
Explained by PC							
25.5%	14.0%	51.0%	11.6%	26.4%	19.8%	49.6%	18.0%

distributing the errors of all the companies in the sample in bins according to the maturity of the bonds and the leverage of the issuing companies. With a balanced panel, it is straightforward to do this analysis for differences. In our case, we do not observe the spreads at fixed intervals. As a result, changes in spreads and the corresponding errors carry a double time index, and it is not feasible to assign them to bins. We therefore perform the analysis using bins for the levels regressions (1).

Collin-Dufresne et al. (2001) construct 15 bins by classifying the companies in five leverage groups and the bonds in three maturity ranges. However, because all swaps in our sample have (roughly) a five-year maturity, it is not feasible to use maturity as a classification variable. Also, we have only one kind of swap per company, and not a collection of bonds. Therefore we construct our bins using only the leverage dimension, so that we have five bins delimited by the quintiles of the distribution of leverage of the different companies. The time interval defining the bins is 15 days. Table 7 reports on this analysis. The first principal component for the bid (offer) errors explains only 35.6% (36.4%) of the variation of the bins, compared to 68.6% (66.1%) for the bid (offer) quotes.

TABLE 7

Principal Component Analysis using Data in Leverage Bins

Table 7 presents results of a principal component analysis using data on all companies grouped in five leverage bins. Principal component analysis is applied either to the levels of the default swap spreads or the errors from regression (1) on the levels of spreads. For each exercise, the first two vectors and the percentage of the variance explained by each factor are reported.

	Leverage (%)		Regressions Errors		Spreads	
Quintile	From	To	First Component	Second Component	First Component	Second Component
Panel A. Bid Levels						
1st	17.3	36.8	0.41	−0.08	0.46	0.19
2nd	36.8	47.8	0.48	−0.25	0.48	0.05
3rd	47.8	59.6	0.33	−0.60	0.27	−0.96
4th	59.6	70.1	0.61	0.13	0.49	0.17
5th	70.1	91.0	0.36	0.74	0.49	0.13
			Explained by PC 35.6%	20.8%	68.6%	16.2%
Panel B. Offer Levels						
1st	15.1	34.0	0.24	0.77	0.39	−0.65
2nd	34.0	44.4	0.39	−0.62	0.47	−0.11
3rd	44.4	55.5	0.39	−0.09	0.39	0.70
4th	55.5	65.8	0.60	0.10	0.49	0.21
5th	65.8	81.4	0.52	0.06	0.49	−0.15
			Explained by PC 36.4%	24.0%	66.1%	13.2%

Overall, Tables 6 and 7 suggest that the theoretical determinants of spreads do explain a significant part of the common variation. Regarding the percentage of the variance explained by the first principal component in the error analysis, it varies dependent on whether one uses bins and whether one uses differences or levels, but it varies between 25.5% and 36.4%. A high percentage in this case would indicate that there is a lot of common variation left which cannot be explained by one of the theoretical variables.[21]

To further understand the nature of the residuals, we also ran regressions (1) and (2) with a swap market index included. One would expect such an index to have substantial explanatory power for residual spreads if the variables suggested by theory are inadequate. Unfortunately, no index is available for the swap market over our entire sample. We use the TRACERS index, which is available from September 2001 to the end of our sample, and we repeat our estimation exercise with the swap data available for this period (not reported).[22] It must be noted

[21]The percentage variation explained by the first principal component in the errors is lower than in Collin-Dufresne et al. (2001), but we find it difficult to draw strong conclusions from this as to the validity of the theoretical variables because it is not clear what the benchmark is. It must also be taken into account that the largest eigenvalues are in general severely biased upward, as observed by Ledoit and Wolf (2004).

[22]Morgan Stanley's TRACERS index is a synthetic index of U.S. investment grade credit based on a selection of the most liquid reference entities.

that although this covers less than half of the time period of our swap sample, it covers the majority of the data points because the number of quotes increases through time. Interestingly, we find that including the market index does not noticeably affect the explanatory power of the regression. These results confirm that the theoretical variables perform rather well in explaining spreads.

IV. Conclusion

Using a new dataset of bid and offer quotes credit default swaps, we investigate the relationship between theoretical determinants of default risk and actual spreads. These determinants are firm leverage, volatility, and the riskless interest rate. We find that these variables are statistically significant, and that their effect is economically important as well as intuitively plausible. Moreover, the estimates of the economic effects of leverage and volatility are very similar regardless of whether one estimates on levels or differences and regardless of the econometric methodology. A 1% increase in annualized equity volatility raises the spread by 1–2 bps. A 1% change in the leverage ratio raises the spread by approximately 5–10 bps. These effects are not out of line with some of the estimates available in the literature on corporate bond spreads, even though Campbell and Taksler (2003) estimate a stronger effect for a change in volatility.

The explanatory power of the theoretical variables depends on the econometric method and on whether one uses levels or differences. Using time-series regressions for a minimal set of theoretical determinants of default risk (firm leverage, volatility, and the riskless interest rate), the R^2 for changes in spreads is approximately 23%, and the explanatory power for the levels of the spreads is approximately 60%. The R^2 for levels regressions goes up to more than 70% if we add in other theoretical determinants of default risk and recovery risk as in Collin-Dufresne et al. (2001). The high R^2s for the levels regressions, coupled with our analysis of the residuals and the similarity of the point estimates for the levels and differences regressions, lead us to conclude that the theory is useful for explaining the variation in spreads. The R^2s for our difference regressions are higher than the ones in Collin-Dufresne et al. (2001), which may be due to higher liquidity, to the fact that spreads provide a superior estimate of credit risk, or simply to differences in the composition of the data, such as maturity structure. We note that a large fraction of the variation in spread differences remains unexplained, although given the presence of noise in the data, it is not clear what R^2 can be expected for the difference regressions under the null hypothesis.

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