How Profitable Is Capital Structure Arbitrage?

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First Draft: September 30, 2004

This Version: January 18, 2005

[1]I am grateful to Yong Rin Park for excellent research assistance and Vineer Bhansali, Nai-fu Chen, Darrell Duffie, Philippe Jorion, Dmitry Lukin, Stuart Turnbull, Ashley Wang, Sanjian Zhang, Gary Zhu, and seminar participants at UC-Irvine and PIMCO for insightful discussions. The credit default swap data are acquired from CreditTrade.
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Abstract

This paper examines the risk and return of the so-called "capital structure arbitrage," which exploits the mispricing between a company's debt and equity. Specifically, a structural model connects a company's equity price with its credit default swap (CDS) spread. Based on the deviation of CDS market quotes from their theoretical counterparts, a convergence-type trading strategy is proposed and analyzed using 4,044 daily CDS spreads on 33 obligors. We find that capital structure arbitrage can be an attractive investment strategy, but is not without its risk. In particular, the risk arises when the arbitrageur shorts CDS and the market spread subsequently skyrockets, resulting in market closure and forcing the arbitrageur into liquidation. We present preliminary evidence that the monthly return from capital structure arbitrage is related to the corporate bond market return and a hedge fund return index on fixed income arbitrage.

Capital structure arbitrage has lately become popular among hedge funds and bank proprietary trading desks. Some traders have even touted it as the "next big thing" or "the hottest strategy" in the arbitrage community. A recent Euromoney report by Currie and Morris (2002) contains the following vivid account:

> "In early November credit protection on building materials group Hanson was trading at 95bp—while some traders' debt equity models said the correct valuation was 160bp. Its share held steady. That was the trigger that capital structure arbitrageurs were waiting for. One trader who talked to Euromoney bought €10 million-worth of Hansen's five-year credit default swap over the course of November 5 and 6 when they were at 95bp. At the same time, using an equity delta of 12% derived from a proprietary debt equity model, he bought €1.2 million-worth of stock at £2.91 (€4.40). Twelves days later it was all over. On November 18, with Hanson's default spreads at 140bp and the share price at £2.95, the trader sold both positions. Unusually, both sides of the trade were profitable. Sale of credit default swaps returned €195,000. Selling the shares raised €16,000, for a total gain of €211,000."

In essence, the capital structure arbitrageur uses a structural model to gauge the richness/cheapness of the CDS spread. The model, typically a variant of Merton (1974), predicts spreads based on a company's liability structure and its market value of equities.[1] When the arbitrageur finds that the market spread is substantially larger than the predicted spread, he can entertain a number of possibilities. He might think that the equity market is more objective in its assessment of the price of credit protection and the CDS market is instead gripped by fear. He is also entitled to think the market spread "right" and that it is the equity market that is slow to react to relevant information. If the first view is correct, the arbitrageur is justified in selling credit protection. If the second view is correct, he should sell equity. In practice the arbitrageur is probably unsure, so that he does both and profits if the market spread and the model spread converge to each other. The size of the equity position relative to the CDS notional amount is determined by delta-hedging. The logic is that if the CDS spread widens or if the equity price rises, the best one could hope for is that

[1] A popular choice among traders appears to be the CreditGrades model. See the CreditGrades Technical Document (2002) for details.

the normal relation between the CDS spread and the equity price would prevail, and the equity position can cushion the loss on the CDS position, and vice versa.

Of course, there are other possibilities where neither the CDS nor the equity is in fact mispriced. For example, the market spread could be higher because of demand/supply pressures, a sudden increase in asset volatility, newly issued debt, or hidden liabilities that have come to light. These considerations are omitted in a simple implementation of structural models using historical volatility and balance sheet information from quarterly filings. This is why the CreditGrades Technical Document (2002) specifically warns against using CreditGrades for pricing purposes. These missing links could very well doom the effort to turn capital structure arbitrage into a science.

In the Hanson episode, the CDS and equity market did come to the same view regarding Hanson's default risk. In this case, the market CDS spread increased sharply while the equity-based theoretical spread decreased slightly, realigning themselves. However, should one expect this outcome to be the norm? In Currie and Morris (2002), traders are quoted saying that the average correlation between the CDS spread and the equity price is only on the order of 5% to 15%. The lack of a close correlation between the two variables suggests that there can be prolonged periods when the two markets hold diverging views on an obligor.

Despite these difficulties, and given the complete lack of evidence in favor of or against the strategy, it is necessary to study the risk and return of capital structure arbitrage as commonly implemented by traders. In asking this question, it is expected that such a strategy is nowhere close to what one calls arbitrage in the textbook sense. Indeed, convergence may never occur during reasonable holding periods, and the CDS spread and the equity price seem as likely to move in the same direction as in the opposite direction—all the more reasons to worry whether the traders' enthusiasm is justified. If positive expected returns are found, the next step would be to understand the sources of the profits, i.e., whether the returns are correlated with priced systematic risk factors. From a trading perspective, one may also check if the strategy survives trading costs or constitutes "statistical arbitrage"—one that does not yield sure profit but will do so in the long run.[2] If the strategy does not yield positive expected returns, one needs to look more carefully, perhaps at refined trading strategies that are more attuned to the nuances of the markets on a case-by-case basis.

[2] See Hogan, Jarrow, Teo, and Warachka (2003) for details.

This paper is based on the premise that structural models can price CDS reasonably well. This assumption itself has been the subject of ongoing research. The initial tests of structural models, such as Jones, Mason, and Rosenfeld (1984) and Eom, Helwege, and Huang (2004), focus on corporate bond pricing, and find that structural models generally underpredict spreads. It is now understood that the failure of the models has more to do with corporate bond market peculiarities such as liquidity and tax effects than their ability to explain credit risk.[3] Recent applications to the CDS market has turned out to be more encouraging. For example, Ericsson, Reneby, and Wang (2004) find that several popular structural models fit CDS spreads much better than they do bond yield spreads, and one of the models yields almost unbiased CDS spread predictions. Moreover, industry implementations such as CreditGrades introduce recovery rate uncertainty, which further boosts the predicted spreads. Hence spread underprediction is unlikely to be a persistent problem in the CDS market.

This paper is also related to Liu and Longstaff (2004), who study the risk and return of a particular type of fixed income strategy, namely the swap-spread arbitrage where the trader longs an interest rate swap and shorts a Treasury bond. The two strategies are mechanically similar because both are exploiting the differences between two key covariates. Longstaff, Mithal, and Neis (2003) use a vector-autoregression to examine the lead-lag relationship among bond, equity, and CDS markets. They find that equity and CDS markets contain distinct information which can help predict corporate bond yield spread changes.[4] While there is no definitive lead-lag relationship between equity and CDS markets, a convergence-type trading strategy such as capital structure arbitrage can conceivably take advantage of the distinct information content of the two markets.

In practice, capital structure arbitrageurs often place bets on risky bonds in lieu of CDS. They also trade bonds against CDS to take advantage of the misalignment between bond spreads and CDS spreads. However, this paper does not consider bond-equity or bond-CDS trading strategies for several reasons. First, there is the pragmatic concern for the lack of high frequency data on corporate bonds. Second, CDS is becoming the preferred vehicle in debt-equity trades due to its higher liquidity. Third, there is a simple relationship between CDS and bond spreads which is

[3]See Elton, Gruber, Agrawal, and Mann (2001), Ericsson and Reneby (2003), and Longstaff, Mithal, and Neis (2004).

[4]Zhu (2004) finds the CDS market to lead the bond market in price discovery. Berndt and de Melo (2003) find that the equity price and the option-implied volatility skew Granger-cause CDS spreads, although their analysis is based on just one company, France Telecom.

supported both in theory and by the data. For example, using arbitrage-based arguments Duffie (1999) shows that CDS spreads are theoretically equivalent to the yield spreads on floating-rate notes. Hull, Predescu, and White (2003), Longstaff, Mithal, and Neis (2003), Houweling and Vorst (2003), and Blanco, Brennan, and Marsh (2003) find a close resemblance between CDS spreads and fixed-rate bond spreads, provided that one selects a proper "risk-free" reference interest rate. Finally, several existing studies already explore the relationship between equity and corporate bonds, such as Schaefer and Strebulaev (2004) and Chatiras and Mukherjee (2004). In contrast, the model-based relationship between the equity price and the CDS spread is much less well understood.

The rest of the paper is organized as follows. Section 2 dissects the trading strategy. Section 3 outlines the data used in the analysis. Section 4 uses a case study to illustrate the general approach. Section 5 presents general trading results. Section 6 analyzes the relationship between the trading returns and systematic risk factors. Section 7 contains additional robustness checks. Section 8 concludes.

1 Anatomy of the Trading Strategy

This section dissects the anatomy of capital structure arbitrage. Since the strategy is model-based, we start with an introduction to CDS pricing, and then explore issues of implementation with the help of the analytical framework.

1.1 CDS Pricing

A credit default swap (CDS) is an insurance contract against credit events such as the default on a bond by a specific issuer (the obligor). The buyer pays a premium to the seller once a quarter until the maturity of the contract or the credit event, whichever occurs first. The seller is obligated to take delivery of the underlying bond from the buyer for face value should a credit event take place within the contract maturity. While this is the essence of the contract, there are also a number of practical issues. For example, if the credit event occurs between two payment dates, the buyer owes the seller the premiums that have accrued since the last settlement date. Another complicating issue is that the buyer usually has the option to substitute the underlying bond with other debt instruments of the obligor. This means that the CDS spread has to account for the value of a cheapest-to-deliver option. This option can become particularly valuable when the definition of the credit event includes restructuring, which can cause the deliverable assets to diverge in value. For a simple treatment of CDS pricing, we assume continuous premium payments and ignore the embedded option.[5]

First, the present value of the premium payments is equal to

$$E\left(c\int_0^T \exp\left(-\int_0^s r_u du\right) 1_{\{\tau>s\}} ds\right), \tag{1}$$

where c denotes the CDS spread, T the CDS contract maturity, r the risk-free interest rate, and τ the default time of the obligor. Assuming independence between the default time and the risk-free interest rate, this can be written as

$$c\int_0^T P(0,s)\, q_0(s)\, ds, \tag{2}$$

where $P(0,s)$ is the price of a default-free zero-coupon bond with maturity s, and $q_0(s)$ is the risk-neutral survival probability of the obligor, $\Pr(\tau > s)$, at $t = 0$.[6]

Second, the present value of the credit protection is equal to

$$E\left((1-R)\exp\left(-\int_0^\tau r_u du\right) 1_{\{\tau<T\}}\right), \tag{3}$$

where R measures the recovery of bond market value as a percentage of par in the event of default. Assuming a constant R and maintaining the assumption of independence between default and the risk-free interest rate, this can be written as

$$-(1-R)\int_0^T P(0,s)\, q_0'(s)\, ds, \tag{4}$$

where $-q_0'(t) = -dq_0(t)/dt$ is the probability density function of the default time. The CDS spread is then determined by setting the initial value of the contract to zero:

$$c = -\frac{(1-R)\int_0^T P(0,s)\, q_0'(s)\, ds}{\int_0^T P(0,s)\, q_0(s)\, ds}. \tag{5}$$

The preceding derives the CDS spread on a newly minted contract. If it is subsequently held, the relevant issue is the value of the contract as market conditions change. To someone who holds

[5] Duffie and Singleton (2003) show that the effect of acrrued premiums on the CDS spread is typically small. For detailed discussions on restructuring as a credit event and the cheapest-to-deliver option, see Blanco, Brennan, and Marsh (2003) and Berndt et al. (2004).

[6] Assuming independence between default and the default-free term structure allows us to concentrate on the relationship between the equity price and the CDS spread. The further specialization to constant interest rates below is in the same vein.

a long position from time 0 to t, this is equal to

$$V(t,T) = (c(t,T) - c(0,T)) \int_t^T P(t,s)\, q_t(s)\, ds, \tag{6}$$

where $c(t,T)$ is the CDS spread on a contract initiated at t and with maturity date T, and $q_t(s)$ is the probability of survival through s at time t.

To compute the risk-neutral survival probability, we use the structural approach, which assumes that default occurs when the firm's asset level drops below a certain "default threshold."[7] Since the equity is treated as the residual claim on the assets of the firm, the structural model can be estimated by fitting equity prices and equity volatilities.[8] Because of the focus on trading strategies, the choice of a particular structural model ought to be less crucial. One model might produce slightly more unbiased spreads than another, but it is the daily change in the spread that is of principal concern here. At this frequency, the only contributor to spread changes is the equity price; other inputs and parameters, which can vary from one model to the next, are essentially fixed. In other words, all structural models can be thought of as merely different nonlinear transformations of the same equity price. Of course, different models will produce different hedge ratios that can impact trading profits. However, Schaefer and Strebulaev (2004) show that even a simple model such as Merton's (1974) produces hedge ratios for corporate bonds that cannot be rejected in empirical tests.

Consequently, we use the CreditGrades model to implement the trading analysis. This model is jointly developed by RiskMetrics, JP Morgan, Goldman Sachs, and Deutsche Bank. It is based on the model of Black and Cox (1976), and contains the additional element of uncertain recovery. This latter feature helps to increase the short-term default probability, which is needed to produce realistic levels of CDS spreads.[9] On the practical side, the model provides closed-form solutions to the survival probability and the CDS spread. It is also reputed as the model used by most capital structure arbitrage professionals. For completeness, the appendix gives an overview of

[7] The alternative is the reduced-form approach, which computes the survival probability based on a hazard rate function typically estimated from bond prices. Blanco, Brennan, and Marsh (2003) and Longstaff, Mithal, and Neis (2003) are applications of this approach.

[8] For example, the Merton (1974) model can be estimated by inverting the equations for equity price and equity volatility for asset level and asset volatility. KMV estimates its model for the expected default frquency using a recursive procedure that involves only the expression for equity value [see Crosbie and Bohn (2002) and Vassalou and Xing (2003)]. The structural model can also be estimated using maximum likelihood applied to the time-series of equity prices [see Ericsson and Reneby (2004)].

[9] The same effect can be achieved by assuming imperfectly observed asset value, or coarsened information set observed by outside investors compared to managers. See Duffie and Lando (2001), Cetin et al. (2003), and Collin-Dufresne, Goldstein, and Helwege (2003).

CreditGrades, including the formulas for $q_0(t)$, $c(0,T)$, the contract value $V(t,T)$, and the equity delta, defined as

$$\delta(t,T) = \frac{\partial V(t,T)}{\partial S_t}, \tag{7}$$

where S_t denotes the equity price at t.

1.2 Implementation

We now turn to the implementation of the trading strategy. Assume that we have available a time-series of observed CDS market spreads $c_t = c(t, t+T)$ on freshly-issued, fixed-maturity contracts.[10] Also available is a time-series of observed equity prices S_t, along with information about the capital structure of the obligor. This latter information set allows the trader to calculate a theoretical CDS spread based on his structural model. Denote this prediction c'_t and the difference between the two time-series $e_t = c_t - c'_t$.

If the focus is on pricing, then typically one would like to attain the best possible fit to market data according to some pre-specified metric, for example by minimizing the sum of e_t^2 over time. While this would be akin to inverting implied volatility from the Black-Scholes model for equity options, that is not how the model is used in this context. A simple model such as CreditGrades whose only inputs are equity price, historical equity volatility, debt per share, interest rate, recovery rate, and its standard deviation has very little flexibility to fit the time-series of market spreads precisely. What motivates capital structure arbitrage trading is, instead, the trader's belief that e_t will move predictably over time.

Specifically, suppose that the arbitrageur examines the behavior of e_t and finds that it has mean $E(e)$ and standard deviation $\sigma(e)$. As mentioned before, because of the way the model is implemented one would not expect the pricing error to be unbiased. However, say that there comes a point at which the deviation becomes unusually large, for example when $e_t > E(e) + 2\sigma(e)$. At this point the arbitrageur sees an opportunity. If he considers the CDS overpriced, then he should sell credit protection. On the other hand, if he considers the equity to be overpriced, then he should sell the equity short. Either way, he is counting on the "normal" relationship between the market spread and the equity-implied spread to re-assert itself. In other words, the trading strategy is

[10] This assumption is consistent with the observation that CDS market quotes are predominantly for newly initiated five-year contracts. Secondary market trading also appears in the data, although only very recently.

based on the assumption that "convergence" will occur.

To see this logic more clearly, assume that the theoretical pricing relation is given by $c_t' = f(S_t, \sigma; \theta)$ where S_t is the equity price, σ is an estimate of asset volatility, and θ denotes the other fixed parameters of the model such as the recovery rate. The actual CDS spread is given by $c_t = f\left(S_t, \sigma^{\text{imp}}; \theta\right)$ where σ^{imp} is the implied asset volatility obtained by inverting the pricing equation. When $c_t > c_t'$, it may be that the implied volatility σ^{imp} is too high and shall decline to a lower level σ. The correct strategy in this case is to sell CDS and sell equity as a hedge, which is akin to selling overpriced stock options and using delta-hedging to neutralize the effect of a changing stock price. Another possibility is that the CDS is priced fairly, but the equity price reacts too slowly to new information. In this case the equity is overpriced and one should short CDS as a hedge against shorting equity. Both cases therefore give rise to the same trading strategy. A third possibility is that the volatility estimator can underestimate the true asset volatility, sending a false signal of mispricing in the market. Yet a fourth possibility is that other parameters of the model, such as the debt per share, are mis-measured. This can be a problem when using balance sheet variables from financial reports, which are infrequently updated. Finally, the gap between c_t and c_t' could simply be due to model misspecification. It is possible to address the last three scenarios, for example, by calibrating the model with option-implied volatility, carefully monitoring the changes in a firm's capital structure, and simply trying alternative models. As a first attempt to understand capital structure arbitrage trading, we leave these potential improvements to future research.

While delta-hedging is typically invoked in this context, there are differences from the usual practice in trading equity options where one bets on volatility and uses hedging to neutralize the effect of equity price changes. From what traders describe in media accounts, the equity hedge is often "static," staying unchanged through the duration of the strategy. Moreover, traders often modify the model-based hedge ratio according to their own opinion of the particular type of convergence that is likely to occur. In the above example, the trader may decide to underhedge if he feels confident about the CDS spread falling, or he may overhedge if he feels confident about the equity price falling. Some traders do not appear to use a model-based hedge ratio at all. Instead, they get a sense of the maximum loss that can occur should the obligor default, and shorts an equity position in order to break even.[11] When conducting the trading exercise, we set the hedge ratio to correspond to the observed CDS spread $c_t = f\left(S_t, \sigma^{\text{imp}}; \theta\right)$ because there can be substantial differences between the observed and the predicted spread.

Continuing the description of the trading strategy, now that the arbitrageur has entered the market, he also needs to know when to liquidate his positions. We assume that exit will occur under the following scenarios:

1. The pricing error e_t reverts to its mean value $E(e)$.

2. Convergence has not occurred by the end of a pre-specified holding period or the sample period.

To limit losses, one may wish to set an upper bound for $|e_t - E(e)|$ and terminate the trade when that ceiling is broken. One may also set a lower bound for $|e_t - E(e)|$ at which convergence is declared. These variations to the basic strategy can be experimented upon during the trading exercise. In principle, during the holding period the obligor can also default or be acquired by another company. However, most likely the CDS market will reflect these events long before the actual occurrences and the arbitrageur will have ample time to make exit decisions.

To summarize, the risk involved in capital structure arbitrage can be understood in terms of the subsequent movements of the CDS spread and the equity price. In the preceding example, after the arbitrageur has sold credit protection and sold equity short, four likely scenarios can happen:

1. $c_t \downarrow$, $S_t \downarrow$. This is the case of convergence, allowing the arbitrageur to profit from both positions.

2. $c_t \downarrow$, $S_t \uparrow$. The arbitrageur loses from the equity but profits from the CDS. He will profit overall if the CDS spread falls more rapidly than the equity price rises, allowing convergence to take place partially.

3. $c_t \uparrow$, $S_t \downarrow$. The arbitrageur loses from his CDS bet, but the equity position acts as a hedge against this loss. There will be overall profit if the equity price falls more rapidly than the CDS spread rises.

[11] In the article by Currie and Morris (2002), Boaz Weinstein of Deutsche Bank bought \$10 million-worth of Household Finance bonds at 75 cents on the dollar. He estimated the debt recovery to be 45 cents. Against this potential loss of \$3 million, he shorted \$2.5 million-worth of equity as a partial hedge.

4. $c_t \uparrow$, $S_t \uparrow$. This is a sure case of divergence. The arbitrageur suffers losses from both positions regardless of the size of the equity hedge.

Clearly, delta-hedging is effective in the second and the third scenarios. The likelihood of the first scenario, however, is critical to the success of capital structure arbitrage.

1.3 Trading Returns

An integral part of the exercise is the analysis of trading returns. At the initiation of the strategy, the CDS position has zero market value. Therefore, if the arbitrageur holds a long position in equity, its value is treated as the initial value of the trading strategy. If the arbitrageur holds a short position in equity, it is assumed that an equal amount has to be posted to a margin account along with the proceeds from short-selling. This margin requirement becomes the initial value of the trading strategy.

Through the holding period, the value of the CDS and equity can change. While the latter is trivial, the value of the CDS position has to be calculated according to Eq. (6). Several simplifying assumptions have to be made when implementing this procedure. First, Eq. (6) requires secondary market quotes on an existing contract, while the CDS market predominantly quotes spreads on freshly-issued contracts with a fixed maturity, say 60 months. We bypass this problem by approximating $c(t,T)$ with $c(t,t+T)$. Since the holding period t is short compared to T, the difference between the two should be much smaller than the difference between $c(0,T)$ and $c(t,t+T)$. Second, the value of the CDS is essentially that of a default-contingent annuity whose value depends on the term structure of survival probabilities. Consistent with using a hedge ratio that corresponds to the market spread, we plug the implied asset volatility into the CG model to compute the survival probabilities.[12]

In practice, there was very little secondary trading during the earlier phase of the CDS market. In more recent periods the market is moving toward quoting spreads on contracts with fixed maturity dates, similar to those in the equity options market, which facilitates secondary market trading. Still, our CDS database does not provide any information on the secondary market value of the contracts. What often occurs in practice is that once the trader buys a CDS from a dealer and

[12]Clearly we could have assumed survival probabilities that correspond to the theoretical CDS spread. This is one sense of “basis risk” as used by capital structure arbitrageurs. Another sense of the term is when choosing the hedge ratio. Here one also has a choice between the hedge ratio at the theoretical spread or the market spread.

then the spread rises, he can try to sell it back to the same dealer. The price for taking the position off his hands is subject to negotiation. If the trader finds the dealer's offer unacceptable, he can choose to enter an offsetting trade and receive the cash flow of the default-contingent annuity. He might also receive offers on the existing CDS position from active secondary market participants. In any case, all parties involved are likely to judge the value of the contract based on their own proprietary models. This is why we choose to use the survival probabilities from the CreditGrades model.

2 Data

For the CDS data we use historical quotes provided by CreditTrade, a CDS brokerage firm and data vendor. The initial dataset contains 249,539 intra-daily single-name CDS quotes on 759 North American industrial corporate obligors from January 1997 to July 2004. We apply several filters to the data to generate a subset that is suitable for the trading analysis:

1. We select quotes for senior unsecured, USD-denominated, five-year CDS with at least $5 million in notional value.[13] While this appears straightforward, the maturity variable deserves some discussion. Early on in the sample period, most of the quotes are for freshly-issued contracts. This is evidenced by contract maturities in multiples of 12 months, principally 60 months. Later on in the sample period more and more quotes have maturity dates specified instead of maturities, with typically just four fixed maturity dates throughout the year, 03/20, 06/20, 09/20, and 12/20. We were told by traders that this reflects a shift toward secondary trading as the market matures. As a result of this shift, most contracts have maturities close to but not exactly five years. To make efficient use of the data, we aggregate quotes with maturities from 57 to 63 months into the category of "five-year" quotes.

2. We construct daily mid-quotes following the procedure in Berndt et al. (2004). For each obligor, we identify days with both bid and ask quotes and calculate a daily bid-ask spread by subtracting the average bid from the average ask for the day and then multiplying by one half. The average bid-ask spread is the time-series average of the daily bid-ask spreads.

[13] Quotes with notional amount at least $5 million constitute 85% of the sample. Contracts with five-year maturity constitute 92% of the sample. Selecting five-year contracts follows a convention in this literature, while removing contracts with notional amount unspecified or less than $5 million can help eliminate some of the suspicious quotes.

For days with only bids (asks), we add (subtract) the average bid-ask spread to obtain the corresponding ask (bid) quotes. The daily mid-market CDS spread is defined as the mid-point between the average bid and the average ask. The bid-ask spread provides a rough estimate of trading costs, which will be useful in the trading analysis.

3. We merge the CDS data with the equity price, shares outstanding, and the equity market capitalization from CRSP and total liabilities from Compustat quarterly files.[14] The quarterly balance sheet variables are lagged for one month from the end of the quarter to ensure that we only use available information. We also obtain five-year constant maturity Treasury yields and three-month Treasury bill rates from Datastream. These additional variables are used to implement a simplified version of the CreditGrades model.

4. In order to conduct the trading exercise, a reasonably continuous sequence of quotes must be available. For each obligor, we search for strings of more than 40 daily mid-market spreads that are no more than five trading days apart, which also have available the associated equity and balance sheet information. These strings are at least two-month long, a reasonable length given the anecdotal accounts of capital structure arbitrage trading.

After applying Step 1, there are 189,748 quotes remaining on 677 obligors. After computing daily spreads and merging with CRSP and Compustat data, there are still 26,775 daily mid-market spreads on 461 obligors. The sample size is reduced dramatically after Step 4, however, with only 4,417 daily spreads on 35 obligors. Although the initial coverage of the CDS dataset is extensive, most of the obligors have only a few quotes or just a few days of coverage. This fits the behavior of the CDS market, where contracts are traded only when there is significant (typically negative) news about an obligor, and trading ceases when its outlook improves or the uncertainty is resolved.

Out of the remaining 35 obligors, we drop Black and Decker and Caterpillar because their sample consists mostly of constant quotes in 1999 when the market was not yet liquid. Philipp Morris Companies Inc. underwent a name change to Altria Group on January 27, 2003, and we record them as two separate obligors (with non-overlapping coverage) in the sample. AOL and Time Warner merged on January 11, 2001 and changed its name from AOL Time Warner to Time

[14] When these variables are not available from CRSP and Compustat, we search alternative sources such as SEC filings and Yahoo! Finance for the missing data.

Warner on October 16, 2003. However, the CreditTrade database disregards this name change and quotes only Time Warner during this period. Therefore, we screen for data after January 11, 2001 and designate them as quotes for Time Warner. Sprint combined its FON and PCS groups and the new entity commenced trading as FON on April 23, 2004. AT&T initiated a one-for-five reverse stock split and spun off AT&T Broadband on November 19, 2002. We truncate these two time-series after the respective event dates. This additional step results in 4,044 daily spreads on 33 obligors.

[Insert Table 1 here.]

Table 1 presents the summary statistics for the remaining 33 obligors used for the subsequent trading analysis. We observe that most of the obligors have median rating equal to A or Baa. Only one obligor (SBC) is rated Aa and two obligors (MGM Mirage and HCA) below investment-grade. The number of days with CDS quotes is greater than 40 in all cases as required by the filter we applied, but note that some of the obligors with larger number of observations may have more than one string of quote coverage. For example, Worldcom has two separate strings that are four months apart. The median CDS spread ranges from 33bp for Cardinal Health to 408bp for Interpublic. The median equity market capitalization ranges from \$2.5 billion to \$110 billion; the obligors are therefore all major corporations. We also observe that the bid/ask spread can be fairly wide; across all obligors, the bid/ask spread is on average 18 percent of the CDS spread. This can be a significant hurdle to clear for capital structure arbitrageurs. Most notably, the correlation between daily changes in the CDS spread and the equity price is negative for most of the obligors as predicted by structural models. The average correlation across all obligors is -0.19, consistent with the numbers quoted from traders. However, it does vary widely across obligors. For instance, for Cardinal Health the equity-CDS correlation is a highly negative and significant -0.68, while for Bellsouth it is only 0.08 and statistically insignificant. This variation raises the possibility that capital structure arbitrage may work for some obligors and not others.

3 Case Study of Altria Group

In this section we use the Altria Group as an example to illustrate the general procedure. As is well known, Altria (Philip Morris) has been mired in tobacco-related legal problems since the early nineties. In March 2003, a circuit court Judge in Illinois ordered Altria to post a \$12 billion bond to appeal a class action lawsuit. This news led to worries that Altria may have had to file for bankruptcy, triggering Moody's to downgrade Altria from A2 to Baa1 on March 31, 2003. For the trading analysis we isolate the period from January 27, 2003 to July 14, 2004, which consists of 255 daily observations of CDS mid-market spreads. We set aside the first ten daily observations for use in the model estimation procedure explained below.

For the first step, we compute the theoretical CDS spreads using the CreditGrades (CG) model. As shown in the appendix, CG requires the following inputs: the equity price S, the debt per share D, the mean global recovery rate $\overline{L}$, the standard deviation of the global recovery rate λ, the bond-specific recovery rate R, the equity volatility σ_S, and the risk-free interest rate r. Specifically, we assume that

$$
\begin{aligned}
D &= \frac{\text{total liabilities}}{\text{common shares outstanding}}, \\
\sigma_S &= \text{1,000-day historical equity volatility}, \\
r &= \text{five-year constant maturity Treasury yield}, \\
\lambda &= 0.3, \\
R &= 0.5.
\end{aligned}
$$

The CreditGrades Technical Document (2002, CGTD) motivates the above choice of λ and σ_S. It also has a more complex definition of the debt per share variable, taking into account preferred shares and the differences between long-term and short-term, and financial and non-financial obligations. The value of R is consistent with Moody's estimated historical recovery rate on senior unsecured debt. The choice of r is consistent with the existing literature that uses Treasury or swap rates to proxy for the risk-free interest rate.

Our implementation of the CG model, however, differs from that of the CGTD in one crucial aspect. The CGTD assumes that $\overline{L} = 0.5$ and uses a bond-specific recovery rate R taken from a proprietary database from JP Morgan. In practice, traders usually leave R as a free parameter to fit the level of market spreads. In so doing, they often find that the market implies unreasonable recovery rates, say negative or close to 1. We note that in the CG model, the expected default barrier level is given by $\overline{L}D$, where $\overline{L}$ is exogenously specified. However, the literature on structural models suggests that both D and $\overline{L}$ should depend on the fundamental characteristics of the firm.[15] For example, low risk firms (characterized by low asset volatility) should take on more debt and in particular more short-term debt. Presumably, a higher proportion of short-term debt in the capital structure should correspond to a higher default barrier, other things being equal. In any case, it seems appealing on both theoretical and practical grounds to assume a fixed debt recovery rate R and let the data speak to the value of $\overline{L}$. Following this prescription, we fit the 10 daily CDS spreads prior to the start of the sample period to the CG model by minimizing the sum of squared pricing errors over $\overline{L}$. We find that the implied $\overline{L}$ is equal to 0.83. Plugging this estimate along with the above assumed parameters into the CG model, we then compute the theoretical CDS spread for Altria.

[Insert Figure 1 here.]

Figure 1 compares the theoretical and market CDS spreads for the Altria Group. For ease of comparison, it also shows the Altria equity price and equity volatility during the same period. Two key observations are noted from this figure. First, comparing the market spread in the first panel and the equity price in the second panel, there appears to be a negative association between the two. In fact, Table 1 confirms that the correlation between changes in CDS spread and the equity price for Altria is -0.46. In particular, the three episodes of rapidly rising CDS spreads are all accompanied by falling equity prices. Meanwhile, the 1,000-day historical equity volatility presented in the third panel appears quite stable throughout the sample period. Second, despite calibrating the model using only the first ten observations, for the entire sample period of 18 months the predicted spread stays quite close to the market spread and roughly follows the same trend. One key difference between the two, however, is that the predicted spread appears much less volatile. During the three episodes of rising market spreads, the predicted spread increases as a result of falling Altria share prices, but the increase pales in comparison to the galloping market spread. For example, when Moody's downgraded Altria from A2 to Baa1 on March 31, 2003, the market spread rose from 222bp the previous day to 299bp, while the predicted spread went up only 12bp. Four days later, the market spread again rose 111bp in one single day, while the predicted spread increased by only 9bp. These are exactly the sort of trading opportunities that capital structure arbitrageurs feed on.

[15] For example, see Leland (1994) and Leland and Toft (1996).

We next conduct a simulated trading exercise following the ideas laid out in Section 2. For each of the 245 days in the Altria sample period (excluding the first ten days used to calibrate the model), we check whether the market spread and the predicted spread differ by more than a threshold value. If so, then a CDS position is entered into along with its equity hedge using the hedge ratio from the CreditGrades model. This position is held for a fixed number of days or until convergence, where convergence is defined as the absolute difference between the market and model spreads being less than one half the threshold value. To make the trading exercise more realistic, the positions are liquidated when their value declines by more than 20 percent from the initial level.[16]

[Insert Table 2 here.]

Table 2 presents the summary statistics for the holding period returns. Sixteen trading strategies are simulated. Among these, we vary the size of the hedge ratio, the length of the holding period, and the threshold value required to initiate a trade. If the results are suggestive of a clear pattern, it is that the trading strategy is very risky. At the beginning of the sample period, the Altria model spread stood at 160bp and close to the market spread by design. However, the two diverged from each other shortly thereafter. Using a threshold value of 40bp, 196 trades are made out of a possible total of 245. Out of these trades, the maximum holding period return is 180 percent, and the minimum is -59 percent despite having the early liquidation criterion in place. Another indication of the risk involved in the trades is that only two of the 196 trades ended in convergence, and 48 were liquidated early because the positions suffered more than 20 percent losses. Therefore, a difference between the market and model spreads of 40bp does not appear to be a reliable indicator of mispricing across the CDS and equity markets.

When the threshold value is raised to 80bp, 120bp, and eventually to 160bp, another pattern becomes clear. Because of the higher hurdle value, a smaller number of trades are made. However, the mass of the distribution of the holding period returns shifts to the right, generating higher mean returns. This shift in the distribution is most evident in Figure 2, which illustrates the histograms of the holding period returns. The fraction of trades ending in convergence and the

[16] As in Liu and Longstaff (2004), we impose this condition to mimick the constraints commonly faced by hedge funds. Unlike the swap-spread arbitrage where such constraints are rarely binding, a large fraction of the trades here are liquidated earlier due to this criterion. The risk involved in capital structure arbitrage is understandably much higher than swap-spread arbitrage.

fraction of trades with positive returns are also higher. These results, when taken together, seem to suggest that one should trade only on "exceptionally large" differences between the market and the model spreads. However, we should caution that even for the most optimistic cases, there is still a significant likelihood of negative returns.

Upon closer inspection of the trading simulation, most of the trades with positive returns are made in April and July-August 2003, when the Altria market spread shot up but the model spread remained stable. Ironically, most of the trades with large negative returns are also made during these periods. This is because the market spread may continue to go up after the trades are entered into. For example, with the threshold at 80bp, a short CDS position and a short equity hedge are initiated on April 1, 2003 and terminated three days later because of the early liquidation trigger. The market spread increased by 103bp during these two days while the equity price also increased by $0.20, rendering the hedge ineffective and producing a return of -59 percent, the minimum return of all 16 trades for this scenario.

While the equity hedge would never be effective for the April 1 trade, Table 2 presents some evidence on the overall effectiveness of the equity hedge for the whole sample period. Specifically, it shows that by doubling up on the hedge ratio from the CG model, the variation in the holding period returns becomes more moderate. For Altria, rapidly rising CDS spreads are generally accompanied by falling equity prices during the sample period. A larger equity hedge would clearly be beneficial in these instances, but we note that the maximum returns are mitigated as well.

One may rightly be concerned that the evidence here pertains to just one issuer. After all, in all three cases where the Altria market spread diverged from the model spread, they eventually converged. Not having the early liquidation criterion would in fact lead to higher average returns precisely for this reason. However, what if the market spread had continued to rise in April 2003, possibly leading to bankruptcy and (perhaps more relevantly) the collapse of the CDS market for Altria? These concerns can only be addressed by examining a broader sample, as we do in the next section.

4 General Trading Results

In this section we replicate the preceding trading strategy for all 33 obligors. Ideally, we should set aside a part of the sample period for each obligor. We could use this sub-sample to analyze the difference between the market spread and the model spread, which helps to tailor the trading strategy to each obligor. Among other parameters, such an analysis would help to determine the threshold value required for entering a trade. However, as Section 3 shows, the sample size is limited even for obligors with the most generous coverage. Therefore, we follow the example of Altria and set a fixed threshold for all obligors. Specifically, a trade is initiated whenever the absolute difference between the two spreads exceeds 0.25, 0.5, or 0.75 times the model spread. The trade is liquidated when the absolute difference between the two spreads becomes less than one half the initial threshold value, the value of the positions drops below 80 percent of the initial investment, or the holding period reaches 28 calendar days, whichever occurs first. In the case of shorting equity, the margin is assumed to be 100 percent. The margin account and all intermediate cash flows, such as dividends and CDS premiums paid or received, are assumed to earn or be financed at the risk-free rate.

[Insert Tables 3-4 and Figures 3-4 here.]

The results of this trading exercise are summarized in Tables 3-4 and Figures 3-4, which contain the average holding period return for each obligor and the histogram of the holding period returns across all obligors. First, we notice that the results are qualitatively similar to those obtained for the Altria Group. Namely, the holding period returns are extremely volatile, the average returns increase with the trading threshold, and the returns become less volatile when the size of the equity hedge is increased. Specifically, Table 3 shows that 18 out of 31, 17 out of 27, and 14 out of 20 cases have positive average holding period returns when the threshold is set to 25, 50, and 75 percent, respectively. The corresponding average return across all obligors is -0.99, -0.53, and 4.10 percent. The standard deviation of the returns is in the range of 30 to 40 percent, fairly large for the holding period under consideration, which is generally less than a month.[17] Figures 3-4 show that the distribution of the returns shifts to the right when the threshold value is increased and becomes tighter when the hedge ratio is doubled. Table 4 shows that doubling the hedge ratio roughly cuts the standard deviation of the returns in half while leaving the average returns unchanged.

[Insert Figure 5 here.]

[17]Later on we shall construct monthly returns from capital structure arbitrage more carefully. Because we impose a 28-day holding period in the trading exercise, the realized holding period is usually less than or close to one month.

Since our sample is not large, we inspect the CDS spreads for each obligor. We find that the obligors can be roughly separated into three categories. In the first category, the market and model spreads are tightly integrated. In instances where the market spread deviates from the model spread, the former invariably comes back to the "correct" level. This category includes, among others, Interpublic, MGM Mirage, and Walt Disney, which are illustrated in Figure 5.[18] The feature common to these obligors is that the market spread shows occasional spikes, only to quiet down a short period later. In other words, the market at times becomes concerned about the credit quality of these companies, but they eventually survived (at least during the sample period that we have). As expected, this group consistently produces positive returns.

[Insert Figure 6 here.]

For companies in the second category, their market spread and model spread are tightly linked only up to a point, after which they diverge from each other. This group includes, among others, Sprint, Time Warner, and Worldcom, which are illustrated in Figure 6. In the first two cases, the spreads eventually converge to each other, but not before several months have passed with no CDS trading in the interim. For Worldcom, the sample period ends with its CDS spread above 1,400bp and the company at the brink of bankruptcy. Anyone who followed the type of capital structure arbitrage described in this paper would have suffered huge losses, as is evident from Tables 3-4.

Interestingly, the CreditGrades Technical Document (2002) contains a case study on Worldcom, which shows that if one longs CDS and equity (with an appropriate hedge ratio) in September 2001 and terminates the positions in March 2002 he would boast a 79 percent return. Indeed, following our criteria a long CDS and equity position is entered into on October 5, 2002 when the market spread was 172bp and the CG model spread was 229bp, both of which are very close to the numbers given in the CGTD case study. However, the trade is terminated on October 26 when the market spread rose to 202bp and the model spread remained at 226bp, producing a return of 20 percent. Thereafter, the market spread continued to rise and a large positive deviation from the theoretical spread appeared. Following our criteria one should short CDS and equity, which would have generated heavy losses given the subsequently skyrocketing market spread. The point here is that ex post it is easy to justify buying and holding credit protection before Worldcom ran into trouble.

[18] The Altria Group, which is the subject of Section 4, also falls into this category.

But doing so would be inconsistent with a disciplined application of the basic principles of capital structure arbitrage, i.e., entering a trade on a large deviation between the market and the model and liquidating when the gap disappears. Instead, the strategy presented in the CGTD case study is basically a gamble that Worldcom will not survive.

One may wonder whether the equity hedge can be an effective tool against the above scenario. We compute the hedge ratio which would break even in the case of bankruptcy by assuming a recovery rate of 50 percent and an equity price of zero. Generally such hedge ratios are many times larger than that implied from the CG model. We repeat the trading simulation using these larger hedge ratios. We find that although the losses are mitigated and the returns have lower standard deviations, the average return across all obligors has not increased.

[Insert Figure 7 here.]

Finally, we note that some obligors seem to belong to a third category, where the trading strategy is perhaps confounded by model misspecification. Figure 7 illustrates the CDS spreads of Cendant, Schering-Plough, and Wyeth. Here we see that after the first ten observations which are used in calibrating the CG model, the market and model spreads start to drift apart in a smooth manner in the absence of any major shock to either series. This observation leaves model specification as the most likely explanation to the prevalence of negative returns for these obligors—we may simply be trading on the wrong signals.

5 Sources of the Returns

The analysis of trading returns in the preceding section suggests that capital structure arbitrage works well when the market spread and the theoretical spread follow each other closely. Occasional deviations are the source of trading profits as long as they are only temporary. Large and prolonged deviations, however, are responsible for the deep losses presented in Tables 3-4. Apart from the obvious consequences from not converging, such a scenario makes it difficult to set an appropriate threshold level for initiating a trade. Many losses, in fact, occur because the trade is initiated too early when the market spread is rising rapidly. Moreover, the equity position is only an instantaneous hedge which becomes ineffective when there are large changes in the spread. These observations suggest that the risk facing a capital structure arbitrageur is no different from the systematic default risk facing a bond investor. In other words, companies can become financially distressed. But when the economy-wide default risk is low, many of these companies will eventually recover. This will not be the case when the economy-wide default risk is high. Therefore, it may be informative to examine the relationship between capital structure arbitrage returns and some of the well known common risk factors.

Before conducting such an analysis, we first aggregate the individual trading returns into a time-series of monthly portfolio returns. Take the first column of Table 3 as an example. With a threshold of 25 percent there are a total of 2,273 trades, the first of which is initiated on April 20, 2001 and the last of which on July 13, 2004. Recalling that a trade is terminated whenever the spreads converge, trading loss exceeds 20 percent, or the holding period exceeds 28 calendar days, the realized holding period for each trade is variable. If the holding period is greater than 30 days, we convert the return to 30 days by daily compounding.[19] If the holding period is less than 30 days, we assume that the balance is invested at the risk-free rate for the remainder of 30 days. For all trades initiated in a given month, we compute the equally-weighted average of all converted 30-day returns.

[Insert Table 5 here.]

Table 5 summarizes the resulting monthly returns from the trading strategy with various combinations of the hedge ratio and trading threshold. Take the first row as an example. When the hedge ratio is set to the CG model value and trades are initiated at a 25 percent threshold level, the mean monthly excess return is 1.87 percent with a standard deviation of 16.47 percent. This translates into an annualized Sharpe ratio of 0.39. When the threshold level is increased, the number of monthly returns and the average number of trades per month both decrease—some months no longer contain a trade due to the smaller total number of trades initiated. The mean return, however, increases substantially when the threshold is raised to 75 percent, yielding a Sharpe ratio well above one. Among other observations, the returns show no significant autocorrelation. Although ρ is somewhat positive for the 75 percent threshold level, none of the autocorrelations are significant at the five percent level. We also note that both the mean return and the standard deviation decrease and the Sharpe ratio remains stable when the size of the hedge is increased,

[19] Although the trades are liquidated when the holding period exceeds 28 calendar days, the days with CDS quotes may be several days apart, thus the possibility of holding periods longer than 30 days.

which supports the evidence from all trades in Table 4.

Additionally, we test whether the trading returns give rise to statistical arbitrage following the procedure prescribed by Hogan, Jarrow, Teo, and Warachka (2004). A statistical arbitrage is a zero initial cost self-financing trading strategy with positive expected discounted profits, a probability of a loss converging to zero, and a time-average variance converging to zero. We apply their constrained mean test to the 40 monthly returns from capital structure arbitrage.[20] Specifically, denoting the capital structure arbitrage return in month i as r_i and and risk-free rate in month i as r_i^f, we start by borrowing one dollar at r_i^f and investing it at r_i. This is repeated each month with the profit from the previous month invested at the risk-free rate. The total profit V_i at month i then satisfies $V_i = r_i - r_i^f + V_{i-1}\left(1 + r_i^f\right)$. This profit is discounted back to the starting point to produce the incremental discounted profit Δv_i, for which we perform the test of statistical arbitrage. With only 40 monthly returns, we find that none of the trading returns give rise to statistical arbitrage at conventional significance levels. However, among the six strategies tested, four yield point estimates of the expected return and the rate of decay for the variance of Δv_i that are of the correct sign. As data coverage continues to expand, we expect this test to produce a more meaningful inference on the long-horizon profitability of the trading strategy.

With the monthly portfolio returns, we can now investigate the relationship between capital structure arbitrage profitability and systematic risk factors. In particular, we use the excess return on the S&P Industrial Index to proxy for equity market risk and the excess return on the Lehman Industrial Bond Index to proxy for corporate bond market risk. In addition, we include the excess return on the CSFB/Termont Fixed Income Arbitrage Index.[21] Liu and Longstaff (2004) show that this index is related to the return on their swap-spread arbitrage strategy, which basically longs an interest rate swap and shorts a Treasury bond. All monthly excess returns are constructed by subtracting the three-month T-bill rate.

[Insert Table 6 here.]

Unfortunately, since CDS trading is a relatively new phenomenon, our sample size for the monthly returns is small. Consequently the regression results in Table 6 are not definitive. Nevertheless, in general we can see that the capital structure arbitrage returns are positively related

[20] Whenever a monthly return is missing, we fill it with the risk-free rate.

[21] The additional variables used in this section are taken from Datastream.

to the Lehman Industrial Bond Index return and the Fixed Income Arbitrage Index return. The relation with equity market return, however, appears to be the weakest. In addition, in most cases the intercept is positive and large compared to the mean return presented in Table 5, which suggests that a major component of the return is unrelated to these market factors.

6 Robustness of the Results

The trading returns depend on how the model is implemented. With regard to this we have attempted the following. First, for the obligors with more than one string of continuous spread coverage, we estimate the CG model at the beginning of each string using the first five daily spreads. Recall that in the original implementation, we use the first ten daily spreads for the calibration and the model parameters are then fixed for that obligor. Re-calibrating the default threshold level can help avoid model misspecification, particularly if the two strings are well separated in time. In the case of Sprint, the second string appears more than a year after the first string ended (see Figure 6), and by that time the company has undergone a major restructuring. Evidently this is the reason why there is a significant gap between the market and model spreads for the entire duration of the second and third strings for Sprint. We find, however, that this re-calibration procedure does not qualitatively change our results. The number of trades declines as expected because of the tighter fit, but the size of the returns has not changed much.

Second, in calculating the hedge ratio and the market value of the CDS position we have used the implied asset volatility that would force the CG spread to be equal to the market spread. Purely on theoretical grounds we could have chosen the historical volatility estimator instead. When we apply this alternative method, we find that many of the losses when selling CDS are amplified. This is because when the market spread is above the model spread the alternative would generally underhedge. Moreover, the default probability corresponding to the model spread is less than the implied default probability, and the market value of the survival-contingent annuity is thus overstated. Of course, this bias is reversed if one buys CDS as the market spread drops below the model spread, but the first scenario appears much more often in our sample and as explained in Section 5, is responsible for most of the large trading losses. Overall, this alternative calculation results in slightly smaller trading profits.

Third, we acknowledge that trading cost (on the order of 18 percent of the CDS spread, as shown in Section 3) can significantly reduce trading profits. If every trade ends in convergence, trading cost would not be a major problem, for one can compensate for the trading costs by setting a higher initial threshold and a lower threshold for liquidation. However, as we have seen in the case of Altria, most of the trades in fact do not end with convergence of the spreads. Instead, they may end in forced liquidation as the market value of the positions declines dramatically, or when the pre-specified holding period (say, 28 calendar days) ends. We repeat the simulated trading exercise taking into account a 10 percent bid/ask spread. We find that almost none of the obligors in our sample yields a positive average return regardless of the initial threshold level. Therefore, the trading profit vanishes for someone who has to face the bid/ask spread in the CDS market.[22]

7 Conclusion

This paper examines the profitability of capital structure arbitrage, a new niche widely exposed in the financial press. While the media accounts give the impression that there is nothing to lose, we attempt to conduct the most comprehensive study of capital structure arbitrage returns to date. We find, however, that our study is limited by several important constraints. First, from a time-series perspective the CDS market data coverage is still quite sparse. Using 249,539 intra-daily quotes on North American Industrial obligors from CreditTrade, we eventually obtained only 33 obligors with relatively continuous daily spread coverage from April 2001 to July 2004, which constitutes the sample used in this study. Second, to conduct simulated trading there has to be secondary market quotes and market values for existing contracts. The latter simply do not exist and the former are lacking in the early part of the sample, which consists exclusively of quotes on newly initiated contracts. Therefore, certain compromises have to be made in using the available data. Last but not least, we focus on an implementation using one particular structural model—the CreditGrades model, and for inputs to the model we use historical equity volatility and balance sheet information from Compustat quarterly files. Specifically, we enter a trade when the gap between the market spread and the CG model spread reaches a threshold level. We liquidate when the gap goes down to a certain level, the mark-to-market/model value of the positions declines by more than 20 percent, or the holding period exceeds 28 calendar days.

[22] Of course, our analysis suggests that it could be profitable for CDS market makers who do not bear the trading costs.

Despite the numerous difficulties listed above, we obtain several interesting results. First, we find that capital structure arbitrage is generally very risky. The most promising version of the trading strategy yields an average monthly excess return of ten percent with an annualized Sharpe ratio of 1.54, although the maximum loss in any given month can be as high as 33 percent. We find that most of the losses occurred when the arbitrageur shorts CDS and finds the market spread to be subsequently skyrocketing, at which point hedging becomes ineffective, CDS trading ceases, and the arbitrageur is forced to liquidate. This is true in several cases when the obligor later underwent bankruptcy filing or restructuring. Based on this observation, we examine the relationship between monthly trading returns and systematic risk factors. We find that the returns are positively related to the returns on the Lehman Industrial Index and the CSFB/Termont Fixed Income Arbitrage Index. However, a significant part of the trading return is unrelated to these factors.

Admittedly, the second finding is based on weak statistical significance because of the small sample period (40 months between 2001 and 2004), and the trading returns are not robust to the inclusion of CDS trading costs, which can be a significant part of the market spread. However, it is our hope that this paper will provide the impetus to future studies with better data coverage and improved methodology.

A CreditGrades Model

This appendix contains a summary of the CreditGrades model, including its basic assumptions and the requisite formulas for implementing the trading strategy described in the main text. Further details about the model can be found in the CreditGrades Technical Document (2002).

The CreditGrades model assumes that under the pricing measure the firm's value per equity share is given by

$$\frac{dV_t}{V_t} = \sigma dW_t, \tag{8}$$

where W_t is a standard Brownian motion and σ is the asset volatility . The firm's debt per share is a constant D and the default threshold is

$$LD = \overline{L}De^{\lambda Z - \lambda^2/2}, \tag{9}$$

where L is the (random) recovery rate given default, $\overline{L} = E(L)$, Z is a standard normal random variable, and $\lambda^2 = var(\ln L)$. The variable L represents the global recovery on all liabilities of the firm, while R defined in the main text is the recovery on a specific debt issue which constitutes the underlying asset for the credit default swap. Note also that the firm value process is assumed to have zero drift. This assumption is consistent with the observation of stationary leverage ratios and the model of Collin-Dufresne and Goldstein (2001).

Default is defined as the first passage of V_t to the default threshold LD. The density of the default time can be obtained by integrating the first passage time density of a geometric Brownian motion to a fixed boundary over the distribution of L. However, CreditGrades provides an approximate solution to the survival probability using a time-shifted Brownian motion, yielding the following result:[23]

$$q(t) = \Phi\left(-\frac{A_t}{2} + \frac{\ln d}{A_t}\right) - d \cdot \Phi\left(-\frac{A_t}{2} - \frac{\ln d}{A_t}\right), \tag{10}$$

where $\Phi(\cdot)$ is the cumulative normal distribution function,

$$\begin{aligned} d &= \frac{V_0}{\overline{L}D}e^{\lambda^2}, \\ A_t^2 &= \sigma^2 t + \lambda^2. \end{aligned}$$

[23]The approximation assumes that W_t starts not at $t = 0$, but from an earlier time. In essence, the uncertainty in the default threshold is shifted to the starting value of the Brownian motion. As a result, even for very small t (or even $t = 0$, for that matter) the default probability is not equal to 0. While this may be a practical way to increase short-term default probability, a theoretically more appealing approach is given by Duffie and Lando (2001).

Substituting $q(t)$ into Eq. (5) and assuming constant interest rate r, the CDS spread for maturity T is given by

$$c(0,T) = r(1-R)\frac{1-q(0)+H(T)}{q(0)-q(T)e^{-rT}-H(T)}, \tag{11}$$

where

$$\begin{aligned} H(T) &= e^{r\xi}\left(G(T+\xi)-G(\xi)\right), \\ G(T) &= d^{z+1/2}\Phi\left(-\frac{\ln d}{\sigma\sqrt{T}}-z\sigma\sqrt{T}\right)+d^{-z+1/2}\Phi\left(-\frac{\ln d}{\sigma\sqrt{T}}+z\sigma\sqrt{T}\right), \\ \xi &= \lambda^2/\sigma^2, \\ z &= \sqrt{1/4+2r/\sigma^2}. \end{aligned}$$

Normally, the equity value S as a function of firm value V is needed to relate asset volatility σ to a more easily measurable equity volatility σ_S. Instead of using the full formula for equity value, CreditGrades uses a linear approximation $V = S + \overline{L}D$ to arrive at

$$\sigma = \sigma_S \frac{S}{S+\overline{L}D}. \tag{12}$$

To find the value of an existing contract using Eq. (6), we need an expression for $q_t(s)$, the survival probability through s at time t. In structural models with uncertain but fixed default barriers, the hazard rate of default is zero unless the firm value is at its running minimum. Therefore, although the uncertain recovery rate assumption in the CreditGrades model may help increase short-term default probabilities at one point in time, it cannot do so consistently through time. To circumvent this problem we assume that t is small compared to the maturity of the contract T. The value of the contract is then approximated by

$$\begin{aligned} V(0,T) &= \left(c(0,T)-c\right)\int_0^T e^{-rs}q(s)\,ds \\ &= \frac{c(0,T)-c}{r}\left(q(0)-q(T)e^{-rT}-e^{r\xi}\left(G(T+\xi)-G(T)\right)\right). \end{aligned} \tag{13}$$

In this expression, c is the CDS spread of the contract when it was first initiated, and $c(0,T)$ is a function of the equity price S as shown in Eq. (11). The proper way to understand Eq. (13) is that it represents the value of a contract which was entered into one instant ago at spread c but now has a quoted spread of $c(0,T)$ due to changes in the equity price.

By Eqs. (7) and (13), the hedge ratio is given by

$$\delta\left(0,T\right)=\frac{1}{r}\frac{\partial c\left(0,T\right)}{\partial S}\left(q\left(0\right)-q\left(T\right)e^{-rT}-e^{r\xi}\left(G\left(T+\xi\right)-G\left(T\right)\right)\right), \tag{14}$$

because by definition c is numerically equal to $c\left(0,T\right)$, which corresponds to an equity price of S. We then differentiate $c\left(0,T\right)$ numerically with respect to S to complete the evaluation of δ.

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OBLIGOR	RTNG	N	CDS	SPD	VOL	LEV	SIZE	CORR
Alltel	-	48	55	13	0.293	0.383	15,542	-0.10
Altria Group	Baa2	255	200	20	0.390	0.432	92,009	-0.46
AT&T	A3	196	227	27	0.444	0.668	53,580	-0.35
AT&T Wireless	Baa2	225	162	27	0.649	0.425	21,596	-0.32
Baxter Intl	A3	77	45	9	0.372	0.354	18,864	-0.21
Bellsouth	A1	106	38	12	0.369	0.387	47,473	0.08
Bristol-Myers Squibb	A1	101	39	7	0.364	0.263	49,678	-0.26
Caesers Entertainment	Baa3	105	289	82	0.502	0.734	2,506	-0.38
Cardinal Health	A2	64	33	9	0.323	0.273	29,729	-0.68
Carnival	A2	77	95	19	0.500	0.250	14,756	-0.41
Cendant	Baa1	145	254	29	0.548	0.659	12,707	-0.08
Centurytel	Baa2	49	122	18	0.342	0.520	4,128	-0.05
Cox Comm.	Baa2	47	362	25	0.439	0.466	15,526	-0.18
Eastman Kodak	Baa2	118	156	18	0.375	0.585	7,909	-0.12
EDS	Baa3	108	223	24	0.583	0.563	9,746	-0.26
HCA	Ba1	127	132	20	0.339	0.437	19,235	-0.08
Hilton Hotels	Baa3	181	208	56	0.439	0.631	4,278	-0.36
Interpublic	Baa3	73	408	47	0.518	0.713	3,903	-0.24
Liberty Media	Baa3	137	159	15	0.523	0.414	27,181	-0.12
Lockheed Martin	Baa3	40	70	12	0.384	0.598	15,604	0.26
MGM Mirage	Ba1	171	262	71	0.437	0.605	5,111	-0.26
Omnicom	A3	116	132	23	0.428	0.456	11,113	-0.27
Philip Morris	A2	45	181	15	0.380	0.365	99,061	-0.25
RJ Reynold	-	43	326	44	0.364	0.543	5,363	0.03
SBC Comm.	Aa3	48	75	15	0.375	0.367	109,551	0.26
Schering-Plough	A3	96	56	7	0.375	0.229	25,657	-0.17
Sprint	Baa2	275	135	29	0.469	0.413	14,631	-0.29
Time Warner	Baa1	285	156	19	0.637	0.486	67,410	-0.22
TJX	A3	49	88	43	0.493	0.183	10,517	0.09
Viacom	A3	81	65	13	0.459	0.826	6,186	-0.24
Walt Disney	A3	316	85	15	0.428	0.396	39,852	-0.16
Worldcom	A3	157	176	31	0.549	0.533	40,661	-0.21
Wyeth	Baa1	89	69	10	0.380	0.289	51,474	-0.40

Table 1: **Summary statistics for the 33 obligors.** RTNG is the median Moody's credit rating. N is the number of days with mid-market CDS spreads. CDS is the median daily CDS spread is basis points. SPD is the average bid/ask spread in basis points. VOL is the median 1,000-day historical equity volatility. LEV is the median leverage defined as total liabilities divided by the sum of total liabilities and equity market capitalization. SIZE is the median equity market capitalization in millions of dollars. CORR is the correlation between daily changes in the CDS spread and the equity price.

Hedge	HP	Bound	Avg. HP	N	N_1	N_2	N_3	Mean	Min	Max
1	14	40	12.44	196	2	48	78	4.43	-59.19	179.94
1	14	80	11.34	96	2	28	33	9.81	-59.19	179.94
1	14	120	10.28	39	15	7	8	36.77	-59.19	179.94
1	14	160	9.25	16	7	4	4	56.99	-52.19	179.94
1	28	40	20.87	196	6	66	83	4.38	-59.19	149.13
1	28	80	17.86	96	7	34	35	9.04	-59.19	149.13
1	28	120	15.29	39	18	7	7	37.83	-59.19	179.94
1	28	160	12.88	16	8	4	4	54.14	-52.19	179.94
2	14	40	14.14	196	2	13	84	2.14	-40.63	85.43
2	14	80	13.56	96	2	6	30	6.72	-40.63	85.43
2	14	120	11.54	39	15	3	4	21.74	-29.93	85.43
2	14	160	11.50	16	7	1	1	37.74	-23.80	85.43
2	28	40	24.82	196	6	37	84	0.97	-40.63	72.14
2	28	80	23.45	96	10	11	29	6.29	-40.63	72.14
2	28	120	17.26	39	21	3	4	23.44	-29.93	85.43
2	28	160	15.50	16	11	1	1	40.58	-23.80	85.43

Table 2: **Summary statistics of holding period returns for the Altria Group.** Hedge refers to the size of the hedge ratio used in trading, which can be one times or two times the CG model's hedge ratio. HP refers to the length of the holding period, which can be 14 or 28 calendar days. Bound refers to the absolute difference between the market spread and the model spread before a trade can be initiated. Average HP is the length of the average holding period in calendar days. N is the number of trades actually entered into (the total number of possible trades is 245). N_1 is the number of trades ending in convergence, N_2 is the number of trades ending in forced early liquidation, and N_3 is the number of trades with negative holding period returns. Mean, minimum, and maximum are given for the holding period return in percentages.

OBLIGOR	Bound = 0.25			Bound = 0.5			Bound = 0.75		
	N	Mean	Stdev	N	Mean	Stdev	N	Mean	Stdev
Alltel	-	-	-	-	-	-	-	-	-
Altria Group	221	4.41	30.07	108	8.50	37.75	70	19.28	48.82
AT&T	170	-6.44	39.19	147	-5.50	41.74	106	-3.76	46.37
AT&T Wireless	175	-3.20	38.36	155	-0.26	40.02	110	5.67	31.17
Baxter Intl	64	-0.11	6.01	58	1.17	3.28	37	1.34	3.55
Bellsouth	63	4.22	11.04	63	4.22	11.04	60	5.06	10.61
Bristol-Myers Squibb	68	5.04	4.92	62	5.02	5.12	44	6.37	3.36
Caesers Entertainment	33	6.95	43.03	4	42.53	59.43	-	-	-
Cardinal Health	40	-7.27	8.96	27	-5.68	9.55	2	-1.86	5.37
Carnival	4	8.12	2.39	-	-	-	-	-	-
Cendant	117	-11.94	13.20	34	-4.14	12.22	-	-	-
Centurytel	39	3.89	7.29	38	3.97	7.37	15	10.29	5.88
Cox Comm.	13	-8.28	18.97	1	4.55	-	-	-	-
Eastman Kodak	33	16.69	22.02	-	-	-	-	-	-
EDS	74	11.21	14.00	16	22.63	9.94	-	-	-
HCA	82	2.22	10.00	58	4.94	10.06	14	15.91	6.32
Hilton Hotels	119	-9.54	46.08	60	0.01	54.18	25	49.09	83.85
Interpublic	14	20.72	92.75	1	207.57	-	1	163.58	-
Liberty Media	28	10.40	11.12	-	-	-	-	-	-
Lockheed Martin	-	-	-	-	-	-	-	-	-
MGM Mirage	81	8.23	39.13	22	15.40	43.19	6	9.18	5.39
Omnicom	65	-8.19	11.00	37	-0.43	6.81	-	-	-
Philip Morris	29	7.45	12.25	23	4.22	9.05	3	10.85	3.19
RJ Reynold	25	7.83	13.63	21	11.97	8.93	-	-	-
SBC Comm.	24	9.70	19.33	4	23.95	7.45	-	-	-
Schering-Plough	67	-2.72	8.87	53	-3.88	9.26	21	-6.66	7.47
Sprint	212	-8.66	25.33	158	-7.23	27.35	59	-14.32	38.65
Time Warner	141	-3.48	31.05	50	-0.51	22.26	36	1.43	51.73
TJX	6	47.45	26.94	-	-	-	-	-	-
Viacom	47	2.71	30.37	13	10.21	5.11	2	32.29	5.14
Walt Disney	121	7.22	18.58	6	23.85	4.77	1	30.85	-
Worldcom	49	-12.72	93.61	15	-91.30	124.30	4	-45.91	173.93
Wyeth	49	-14.97	21.57	36	-15.88	24.14	31	-12.47	23.79
All obligors	2273	-0.99	31.75	1270	-0.53	34.79	647	4.10	38.26

Table 3: **Summary statistics of holding period returns for all obligors.** Bound refers to the trigger level of the absolute difference between the market and model spreads as a percentage of the model spread. N is the number of trades entered into. Mean and standard deviation are given for the holding period return in percentages. The hedge ratio is set to the CG model value. The pre-specified holding period is 28 calendar days.

	Bound = 0.25			Bound = 0.5			Bound = 0.75		
OBLIGOR	N	Mean	Stdev	N	Mean	Stdev	N	Mean	Stdev
Alltel	-	-	-	-	-	-	-	-	-
Altria Group	221	0.98	17.07	108	5.21	19.79	70	13.49	24.75
AT&T	170	-4.36	20.45	147	-3.55	21.56	106	-1.45	23.10
AT&T Wireless	175	-0.30	20.69	155	1.91	19.01	110	7.32	12.31
Baxter Intl	64	-0.10	3.55	58	0.31	3.23	37	0.43	3.45
Bellsouth	63	2.87	6.63	63	2.87	6.63	60	3.33	6.42
Bristol-Myers Squibb	68	3.37	4.40	62	2.86	4.26	44	4.11	3.03
Caesers Entertainment	33	-0.59	21.61	4	20.92	20.08	-	-	-
Cardinal Health	40	0.34	4.16	27	2.35	4.80	2	11.21	2.89
Carnival	4	4.18	1.45	-	-	-	-	-	-
Cendant	117	-4.35	10.76	34	3.55	7.43	-	-	-
Centurytel	39	1.09	3.32	38	1.09	3.37	15	4.02	2.38
Cox Comm.	13	-3.25	9.60	1	1.94	-	-	-	-
Eastman Kodak	33	5.22	5.54	-	-	-	-	-	-
EDS	74	4.84	7.93	16	14.02	8.80	-	-	-
HCA	82	1.27	4.70	58	2.45	4.63	14	7.84	3.53
Hilton Hotels	119	-8.00	25.03	60	-3.21	30.62	25	23.78	27.54
Interpublic	14	2.19	51.94	1	102.42	-	1	84.42	-
Liberty Media	28	7.65	5.65	-	-	-	-	-	-
Lockheed Martin	-	-	-	-	-	-	-	-	-
MGM Mirage	81	1.91	19.67	22	6.81	22.46	6	5.36	2.84
Omnicom	65	-4.32	8.08	37	0.71	4.09	-	-	-
Philip Morris	29	6.45	4.77	23	6.00	4.05	3	8.97	2.27
RJ Reynold	25	2.50	6.95	21	4.83	4.21	-	-	-
SBC Comm.	24	8.09	8.16	4	13.03	4.64	-	-	-
Schering-Plough	67	-2.22	6.12	53	-3.06	6.21	21	-6.15	4.59
Sprint	212	-4.49	15.68	158	-3.57	16.74	59	-7.85	23.39
Time Warner	141	-2.63	20.28	50	-2.72	27.59	36	-1.33	28.51
TJX	6	25.70	15.00	-	-	-	-	-	-
Viacom	47	1.03	8.12	13	10.35	9.05	2	25.73	1.83
Walt Disney	121	3.06	8.53	6	12.61	4.31	1	16.67	-
Worldcom	49	-10.51	42.33	15	-40.17	60.96	4	-13.58	88.24
Wyeth	49	-4.80	9.02	36	-4.00	9.60	31	-2.50	9.01
All obligors	2273	-0.91	16.97	1270	0.29	18.61	647	3.43	20.28

Table 4: **Summary statistics of holding period returns for all obligors with double the hedge ratio of the CG model.** Bound refers to the trigger level of the absolute difference between the market and model spreads as a percentage of the model spread. N is the number of trades entered into. Mean and standard deviation are given for the holding period return in percentages. The pre-specified holding period is 28 calendar days.

Hedge	Bound	N_1	N_2	Mean	Min	Max	Stdev	ρ	Sharpe
1	25%	40	57	1.87	-46.33	39.53	16.47	0.05	0.39
1	50%	36	35	1.75	-56.83	55.82	20.97	-0.03	0.29
1	75%	28	23	15.65	-58.79	163.70	42.62	0.26	1.27
2	25%	40	57	0.28	-28.27	19.84	9.16	0.03	0.11
2	50%	36	35	1.06	-32.39	31.07	12.35	-0.11	0.30
2	75%	28	23	9.87	-32.57	84.48	22.24	0.38	1.54

Table 5: **Summary statistics for monthly capital structure arbitrage portfolio returns.** Hedge refers to the size of the hedge ratio relative to the CG model. Bound denotes the threshold required for entering into a trade. N_1 is the number of months with at least one trade. N_2 is the average number of trades per month. ρ is the autocorrelation of the monthly returns. The mean, minimum, maximum, and standard deviation are given for the monthly excess returns in percentages. Also given is the annualized Sharpe ratio. The risk-free rate is proxied by the three-month Treasury bill rate.

Hedge	Bound	Intercept	SPIND	LHIND	CSTFA	R^2
1	25%	0.57	-0.63	1.24	4.04	0.090
		0.21	-1.14	0.80	1.39	
1	50%	0.98	0.41	1.56	2.78	0.053
		0.26	0.52	0.77	0.72	
1	75%	14.25	-0.40	7.18	7.93	0.122
		1.65	-0.20	1.52	0.91	
2	25%	-0.54	-0.15	0.52	2.77	0.091
		-0.35	-0.49	0.60	1.71	
2	50%	0.32	0.39	0.67	2.57	0.096
		0.15	0.88	0.57	1.16	
2	75%	8.81	-0.05	3.63	5.11	0.137
		1.98	-0.04	1.49	1.13	

Table 6: **Regression of monthly capital structure arbitrage portfolio returns.** Hedge refers to the size of the hedge ratio relative to the CG model. Bound denotes the threshold required for entering into a trade. SPIND is the monthly excess return on the S&P industrial index. LHIND is the monthly excess return on the Lehman industrial bond index. CSTFA is the monthly excess return on the CSFB/Tremont fixed income arbitrage index. The t-statistics are given below the estimates.

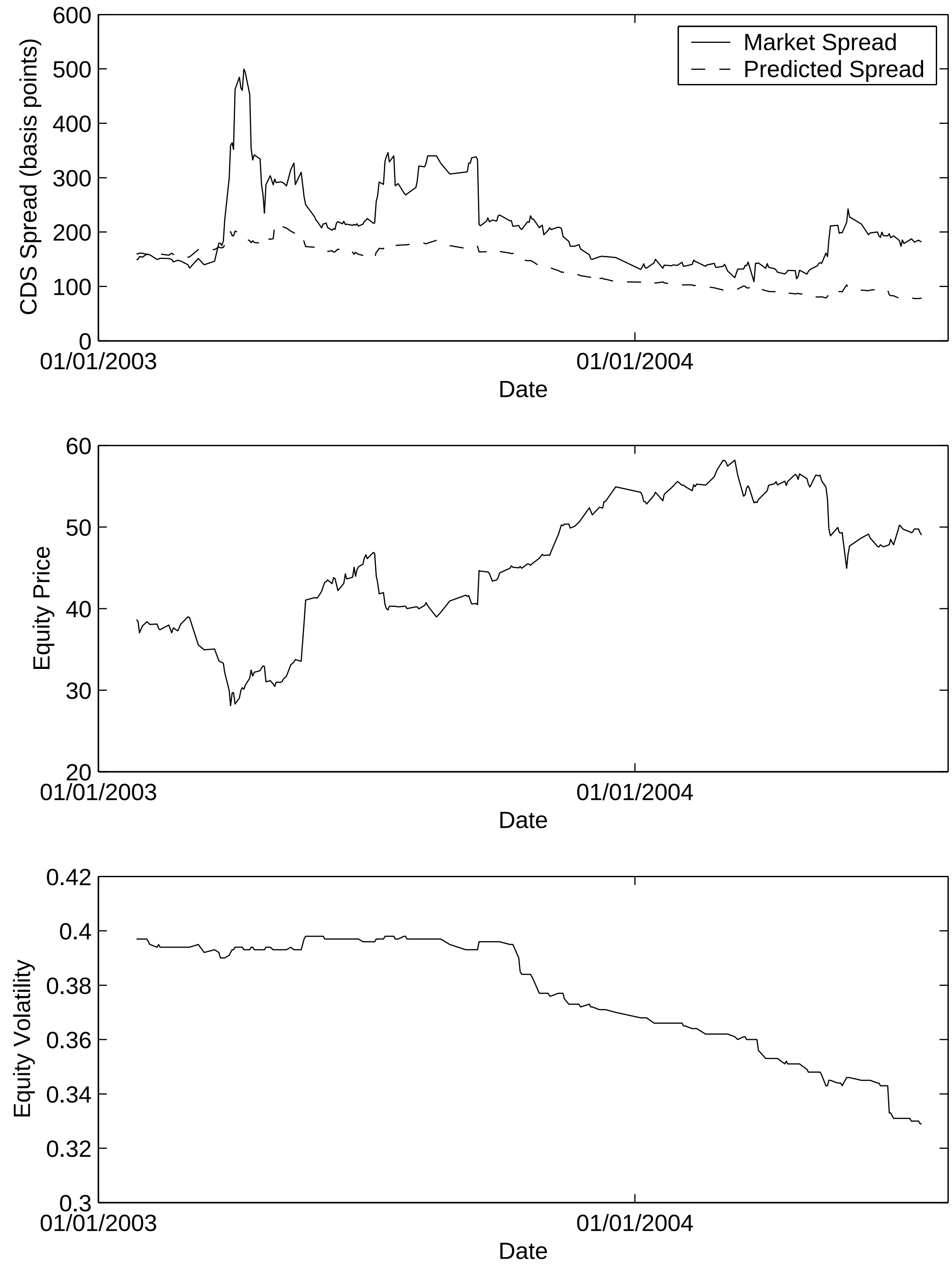

Figure 1: **Time-series of CDS spread, equity price, and equity volatility for the Altria Group from 01/27/03 to 07/14/04.** The top panel plots the market spread as well as the predicted spread from the CreditGrades model. The middle panel presents the equity price. The bottom panel presents the 1,000-day historical equity volatility.

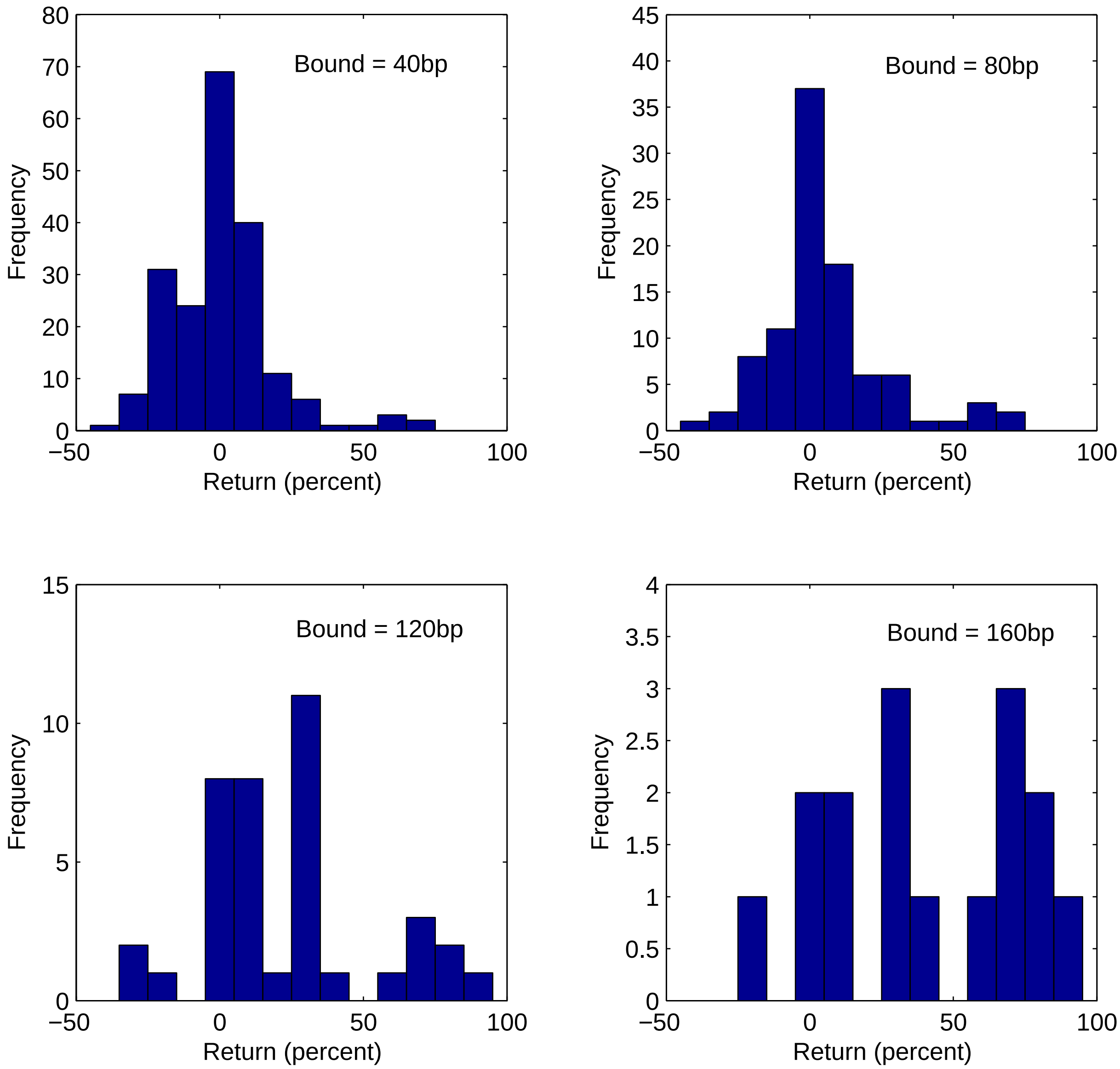

Figure 2: **Histograms of holding period returns for the Altria Group.** The panels are generated by assuming a 28-day holding period, a hedge ratio given by the two times the hedge ratio of the CG model, and a threshold value equal to 40bp, 80bp, 120bp, and 160bp.

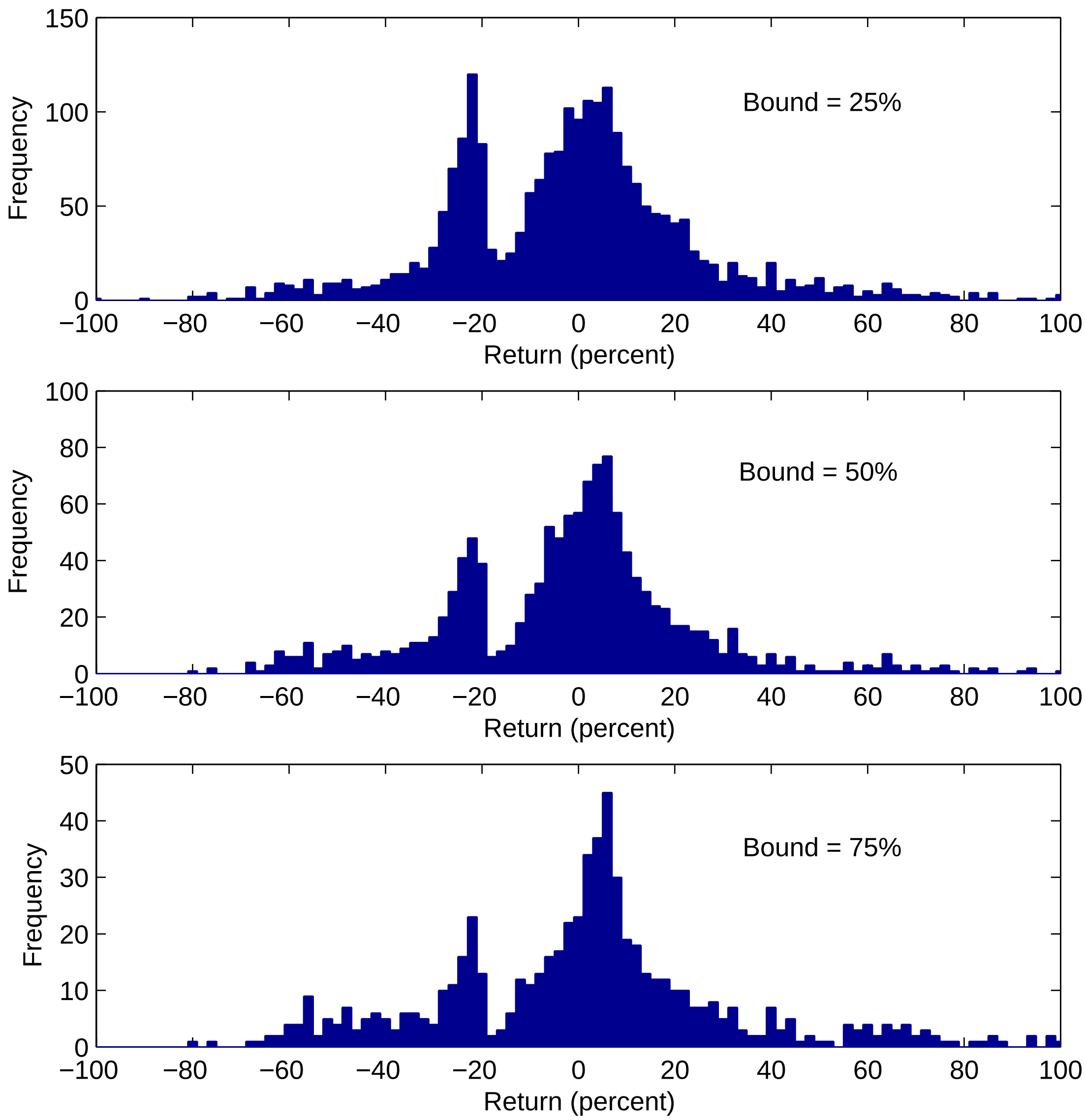

Figure 3: **Histograms of holding period returns for all obligors.** The panels are generated by assuming a 28-day holding period, a hedge ratio given by the CG model, and a threshold value equal to 25 percent, 50 percent, or 75 percent of the model spread.

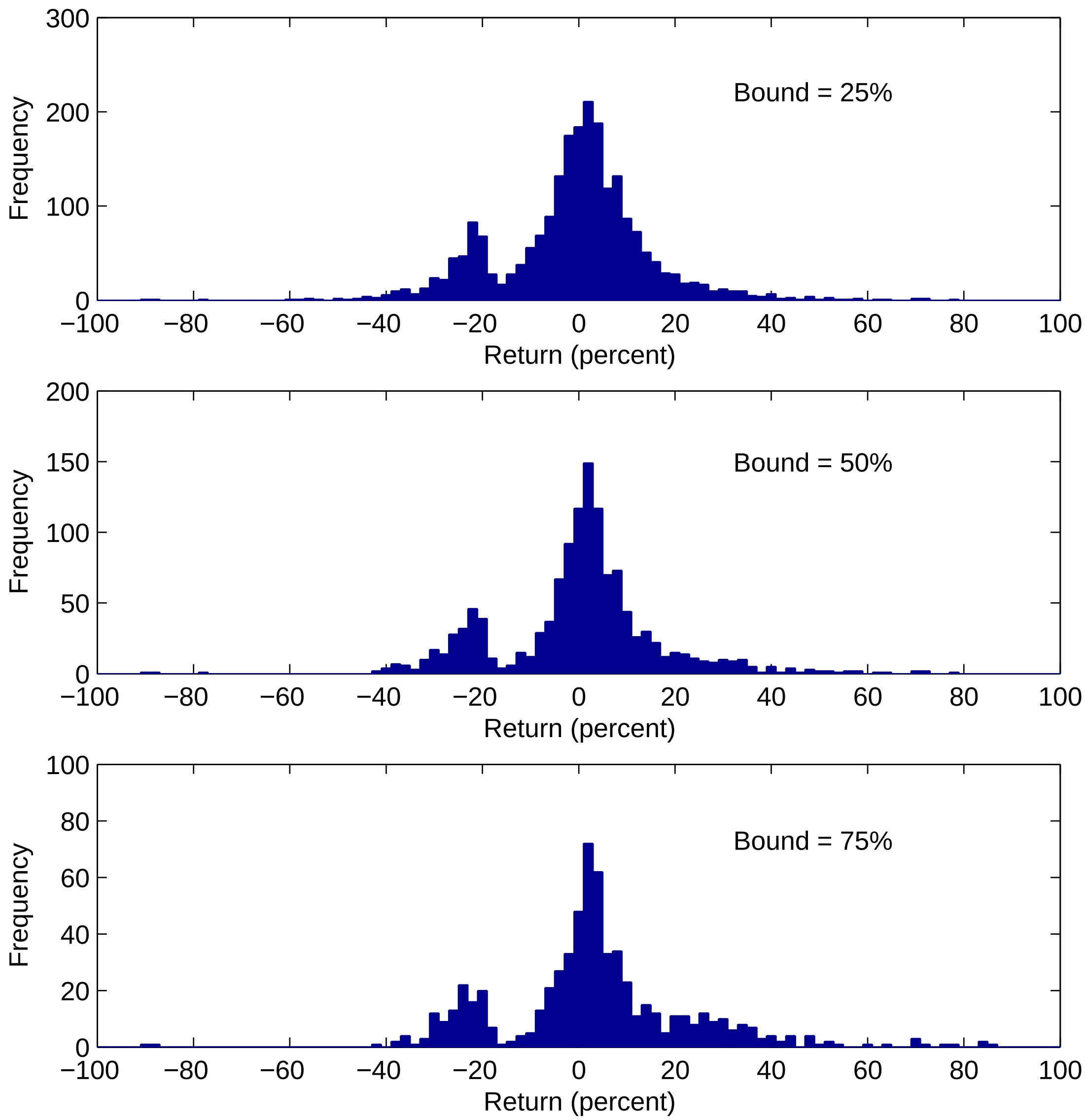

Figure 4: **Histograms of holding period returns for all obligors with double the hedge ratio of the CG model.** The panels are generated by assuming a 28-day holding period, and a threshold value equal to 25 percent, 50 percent, or 75 percent of the model spread.

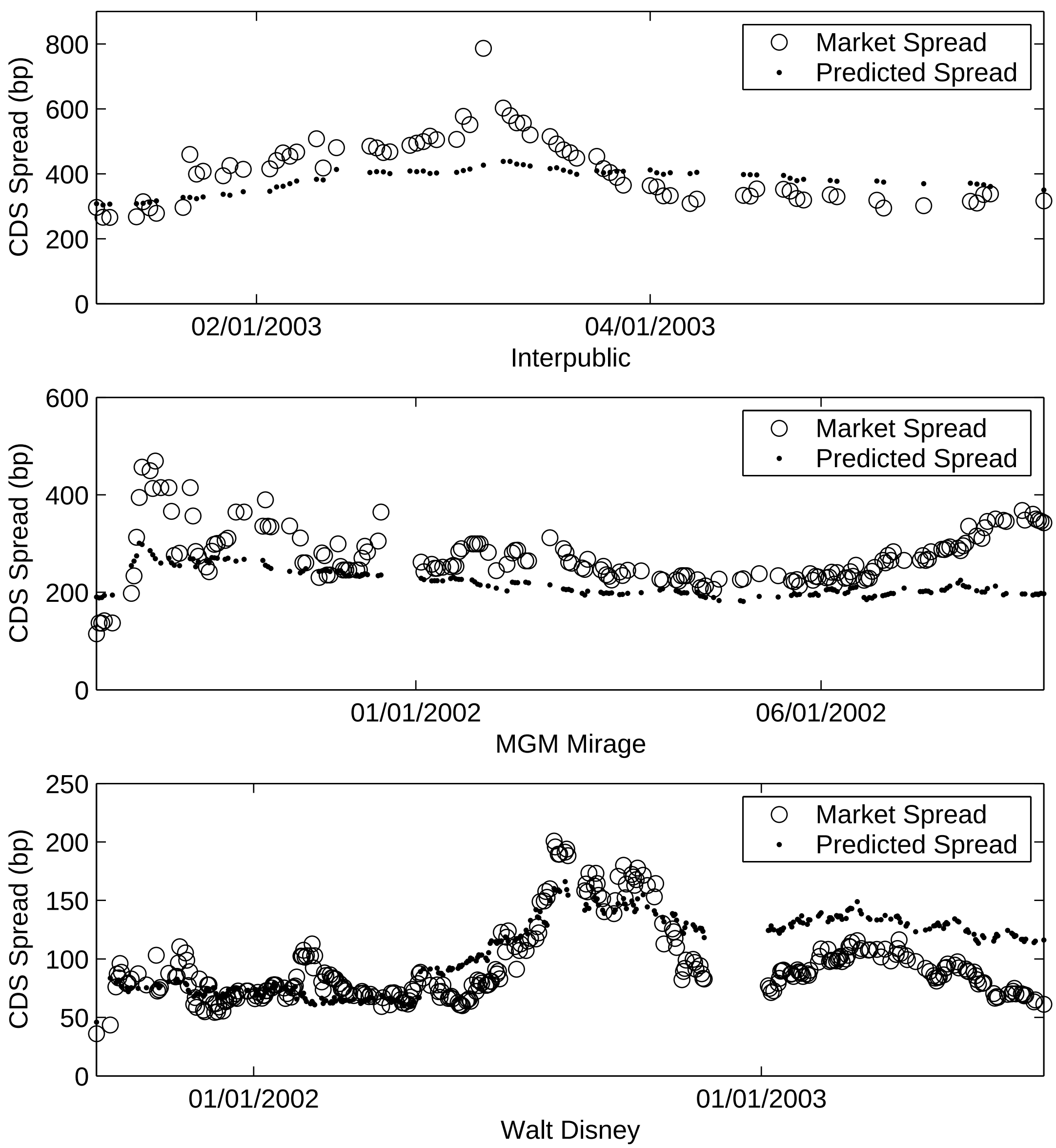

Figure 5: **Market and model spreads for Interpublic, MGM Mirage, and Walt Disney.**

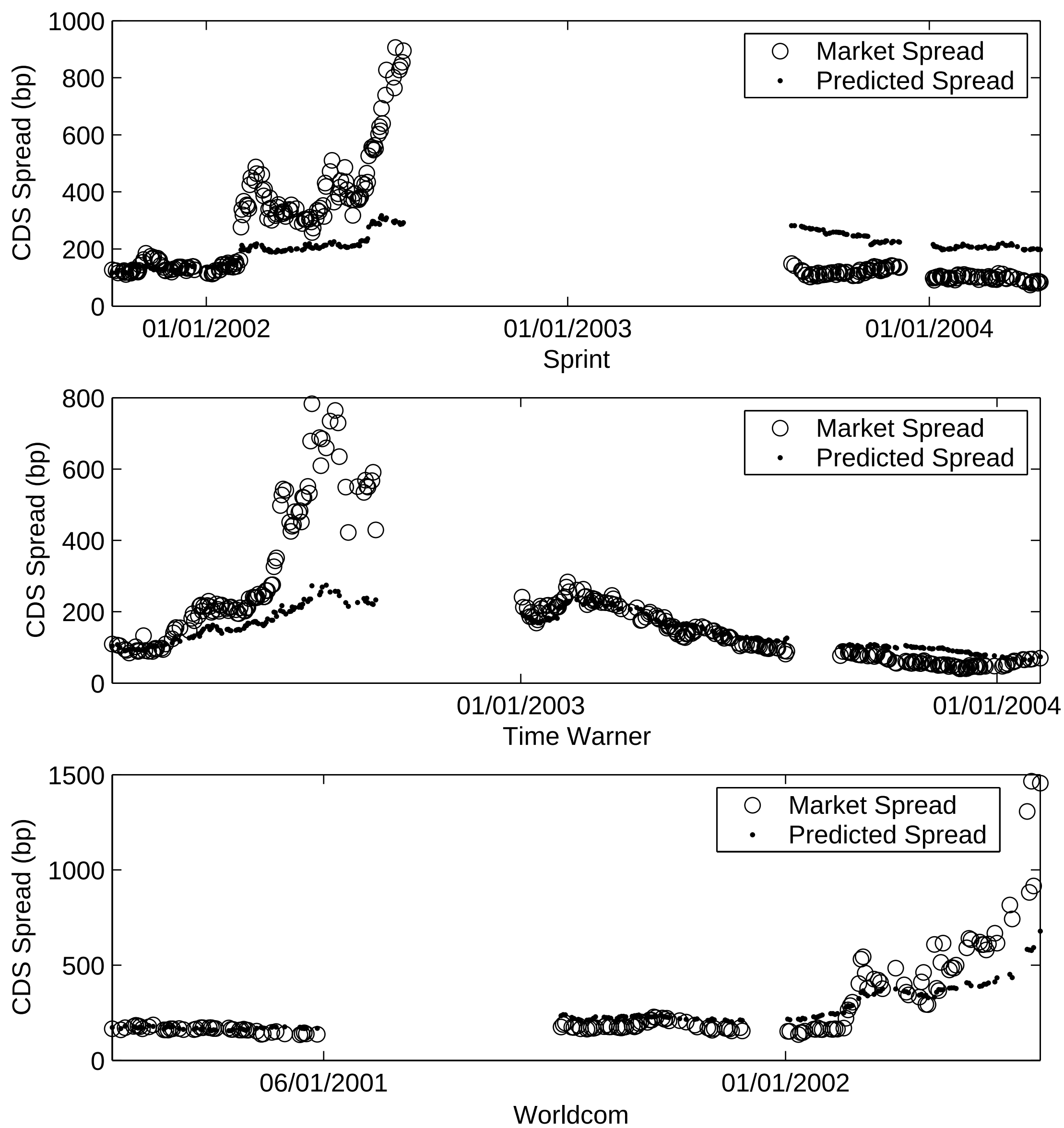

Figure 6: **Market and model spreads for Sprint, Time Warner, and Worldcom.**

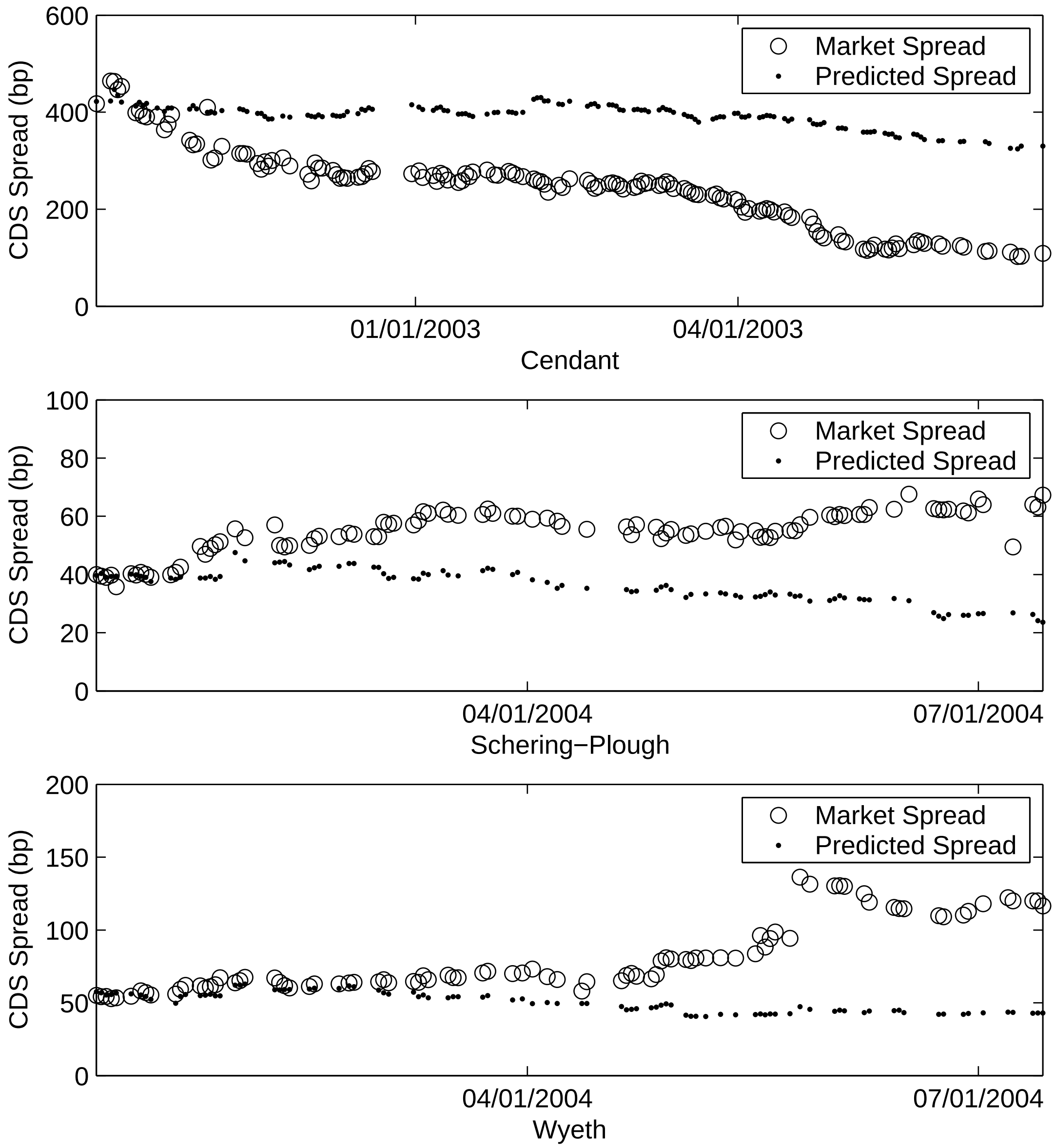

Figure 7: **Market and model spreads for Cendant, Schering-Plough, and Wyeth.**