Capital Structure Arbitrage: Model Choice and Volatility Calibration*

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First Draft: August 28, 2006
Current Version: January 10, 2007

Abstract

When identifying relative value opportunities across credit and equity markets, the arbitrageur faces two major problems, namely positions based on model misspecification and mismeasured inputs. Using credit default swap data, this paper addresses both concerns in a convergence-type trading strategy. In spite of differences in assumptions governing default and calibration, we find the exact structural model linking the markets second to timely key inputs. Studying an equally-weighted portfolio of all relative value positions, the excess returns are insignificant when based on a traditional volatility from historical equity returns. However, relying on an implied volatility from equity options results in a substantial gain in strategy execution and highly significant excess returns - even when small gaps are exploited. The gain is largest in the speculative grade segment, and cannot be explained from systematic market risk factors. However, although the strategy may seem attractive at an aggregate level, positions on individual obligors can be very risky.

*We thank Lombard Risk for access to the credit default swap data. We are grateful to Peter Løchte Jørgensen, Hayne Leland, Stephen Schaefer, Ilya Strebulaev, Carsten Sørensen, participants at the C.R.E.D.I.T. 2006 Doctoral Tutorial in Venice, the Danish Doctoral School of Finance Workshop 2007 and seminar participants at Aarhus School of Business for useful discussions and comments. Any remaining errors are our own.

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1 Introduction

Capital structure arbitrage refers to trading strategies that take advantage of the relative mispricing across different security classes traded on the same capital structure. As the exponential growth in the credit default swap (CDS) market has made credit much more tradable and traditional hedge fund strategies have suffered declining returns (Skorecki (2004)), important questions arise for hedge funds and proprietary trading desks. In particular, do credit and equity markets ever diverge in opinion on the quality of an obligor? What is the risk and return of exploiting divergent views in relative value strategies? Although trading strategies founded in a lack of synchronicity between equity and credit markets have gained huge popularity in recent years (Currie & Morris (2002) and Zuckerman (2005)), the academic literature addressing capital structure arbitrage is very sparse.

This paper conducts a comprehensive analysis of the risk and return of capital structure arbitrage using CDS data on 221 North American obligors in 2002 to 2004. When looking at one security in order to signal the sale or purchase of another, the resulting link and initiation of a trade depends on the chosen model. We address two major problems facing the arbitrageur, namely relative value opportunities driven by model misspecification or mismeasured inputs.

Duarte, Longstaff & Yu (2005) analyze traditional fixed income arbitrage strategies such as the swap spread arbitrage, but also briefly address capital structure arbitrage. Yu (2006) argues for a complete lack of evidence in favor of or against strategies trading equity instruments against CDSs. He conducts the first analysis of the strategy by implementing the industry benchmark CreditGrades with a historical volatility, as reputed used by most professionals.

We show that the more comprehensive model by Leland & Toft (1996) only adds an excess return of secondary order. However, when exploiting a wider array of inputs and securities in model calibration and identification of relative value opportunities, the result is a substantial improvement in strategy execution and returns.

When searching for relative value opportunities, the arbitrageur uses a structural model to gauge the richness and cheapness of the 5-year CDS spread. Using the market value of equity, a volatility measure and the liability structure of the obligor, he compares the market spread with the spread implied from the model. When the market spread is substantially larger(smaller) than the theoretical counterpart, he sells(buys) a CDS and sells(buys) equity. If the market and model spreads subsequently converge he profits. Hence, the model helps identify credits that either offer a discount against equities or trade at a very high level.

As pointed out in Duarte et al. (2005), the nature of capital structure arbitrage puts a premium on models that can explain the link between securities with different characteristics. In fact, the chosen underlying model plays a central role in all parts of the strategy. First, it is used to calculate predicted CDS spreads governing entry and exit decisions in markets. Second, to calculate daily returns on an open position, it is necessary to keep track on the total value of an outstanding CDS position. This is done from the model-based term structure of survival probabilities. Third, the model is used to calculate the equity hedge by a numerical differentiation of the value of the CDS position wrt. the equity price.

CreditGrades loosely builds on Black & Cox (1976), with default defined as the first passage time of firm assets to an unobserved default barrier. This model, like other structural models, is based on a set of restrictive assumptions regarding the default mechanism and capital structure characteristics.

Although allowing for a random recovery, CreditGrades belongs to the class of models with an exogenous default barrier. However, Leland (1994) subsequently extended in Leland & Toft (1996) has pioneered models with endogenous default. In these models, the default barrier is chosen by managers as the asset value where it is no longer optimal for the equityholders to meet the promised debt service payments. Hence, the default barrier is determined not only by debt principal, but also by asset volatility, debt maturity, payout rates and tax rates etc.

As a result of model variations, differences in model calibration exist. For structural models, this is particularly relevant as many key inputs are difficult to measure. Bypassing strict definitions CreditGrades is developed for immediate application, while the calibration of Leland & Toft (1996) is more extensive. Hence, the number and characteristics of parameters to be estimated, as well as the method to infer the underlying asset value process and default barrier, differ across models.

Duarte et al. (2005) and Yu (2006) solely rely on CreditGrades calibrated with a 1000-day historical volatility.[1] When based on a large divergence between markets and smaller gaps are ignored, both find that capital structure arbitrage is profitable on average. At the aggregate level, the strategy appears to offer attractive Sharpe ratios and a positive average return with positive skewness. Yet, individual positions can be very risky and most losses occur when the arbitrageur

[1] That CreditGrades is the preferred framework among professionals is argued in Currie & Morris (2002) and Yu (2006), while the CreditGrades Technical Document by Finger (2002) advocates for the 1000-day historical volatility.

shorts CDSs but subsequently find the market spread rapidly increasing and the equity hedge ineffective.

Due to the substantial differences in model assumptions and calibration, the key observed gap between the market and model spread fueling the arbitrageur may be driven by model misspecification. Furthermore, key inputs may be mismeasured sending the arbitrageur a false signal of relative mispricing. Hence, there is an urgent need to understand how the risk and return vary with model choice and calibration. These caveats are unexplored in Duarte et al. (2005) and Yu (2006).

We address these two major problems facing the arbitrageur, and study how the characteristics of capital structure arbitrage vary with model choice and asset volatility calibration. For this purpose, we apply the CreditGrades model and Leland & Toft (1996). As the volatility measure is a key input to the pricing of credit, we identify relative value opportunities from a traditional 250-day historical volatility used extensively in the bond pricing literature, and a volatility measure implied from equity options.

Based on anecdotal evidence using CreditGrades, Finger & Stamicar (2005*a*) and Finger & Stamicar (2005*b*) show how model spreads based on historical volatilities lag the market when spreads increase, while overpredicting the market as spreads recover. However, the more responsive implied volatility substantially improves the pricing performance. Cao, Yu & Zhong (2006) conduct a more comprehensive study using regression analysis and the CreditGrades model. They find that the more timely option-implied volatility dominates the historical measure in explaining CDS spreads, and that the gain is concentrated among firms with lower credit ratings. While analyzing the determinants of CDS spreads and pricing errors in CreditGrades, they are silent on the risk and return of capital structure arbitrage.

As the arbitrageur feeds on large variations in credit and equity markets, these insights suggest the implied volatility to lead to superior entry and exit decisions and trading returns. Furthermore, the gain from a more timely credit signal is expected to be largest for the obligors of most interest to the arbitrageur, namely those in the speculative grade segment.

Hence, we implement the strategy on 221 North American industrial obligors in 2002 to 2004. Case studies illustrate that while model choice certainly matters in identifying relative value opportunities, the volatility input is of primary importance. The historical volatility may severely lag the market, sending the arbitrageur a false signal of relatively cheap protection in the aftermath of a crisis. The result is large losses for the arbitrager as market spreads continue to tighten. Indeed, the implied volatility may result in the exact opposite positions, with obvious consequences for the arbitrageur.

However, irrespective of model choice and volatility calibration, the strategy is very risky at the level of individual obligors. Convergence may never happen and the equity hedge may be ineffective. This may force the arbitrageur to liquidate positions early and suffer large losses.

When studying the risk and return at an aggregate level, we focus on holding period returns and a capital structure arbitrage index of monthly excess returns. Indeed, both models generally result in insignificant excess returns, when calibrated with a traditional volatility from historical equity returns. However, the gain from identifying relative value opportunities from option-implied volatilities is substantial.

In a variant of the strategy based on CreditGrades, the mean holding period return for speculative grade obligors increases from 2.64 percent to 4.61 percent when implemented with option-implied volatilities. The similar numbers based on Leland & Toft (1996) are 3.14 versus 5.47 percent. However, the incremental return is much smaller for investment grade obligors.

Additionally, the corresponding excess returns are highly significant when option-implied volatilities are used to identify opportunities - even when small gaps are exploited. Based on CreditGrades, the mean excess return is 0.44 percent on investment grade and 1.33 percent on speculative grade obligors, both highly significant. The similar numbers when Leland & Toft (1996) is used to identify relative value opportunities are 0.27 and 2.39 percent, both highly significant. Finally, we do not find the excess returns to represent compensation for exposure to systematic market factors.

We conclude that while model choice does matter for the arbitrageur, is seems second to properly measured key inputs in the calibration. Hence, if the arbitrageur relies on the dynamics of option prices when identifying relative value opportunities across equity and credit markets, the result is a substantial aggregate gain in trading returns above the benchmark application of capital structure arbitrage in Duarte et al. (2005) and Yu (2006).

This paper is based on the premise that structural models price CDSs reasonably well. Ericsson, Reneby & Wang (2006) find that Leland (1994), Leland & Toft (1996) and Fan & Sundaresan (2000) underestimate bond spreads consistent with previous studies, but perform much better in predicting CDS spreads. In fact, the resulting residual CDS spreads are uncorrelated with default proxies as well as non-default proxies. Since the rationale for the strategy is to exploit a lack of integration between various markets, the paper is also related to studies on the lead-lag relationship among bond, equity and CDS markets like Hull, Predescu & White (2004), Norden & Weber (2004), Longstaff, Mithal & Neis (2005) and Blanco, Brennan & Marsh (2005). While the CDS is found to lead the bond market, no definitive lead-lag relationship exists between equity and CDS markets.

Additionally, Hogan, Jarrow, Teo & Warachka (2004) study statistical arbitrages, while Mitchell & Pulvino (2001) and Mitchell, Pulvino & Stafford (2002) are important studies on merger and equity arbitrage. Finally, the paper is related to Schaefer & Strebulaev (2004), who show that structural models produce hedge ratios of equity to debt that cannot be rejected in empirical tests.

The remainder of this paper is organized as follows. Section 2 outlines the trading strategy, while the data is presented in section 3. Section 4 presents the underlying models and calibration, and section 5 illustrates some case studies. Section 6 presents the aggregate results of the strategy, and section 7 concludes.

2 Trading Strategy

This section describes the trading strategy underlying capital structure arbitrage. The implementation closely follows Yu (2006), to whom we refer for a more elaborate description. Since a time-series of predicted CDS spreads forms the basis of the strategy, we start with a short description of how to price a CDS.

2.1 CDS Pricing

A CDS is an insurance contract against credit events such as the default on a corporate bond (the reference obligation) by a specific issuer (reference entity). In case of a credit event, the seller of insurance is obligated to buy the reference obligation from the protection buyer at par.[2] For this protection, the buyer pays a periodic premium to the protection seller until the maturity of the contract or the credit event, whichever comes first. There is no requirement that the protection buyer actually owns the reference obligation, in which case the CDS is used more for speculation rather than protection. Since the accrued premium must also be

[2] In practice, there may be cash settlement or physical settlement, as well as a possible cheapest-to-deliver option embedded in the spread. However, we refrain from this complication. Credit events can include bankruptcy, failure to pay or restructuring.

paid if a credit event occurs between two payment dates, the payments fit nicely into a continuous-time framework.

First, the present value of the premium payments can be calculated as

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

where c denotes the annual premium known as the CDS spread, T the maturity of the contract, r the risk-free interest rate, and τ the default time of the obligor. E^Q denotes the expectation under the risk-neutral pricing measure. 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, $P(\tau > s)$, at $t = 0$[3].

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

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

where R is the recovery of bond market value measured as a percentage of par in the event of default. Maintaining the assumption of independence between the default time and the risk-free interest rate and assuming a constant R, 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 determined such that the value of the credit default swap is zero at initiation

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

and hence

$$c(0,T) = -\frac{(1-R) \int_0^T P(0,s) q_0'(s) ds}{\int_0^T P(0,s) q_0(s) ds}. \tag{6}$$

[3]Later, we focus on constant interest rates. This assumption, together with independence between the default time and the risk-free interest rate, allows us to concentrate on the relationship between the equity price and the CDS spread. This is exactly the relationship exploited in the relative value strategy.

The preceding is the CDS spread on a newly minted contract. To calculate daily returns to the arbitrageur on open trades, the relevant issue is the value of the contract as market conditions change and the contract is subsequently held. To someone who holds a long position from time 0 to t, this is equal to

$$\pi(t,T) = (c(t,T) - c(0,T)) \int_t^T P(0,s) q_t(s) ds, \tag{7}$$

where $c(t,T)$ is the CDS spread on a contract initiated at t with maturity date T. Equation (7) can be interpreted as a survival-contingent annuity maturing at date T, which depends on the model-specific term structure of survival probabilities $q_t(s)$ through s at time t.

Finally, we follow Yu (2006) in defining the hedge ratio $\delta(t,T)$ as

$$\delta(t,T) = N * \frac{\partial \pi(t,T)}{\partial S_t}, \tag{8}$$

where S_t denotes the market value of equity at time t and N is the number of shares outstanding.[4] The choice of underlying model-framework and calibration is discussed in section 4.

2.2 Implementation of the Strategy

Next, we briefly describe the trading strategy as implemented in Duarte et al. (2005) and Yu (2006). Using the market value of equity, a volatility measure and the liability structure of the obligor, the arbitrageur uses a structural model to gauge the richness and cheapness of the CDS spread. Comparing the daily spreads in the market with the theoretical spreads implied from the model, the model helps identify credits that either offer a discount against equities or trade at a very high level.

If the market spread at a point in time has grown substantially larger than the model spread (or vice versa), the arbitrageur sees an opportunity. It might be that the credit market is gripped by fear and the equity market is more objective. Alternatively, he might think that the equity market is slow to react and the CDS spread is priced fairly. If the first view is correct, he should sell protection and

[4] This definition deviates slightly from the one in Yu (2006), since we formulate all models on a total value basis and not per share. Equation (8) follows from a simple application of the chain rule.

if the second view is correct, he should sell equity. Either way, the arbitrageur is counting on the normal relationship between the two markets to return. He therefore takes on both short positions and profits if the spreads converge. This relative value strategy is supposed to be less risky than a naked position in either market, but is of course far from a textbook definition of arbitrage.

Two important caveats to the strategy are positions initiated based on model misspecification or mismeasured inputs. Such potential false signals of relative mispricing are exactly what this paper addresses.

We conduct a simulated trading exercise based on this idea across all obligors. Letting α be the trading trigger, c_t the market spread and c'_t the equity-implied model spread, we initiate a trade each day, if one of the following conditions are satisfied

$$c_t > (1+\alpha)\, c'_t \text{ or } c'_t > (1+\alpha)\, c_t. \tag{9}$$

In the first case, a CDS with a notional of \$1 and shares worth $\$-\delta*1$ are shorted.[5] In the second case, the arbitrageur buys a CDS with a notional of \$1 and buys shares worth $\$-\delta*1$ as a hedge.

Since Yu (2006) finds his results insensitive to daily rebalancing of the equity position, we follow his base case and adopt a static hedging scheme. The hedge ratio is therefore set to correspond to the model CDS spread c'_t when entering the position, and fixed throughout the trade.

Knowing when to enter positions, the arbitrageur must also decide when to liquidate. We assume that exit occurs when the spreads converge, defined as $c_t = c'_t$, or by the end of a pre-specified holding period, which ever comes first. In principle, the obligor can also default or be acquired by another company during the holding period. Yu (2006) notes that in most cases the CDS market will reflect these events long before the actual occurrences, and the arbitrageur will have ample time to make exit decisions.[6] Specifically, it is reasonable to assume that the arbitrageur will be forced to close his positions once the liquidity dries up in the underlying obligor. Such incidents are bound to impose losses on the arbitrageur.

[5] δ is, of course, negative.

[6] This argument seems to be supported in Arora, Bohn & Zhu (2005), who study the surprise effect of distress announcements. Conditional on market information, they find only 11 percent of the distress firms' equities and 18 percent of the distressed bonds to respond significantly. The vast majority of prices are found to reflect the credit deterioration well before the distress announcement.

2.3 Trading returns

The calculation of trading returns is fundamental to analyze how the risk and return differ across model assumptions and calibration methods. Since the CDS position has a zero market value at initiation, trading returns must be calculated by assuming that the arbitrageur has a certain level of initial capital. This assumption allows us to hold fixed the effects of leverage on the analysis. The initial capital is used to finance the equity hedge, and credited or deducted as a result of intermediate payments such as dividends or CDS premia. Each trade is equipped with this initial capital and a limited liability assumption to ensure well-defined returns. Hence, each trade can be thought of as an individual hedge fund subject to a forced liquidation when the total value of the portfolio becomes zero.[7]

Through the holding period the value of the equity position is straightforward, but the value of the CDS position has to be calculated using equation (7). Since secondary market trading is very limited in the CDS market and not covered by our dataset, we adopt the same simplifying assumption as Yu (2006), and approximate $c(t,T)$ with $c(t,t+T)$. That is, we approximate a CDS contract maturing in four years and ten months, say, with a freshly issued five year spread. This should not pose a problem since the difference between to points on the curve is likely to be much smaller than the time-variation in spreads.

Yu (2006) finds his results insensitive to the exact size of transaction costs for trading CDSs. We adopt his base case, and assume a 5 percent proportional bid-ask spread on the CDS spread. The CDS market is likely to be the largest single source of transaction costs for the arbitrageur. We therefore ignore transaction costs on equities, which is reasonable under the static hedging scheme.

3 Data

Data on CDS spreads is provided by the ValuSpread database from Lombard Risk Systems, dating back to July 1999. This data is also used by Lando & Mortensen (2005) and Berndt, Jarrow & Kang (2006). The data consists of mid-market CDS quotes on both sovereigns and corporates, with varying maturity, restructuring clause, seniority and currency. For a given date and reference firm, the database reports a composite CDS quote together with a standard deviation. This composite quote is calculated as a mid-market quote by obtaining quotes from up to 25

[7] This is reminiscent of potential large losses when marked to market, triggering margin calls and forcing an early liquidation of positions.

leading market makers. The composite quote offers a more reliable measure of the market spread than using a single source, and the standard deviation measures how representative the mid-market quote is for the overall market.

We confine ourselves to 5-year composite CDS quotes on senior unsecured debt for North American corporate obligors with currencies denominated in US dollars. Regarding the specification of the credit event, we follow Yu (2006) and large parts of the literature in using contracts with a modified restructuring clause. The frequency of data on CDS quotes increases significantly through time, reflecting the growth and improved liquidity in the market. To generate a subsample of the data suitable for capital structure arbitrage, we apply several filters.

First, we merge the CDS data with quarterly balance sheet data from Compustat and daily stock market data from CRSP. The quarterly balance sheet data is lagged one month from the end of the quarter to avoid the look-ahead bias in using data not yet available in the market. We then exclude firms from the financial and utility sector.

Second, for each obligor in the sample, daily data on the 30-day at-the-money put-implied volatility is obtained from OptionMetrics. OptionMetrics is a comprehensive database of daily information on exchange-listed equity options in the U.S. since 1996. OptionMetrics generates the 30-day at-the-money put-implied volatility by interpolation.

Third, in order to conduct the simulated trading exercise, a reasonably continuous time-series of CDS quotes must be available. In addition, the consensus quote must have a certain quality. Therefore, we define the relative quote dispersion as the standard deviation divided by the mid-market quote. All daily mid-market quotes with an intra-daily quote dispersion of zero or above 40 percent are then deleted.[8]

For each obligor, we next search for the longest string of more than 100 daily quotes no more than 14 calender days apart, which have all information available on balance sheet variables, equity market and equity options data.[9] As noted in Yu (2006), this should also yield the most liquid part of coverage for the obligor, forcing the arbitrageur to close his positions once the liquidity vanishes.

[8] One could argue for a cut-off point at a lower relative dispersion, but on the other hand a trader is likely to take advantage of high uncertainty in the market. The majority of quotes have a relative dispersion below 20 percent.

[9] As discussed below, this may give rise to a survivorship issue. However, we try to minimize this by requiring a string of only 100 spreads, far less than Yu (2006). In any case, this should not pose a problem, since the focus of the paper is on relative risk and return across models and calibration methods, and not absolute measures.

Finally, 5-year and 3-month constant maturity treasury yields are obtained from the Federal Reserve Bank of St. Louis. These interest rates are used to calculate the equity-implied 5-year CDS spread, and to calculate excess returns from the trading strategy.

Applying this filtration to the merged dataset results in 221 obligors with 65,476 daily consensus quotes, dating back to July 2002 and onwards to the end of September 2004. Indeed, this mirrors the exponential growth in liquidity after 2001. Table 1 presents summary statistics for the obligors across the initial credit rating from Standard & Poor's, when entering the sample. The variables presented are averages over time and then rating. The majority of firms are BBB rated, and 16 firms are in the speculative grade segment, including one non-rated obligor. A lower spread is associated with a lower leverage and volatility, which is in line with predictions of structural credit risk models.

We implement the trading strategy using the implied volatility from equity options (IV), and a 250-day volatility from a historical time-series of equity values (HV). On average these volatilities are similar, but it turns out that the dynamics of option prices provide the arbitrageur with superior information. The average correlation between changes in the spread and the equity value is negative as expected from a structural viewpoint, but fairly low. This is consistent with Yu (2006) and correlations ranging from 5 to 15 percent quoted by traders in Currie & Morris (2002). This indicates that the two markets may drift apart and hold divergent views on obligors, which fuels the arbitrageur ex ante. Ex post, it suggests that the equity hedge may be ineffective.

[Table1 about here]

4 Model Choice and Volatility Calibration

Having the trading strategy and data explained, we next introduce the two underlying models and the associated calibration. The formulas for each model including the risk-neutral survival probability $q_t(s)$, the CDS spread $c(0,T)$, the contract value $\pi(t,T)$ and the equity delta $\delta(t,T)$ are described in the appendix. Further details on the models can be found in Finger (2002) and Leland & Toft (1996).

4.1 CreditGrades

The CreditGrades model is jointly developed by RiskMetrics, JP Morgan, Goldman Sachs and Deutsche Bank with the purpose to establish a simple framework linking credit and equity markets. As noted by Currie & Morris (2002) and Yu (2006), this model has become an industry benchmark widely used by traders, preferably calibrated with a rolling 1000-day historical volatility as advocated in Finger (2002).

It loosely builds on Black & Cox (1976), with default defined as the first passage time of firm assets to an unobserved default barrier. Hence, deviating from traditional structural models, it assumes that the default barrier is an unknown constant drawn from a known distribution. This element of uncertain recovery increases short-term spreads, but cannot do so consistently through time.[10]

Originally, the model is built on a per-share basis taking into account preferred shares and the differences between short-term versus long-term and financial versus non-financial obligations, when calculating debt per share. Like Yu (2006), we only work with total liabilities and common shares outstanding. Therefore, we formulate the model based on total liabilities and market value of equity.

Under the risk-neutral measure, the firm assets V are assumed to follow

$$dV_t = \sigma_V V_t dW_t, \tag{10}$$

where σ_V is the asset volatility and W_t is a standard Brownian motion. The zero drift is consistent with the observation of stationary leverage ratios in Collin-Dufresne & Goldstein (2001). The default barrier is LD, where L is a random recovery rate given default, and D denotes total liabilities. The recovery rate L follows a lognormal distribution with mean $\bar{L}$, interpreted as the mean global recovery rate on all liabilities, and standard deviation λ. Then, R in equation (6) is the recovery rate on the specific debt issue underlying the CDS.

Instead of working with a full formula for the value of equity S, CreditGrades uses the linear approximation

$$V = S + \bar{L}D, \tag{11}$$

[10] A theoretically more appealing approach is given by Duffie & Lando (2001).

which also gives a relation between asset volatility σ_V and equity volatility σ_S

$$\sigma_V = \sigma_S \frac{S}{S + \bar{L}D}. \tag{12}$$

The model is easy to implement in practice. In particular, D is the total liabilities from quarterly balance sheet data, S is the market value of equity calculated as the number of shares outstanding multiplied by the closing price, and r is the 5-year constant maturity treasury yield. Furthermore, the bond-specific recovery rate R is assumed to be 0.5 and the standard deviation of the global recovery rate λ is 0.3. All parameters are motivated in Finger (2002) and Yu (2006).

The volatility measure is a key input to the pricing of credit. Instead of using a rolling 1000-day volatility σ_S from historical equity values as Yu (2006), we implement the strategy using a 250-day historical volatility and the implied volatility from equity options. Using insights from Finger & Stamicar (2005*a*) and Cao et al. (2006), the implied volatility may provide a much more timely measure of volatility relevant for CDS pricing, and hence lead to superior entry and exit decisions and thus trading returns. We expect this gain to be most pronounced for the speculative grade sample, where obligors typically experience large variations in spreads. Here, historical volatilities may lag true market levels and send a false signal of mispricing to the arbitrageur.

Finally, the mean global recovery rate $\bar{L}$ is set as a free exogenous parameter, and used to get the model in line with the credit market before conducting the trading exercise. This is consistent with Yu (2006), who infers $\bar{L}$ by minimizing the sum of squared pricing errors over the first 10 CDS spreads. Now, all parameters are in place to calculate the time-series of CDS spreads underlying the analysis, together with hedge ratios and values of open CDS positions.

4.2 Leland & Toft (1996)

This model assumes that the decision to default is made by a manager, who acts to maximize the value of equity. At each moment, the manager must address the question whether meeting promised debt service payments is optimal for the equityholders, thereby keeping their call option alive. If the asset value exceeds the endogenously derived default barrier V_B, the firm will optimally continue to service the debt - even if the asset value is below the principal value or if cash flow available for payout is insufficient to finance the net debt service, requiring additional equity contributions.

In particular, firm assets V are assumed to follow a geometric Brownian motion under the risk-neutral measure

$$dV_t = (r - \rho)V_t dt + \sigma_V V_t dW_t, \tag{13}$$

where r is the constant risk-free interest rate, ρ is the fraction of asset value paid out to security holders, σ_V is the asset volatility and W_t is a standard Brownian motion. Debt of constant maturity Υ is continuously rolled over, implying that at any time s the total outstanding debt principal P will have a uniform distribution over maturities in the interval $(s, s + \Upsilon)$. Each debt contract in the multi-layered structure is serviced by a continuous coupon. The resulting total coupon payments C are tax deductible at a rate τ, and the realized costs of financial distress amount to a fraction α of the value of assets in default V_B. Rolling over finite maturity debt in the way prescribed implies a stationary capital structure, where the total outstanding principal P, total coupon C, average maturity $\frac{\Upsilon}{2}$ and default barrier V_B remain constant through time.

To determine the total value of the levered firm $v(V_t)$, the model follows Leland (1994) in valuing bankruptcy costs $BC(V_t)$ and tax benefits resulting from debt issuance $TB(V_t)$ as time-independent securities. It follows, that

$$\begin{aligned} v(V_t) &= V_t + TB(V_t) - BC(V_t) \\ &= S(V_t) + D(V_t), \end{aligned} \tag{14}$$

where $S(V_t)$ is the market value of equity and $D(V_t)$ the market value of total debt.

To implement the model, we follow Ericsson et al. (2006) in setting the realized bankruptcy cost fraction $\alpha = 0.15$, the tax rate $\tau = 0.20$ and the average debt maturity $\frac{\Upsilon}{2} = 3.38$.[11] Furthermore, as above, P is the total liabilities from quarterly balance sheet data, S is the market value of equity and r is the 5-year constant maturity treasury yield. We also follow Ericsson et al. (2006) in assuming that the average coupon paid out to all debtholders equals the risk-free interest rate, $C = rP$.[12] The asset payout rate ρ is calculated as a time-series mean of

[11] The choice of 15 percent bankruptcy costs lies well within the range estimated by Andrade & Kaplan (1998). 20 percent as an effective tax rate is below the corporate tax rate to reflect the personal tax rate advantage of equity returns. Stohs & Mauer (1996) find an average debt maturity of 3.38 years using a panel of 328 industrial firms with detailed debt information in Moody's Industrial Manuals in 1980-1989.

[12] A firm's debt consists of more than market bonds, and usually a substantial fraction of total debt is non-interest bearing such as accrued taxes and supplier credits. Furthermore, corporate bonds may be issued below par, which also opens up for this approximation.

the weighted average historical dividend yield and relative interest expense from balance sheet data

$$\rho = \left(\frac{Interest\ expenses}{Total\ liabilities}\right) \times L \ + (Dividend\ yield) \times (1 - L) \tag{15}$$
$$L = \frac{Total\ liabilities}{Total\ liabilities + Market\ equity}.$$

Since the default barrier V_B is endogenously determined and depends on model parameters, it does not need to be inferred from market data. Instead, the default barrier varies with fundamental characteristics of the firm such as leverage, asset volatility, debt maturity and asset payout rate. Contrary to the implementation of CreditGrades in Yu (2006), this allows us to instead fit the bond-specific recovery rate R from the first 10 CDS spreads. As Yu (2006) argues, this is also the free parameter used in practice by traders to fit the level of market spreads.

Before calibration of the bond-specific recovery rate R, the asset value V and asset volatility σ_V must be estimated. Due to the full-blown relationship between equity and assets, this is a more troublesome exercise in Leland & Toft (1996). When analyzing the trading strategy with a 250-day historical volatility, we infer the unobserved time-series of asset values and asset volatility using the iterative algorithm of Moody's KMV, outlined in Crosbie & Bohn (2003) and Vassalou & Xing (2004).

This iterative algorithm is preferable over an instantaneous relationship between asset volatility σ_V and equity volatility σ_S, governed by Ito's lemma. The latter underlies the implementation of CreditGrades in equation (12), and is used in Jones, Mason & Rosenfeld (1984). As noted in Lando (2004), the iterative algorithm is particularly preferable when changes in leverage are significant over the estimation period.

In short, the iterative scheme goes as follows. The market value of equity S_t is a function of a parameter vector θ, the asset value V_t, default barrier $V_B(\sigma_V)$ and asset volatility σ_V, $S_t = f(V_t, \sigma_V, \theta)$. Using quarterly balance sheet data, a rolling 250-day window of historical equity values and an initial guess of the asset volatility, we calculate the default barrier and invert the equity pricing formula to infer an implied time-series of asset values $V_t(\sigma_V) = f^{-1}(S_t, \sigma_V, \theta)$. The market value of assets follow a geometric Brownian motion, allowing us to obtain an updated asset volatility and default barrier. This procedure is repeated until the values of σ_V converge.

When analyzing the trading exercise based on implied volatilities from equity options, we do not face the problem of changing leverage in a historical estimation window. Therefore, we solve the instantaneous relationship

$$S_t = f(V_t, \sigma_V, \theta) \tag{16}$$

$$\sigma_S = \frac{\partial S_t}{\partial V_t} \sigma_V \frac{V_t}{S_t} \tag{17}$$

numerically for the unknown asset value V_t and asset volatility σ_V.

4.3 Model Calibration and Implied Parameters

Table 2 presents summary statistics of implied parameters from CreditGrades and Leland & Toft (1996), using a rolling 250-day historical volatility (HV) and implied volatility (IV). The table also shows average calibration targets from the equity and equity options market, together with asset payout rates. In CreditGrades implemented with a historical volatility in panel A, the average market value of assets V is \$20,592 million with a median of \$14,839 million, while the average and median expected default barrier $\bar{L}D$ is \$8,556 million and \$3,846 million, respectively. The mean asset volatility σ_V is 22.8 percent, with a median of 21.3 percent. Finally, the average and median mean global recovery rate $\bar{L}$ is 0.799 and 0.573, respectively. Similar implied parameters result on aggregate when implemented with the implied volatility in panel B.

[Table 2 about here]

When implementing Leland & Toft (1996) in panel C and D, several differences from CreditGrades are apparent. First, the asset values appear larger and asset volatilities lower. This is due to the observation that the relatively high endogenous default barrier V_B increases the theoretical equity volatility, ceteris paribus. Hence, the model implies a higher asset value and/or lower asset volatility in order to match the theoretical and observed equity volatility.

Second, the variation in implied bond recovery R across the two volatility measures is large. Based on the historical volatility, both the average and median implied bond recovery are highly negative, indicating that the model underestimates the level of market spreads in the beginning of the sample period.[13] Implied recov-

[13] This should not be a problem for the current trading strategy, since subsequent movements in relative prices across equity and credit markets drive the arbitrageur, not absolute levels. The most extreme bond recovery of -1,858 results from an underestimation of only 50 bps. In this case, the market spread is close to 50 bps, while the model spread with a reasonable bond

eries are more plausible when inferred from option-implied volatilities. Although the mean continues to be negative, the median is 0.233. This is indicative of an implied volatility that varies stronger with changes in the CDS spread. Indeed, calculating the mean correlation between changes in CDS spreads and changes in volatility measures, the correlation is 1.8 and 9.9 percent based on historical and implied volatilities, respectively.

The variation in implied mean global recovery $\bar{L}$ in CreditGrades is much smaller across volatility measures. This is a manifestation of the difference in information used at various stages, when calibrating the two models. In CreditGrades the expected default barrier is exogenous, while it is endogenously determined in Leland & Toft (1996). As a result of the linear approximation in equation (11), asset values, the asset volatility and the expected default barrier are not nailed down and determined in CreditGrades until the mean global recovery rate is inferred from the initial CDS spreads. Subsequent to nailing down this key parameter, there is a one-to-one relationship between changes in equity and assets, $\frac{\partial S}{\partial V} = 1$.

The default mechanism in Leland & Toft (1996) implies a different use of market data. Here, the asset value and asset volatility are solely determined from the equity and equity options market. Together with the endogenous default barrier, this gives far less flexibility when fitting the final bond recovery from initial CDS spreads. The result is more extreme values for this parameter.[14] However, the subsequent relationship and wedge between equity and assets vary with the distance to default. When close to default, $\frac{\partial S}{\partial V}$ is very steep and below one. Although delta may go above one as the credit quality improves, the relationship approaches one-to-one when far from default. Hence, the variation in asset dynamics across the two models may be substantial for speculative grade obligors, with direct consequences for the arbitrageur.

From the discussion in section 2, the chosen structural model plays a central role in all parts of capital structure arbitrage. In particular, the model underlies survival probabilities and predicted CDS spreads, hedge ratios, valuation of open CDS positions and trading returns. As shown above, assumptions behind CreditGrades and Leland & Toft (1996), as well as practical implementation, vary substantially. How these differences in model choice and calibration manifest in

recovery is close to zero.

[14]If CreditGrades is implemented with a mean global recovery of 0.5 as suggested in Finger (2002), we qualitatively get the same results for the implied bond recovery as in Leland & Toft (1996).

profitability and strategy execution is analyzed next. Before turning to the general results across all obligors, some case studies are analyzed.

5 Case Studies

In this section, the two models calibrated with historical and option-implied volatilities are used to identify divergent views in equity and credit markets. The case studies illustrate that while model choice certainly matters in identifying relative value opportunities, the volatility input is of primary importance. In fact, the two volatility measures may result in opposite positions, with obvious consequences for the arbitrageur. The final study illustrates that the strategy is very risky at the level of individual obligors.

5.1 Sears, Roebuck and Company

Figure 1 illustrates the fundamentals of capital structure arbitrage for the large retailer Sears, Roebuck and Company, rated A by S&P and Baa1 by Moody's. Panel A and B depict model and market spreads from September 2002 to June 2004 (excluding the initial 10 spreads reserved for calibration), while panel C and D depict equity volatilities and the market value of equity, respectively.

The uncertainty in the markets increases substantially in the beginning of the period. Moody's changes their rating outlook to negative on October 18 2002, due to increasing uncertainty in the credit card business and management changes. In this period, equity prices tumble and CDS spreads reach 379 bps on October 24 2002, a doubling in 2 weeks. While the markets begin to recover shortly thereafter, model spreads based on the sticky historical volatility continue far into 2003 to suggest the arbitrageur to buy protection and buy equity as a hedge. However, with only few exceptions the market spreads tighten in the succeeding period, and the market and model spreads never converge. Depending on the size of the trading trigger and the chosen model, many losing positions are initiated although partially offset by an increasing equity price.

Panel C illustrates how the historical volatility severely lags the more timely implied volatility, sending the arbitrageur a false signal of relatively cheap protection in the aftermath of the crisis. In fact, spreads inferred from implied volatilities quickly tighten and may initiate the exact opposite strategy. Particularly spreads in Leland & Toft (1996) indicate that protection is trading too expensive relative to equity from the end of 2002. Indeed, selling protection and selling equity as hedge result in trading returns of 5 to 15 percent on each daily position, due to tightening market spreads and convergence on June 5, 2003. Subsequent to convergence, implied volatilities suggest the equity and credit markets to move in tandem and hold similar view on the credit outlooks.

As a final observation, model spreads in CreditGrades react stronger to changes in volatility than Leland & Toft (1996), widening to over 1000 bps as the implied volatility from equity options peaks. This may be due to the endogenous default barrier in the latter model. Indeed, increasing the asset volatility causes equity-holders to optimally default later in Leland & Toft (1996). This mitigates the effect on the spread.

[Figure 1 about here]

5.2 Time Warner and Motorola

Simulating the trading strategy on Time Warner and Motorola supports the former insights. Figure 2 depicts Time Warner, rated BBB by S&P and Baa1 by Moody's. In August 2002 just prior to the beginning of the sample, Moody's changes their outlook to negative as the SEC investigates the accounting practices and internal controls. As markets recover in late 2002, CreditGrades with historical volatility indicates that protection is cheap relative to equity, while spreads in Leland & Toft (1996) are more neutral. Although equity prices increase throughout 2003, many losing trades are initiated as market spreads are more than cut by half within few months, and Moody's changes their outlook back to stable.

Again, the historical volatility lags the market after the crisis, while the implied volatility is more responsive to changes in the equity value. In October and November 2002, where market spreads have already tightened substantially, model spreads inferred from implied volatilities suggest that protection is expensive relative to equity and should tighten further. Selling protection at 339 bps and equity at $14.75 on October 31, 2002, result in convergence and 15 percent returns on December 12, where the CDS and equity are trading at 259 bps and $13.56, respectively. However, spreads inferred from implied volatilities are volatile as market spreads tighten, resulting in rather noisy estimates of credit outlooks and frequent liquidation of positions. Operating with a very low trigger may reverse positions several times during this period, while a trigger of 0.5 results in only few positions.

In figure 3, the key variables for Motorola, rated BBB by S&P, are depicted. Building on historical volatilities, the arbitrageur initiates many trades and suffers losses, while implied volatilities suggest the two markets to move in tandem and hold similar views on the obligor. In the latter case, only few relative value opportunities are apparent.

[Figure 2 and 3 about here]

5.3 Mandalay Resort Group

Capital structure arbitrage is very risky when based on individual obligors, and the arbitrageur may end up in severe problems irrespective of model choice and calibration. Figure 4 presents the fundamental variables behind Mandalay Resort Group, rated BB by S&P. Throughout the coverage, spreads in Leland & Toft (1996) based on historical volatilities diverge from market spreads in a smooth manner, while spreads in CreditGrades diverge more slowly. The arbitrageur sells protection and equity as hedge, and suffers losses as positions are liquidated after the maximum holding period.

May and June 2004 are particularly painful, as model spreads inferred from implied volatilities plunge and stay tight throughout the coverage. On June 4, 2004 the competitor MGM Mirage announces a bid to acquire Mandalay Resort Group for $68 per share plus assumption of Mandalay's existing debt. Moody's places the rating on review for a possible downgrade, due to a high level of uncertainty regarding the level of debt employed to finance the takeover. As a result, the equity price increases from $54 to $69 over a short period, the implied volatility plunges and the CDS spread widens from 188 bps to 227 bps.[15] On June 15, 2004 a revised offer of $71 per share is approved, and the transaction is completed on April 26, 2005.

The opposite reaction in equity and credit markets gives the arbitrageur short in markets a painful one-two punch similar to the one experienced by hedge funds in May 2005, where General Motors is downgraded while the equity price soars.[16] Luckily, not many trades are open during the takeover bid as model and market spreads recently converged. However, the short positions initiated in May 2004, where credit seems expensive relative to equity, suffer large losses on both legs.

[Figure 4 about here]

[15] Implied volatilities from at-the-money calls plunge as well.
[16] This case study is discussed in Duarte et al. (2005).

6 General Results

In this section, we simulate the trading strategy for all 221 obligors. Following Yu (2006), we assume an initial capital of $0.5 for each trade and $1 notional in the CDS. The strategy is implemented for trading triggers α of 0.5 and 2, and maximum holding periods of 30 and 180 days.

Naturally, absolute trading returns will vary with the above characteristics, as well as the particular period studied and how to account for vanishing liquidity etc. However, these characteristics are all fixed when studying the relative risk and return across models and calibration methods. Therefore, a scaling of returns with the amount of initial capital is unlikely to influence our conclusions.[17] Indeed, although based on a different dataset, the benchmark results for CreditGrades with a historical volatility are similar to the findings in Yu (2006).

Table 3 and 4 present the summary statistics of holding period returns based on CreditGrades and Leland & Toft (1996), respectively. A longer maximum holding period leads to more converging trades, fewer trades with negative returns and higher average returns. This fundamental result underlies both models and volatility measures. Consistent with Yu (2006), although the distribution of returns becomes less dispersed, a higher trading trigger does not necessarily lead to higher mean returns.

When identifying relative value opportunities from implied not historical volatilities, the number of initiated trades rises for investment grade obligors and falls for speculative grade obligors. This results from both models, although the absolute number of trades is larger in Leland & Toft (1996). This is consistent with findings in Finger & Stamicar (2005*a*) and Cao et al. (2006), where the advantage of implied volatility in tracking market spreads with CreditGrades is concentrated among speculative grade obligors. We find this measure to identify fewer relative value opportunities on obligors with larger variations in spreads.

The results clearly show a difference in risk and return across models and volatility input. Identifying relative value opportunities on speculative grade obligors in CreditGrades with a historical volatility, a maximum holding period of 180 days and a trading trigger of 2 yields a mean holding period return of 2.64 percent. However, simulating the trading strategy with option-implied volatilities increases the return to 4.61 percent.[18] The corresponding numbers based on Leland & Toft

[17] Yu (2006) also conducts his analysis with an initial capital of $0.1. The resulting returns are scaled up accordingly. Unreported results with this initial capital and other trading triggers leave our conclusions unchanged.

[18] While the average profitability increases when identifying relative value opportunities from

(1996) are 3.14 and 5.47 percent. The gain from implied volatilities across trading triggers and maximum holding periods is also apparent from the number of trades ending in convergence and the fraction of trades with negative returns. However, the incremental return is much smaller for investment grade obligors.

On top of this, the mean holding period return and dispersion are both higher on speculative grade obligors compared to the investment grade sample. This supports the similar result in Yu (2006) and happens irrespective of model choice and volatility measure. Although more likely to suffer from vanishing liquidity and default, this supports his observation that the aggregate success of the strategy depends on the availability of large variations in spreads. For these obligors in particular the implied volatility, being more responsive to changes in equity values, results in incremental trading returns from superior entry and exit decisions.

The holding period returns are more favorable when Leland & Toft (1996) is used to identify relative value opportunities. However, in practice it is hard to discern exactly where the difference arises, as the models differ in many respects and enter in all parts of the strategy. While model choice does matter, it seems second to properly measured key inputs.

[Table 3 and 4 about here]

6.1 Capital Structure Arbitrage Index Returns

As illustrated in the previous sections, capital structure arbitrage is very risky at the level of individual trades. The hedge may be ineffective and the markets may continue to diverge, resulting in losses and potential early liquidations. However, when initiated on the cross-section of obligors, the strategy may be profitable on average depending on the particular implementation. Having established this finding, the next step is to understand the sources of the profits, i.e. whether the returns are correlated with priced systematic risk factors. Hence, we construct a monthly capital structure arbitrage excess return index from all individual trades, following Duarte et al. (2005) and Yu (2006).

Specifically, we compute daily excess returns for all individual trades over the entire holding period. On a given day, thousands of trades may be open. By essentially assuming that the arbitrageur is always invested in an equally-weighted portfolio of hedge funds, where each fund consists of one trade, we calculate an

implied volatilities, so does the volatility of returns. As the mean holding period return consists of many overlapping holding periods, the statistical significance of trading returns is analyzed from a return index below.

equally-weighted average of the excess returns on a daily basis. These average daily excess returns are then compounded into a monthly frequency.

Table 5 presents the summary statistics of monthly excess returns based on a maximum holding period of 180 days, covering 24 months in 2002-2004. However, some strategies result in months with no trades. In this case, a zero excess return is assumed.

Again, although also present in the investment grade segment, the benefit of option-implied volatilities is concentrated among speculative grade obligors. Additionally, timely inputs are relatively more important than the exact structural model underlying the strategy. In particular, when based on CreditGrades with option-implied volatilities and a trading trigger of 2, the mean excess return is 0.44 percent on investment grade and 1.33 percent on speculative grade obligors. These numbers are highly significant after correcting for serial correlation. The corresponding numbers when Leland & Toft (1996) is used to identify relative value opportunities are 0.27 and 2.39 percent, respectively, both highly significant.

The excess returns resulting from a historical volatility are much smaller and most often insignificant. Indeed, the mean excess return from this measure may turn negative and significant at a lower trading trigger of 0.5, while it continues to be positive and significant based on implied volatilities.

Addressing whether fixed income arbitrage is comparable to picking up nickels in front of a steamroller, Duarte et al. (2005) find that most of the strategies result in monthly excess returns that are positively skewed. While our results are mixed when relative value positions are identified from historical volatilities, the skewness is always positive when based on the implied measure. Thus, while producing large negative returns from time to time, this strategy tends to generate even larger offsetting positive returns.

[Table 5 about here]

As a final exercise, we explore whether the excess returns represent compensation for exposure to systematic market factors.[19] In particular, we use the excess return on the S&P Industrial Index (S&PINDS) to proxy for equity market risk. To proxy for investment grade and speculative grade bond market risk, the excess returns on the Lehman Brothers Baa and Ba Intermediate Index (LHIBAAI) and (LHHYBBI), respectively, are used. These variables are obtained from Datas-

[19] For brevity, only regressions with a trading trigger of 2 are reported. Similar results are obtained at a lower threshold of 0.5.

tream. As argued by Duarte et al. (2005), such factors are also likely to be sensitive to major financial events, such as a sudden flight-to-quality or flight-to-liquidity. As the same risk would be present, and presumably compensated, in the excess returns from these portfolios, we may be able to control for the component of returns that is compensation for bearing the risk of major, but not yet realized, financial events.

As the CDS market was rather illiquid before mid-2002, the regressions consist of no more than 24 monthly excess returns. Hence, the results must be interpreted with caution. Yu (2006) finds no relationship between capital structure arbitrage monthly excess returns and any of the factors, and the factors cannot bid away the alphas (regression intercepts) of the strategy. Our R^2 range from 8 to 35 percent, but the market factors are either insignificant or only weakly significant. Surprisingly, the occasional weak significance is not related to the size and significance of excess returns, nor rating category. Hence, the evidence does not indicate that the excess returns represent compensation for exposure to factors proxying equity and bond market risk.

As we only have 24 monthly excess returns, there is little chance of detecting significant alphas after controlling for the market risk. However, the structure of excess returns after a risk-adjustment is similar to the structure of raw excess returns in table 5. Indeed, the largest difference in alphas across the historical and option-implied volatility is in the speculative grade segment. While three of four intercepts are negative based on the investment grade obligors, it is always positive on speculative grade obligors.

[Table 6 about here]

7 Conclusion

This paper conducts a comprehensive analysis of the risk and return of capital structure arbitrage. As a structural credit risk model underlies the identification of relative value opportunities across equity and credit markets, the chosen model plays a central role in all parts of the strategy. Different structural models may generate different predicted CDS spreads, entry and exit decisions in markets, hedge ratios and valuations of open CDS positions. Particularly, an observed difference in market and equity-implied model CDS spread may be driven by model misspecification, and key inputs may be mismeasured, sending a false signal of mispricing in the market.

We address these two major problems facing the arbitrageur, and study how the risk and return vary with model choice and asset volatility calibration. The industry benchmark CreditGrades and the Leland & Toft (1996) model differ extensively in assumptions governing default and calibration method. However, while model choice certainly matters, the exact model underlying the strategy is of secondary importance. Studying an index of monthly capital structure arbitrage excess returns across 221 North American industrial obligors in 2002-2004, both models generally result in insignificant excess returns, when calibrated with a traditional rolling 250-day volatility from historical equity returns.

However, as the arbitrageur feeds on large variations in equity and credit markets, and the asset volatility is a key input to the pricing of credit, a more timely volatility measure is desirable. In such markets, the historical volatility may severely lag the market, suggesting the arbitrageur to enter into unfortunate positions and face large losses. Indeed, basing the strategy on a volatility measure inferred from the dynamics of equity options may lead to the exact opposite positions. The result is highly significant excess returns, even at low thresholds for strategy initiation. The incremental return is largest for the speculative grade obligors, and cannot be explained by well-known equity and bond market factors.

While profitable on an aggregate level, individual trades can be very risky. Irrespective of model choice and volatility measure, the market and equity-implied spread may continue to drift apart, and the equity hedge may be ineffective. This may force the arbitrageur to liquidate individual positions early, and suffer large losses.

Duarte et al. (2005) and Yu (2006) conduct the first analysis of the strategy by implementing CreditGrades with a historical volatility, as reputed used by most professionals. We show that the more comprehensive model by Leland & Toft (1996) only adds an excess return of secondary order. However, exploiting a wider array of inputs and securities in the identification of relative value opportunities leads to a substantial improvement in strategy execution and returns.

A structural model allows for numerous implementations of capital structure arbitrage, as it links firm fundamentals with equities, equity options, corporate bonds and credit derivatives. As we often find the hedge in cash equities ineffective, a further improvement may lie in offsetting positions in equity options such as out-of-the-money puts. This non-linear product may also reduce the gamma risk of the strategy, which can cause losses in a fast moving market. As CDS data continues to expand, future research will shed light on many unexplored properties of relative value trading across equity and credit markets.

A Appendix

The appendix contains formulas for the risk-neutral survival probability $q_t(s)$, the CDS spread $c(0,T)$, the contract value $\pi(t,T)$ and the equity delta $\delta(t,T)$. Both models assume constant default-free interest rates, which allow us to concentrate on the relationship between the equity price and CDS spread, also exploited in the relative value strategy.

A.1 CreditGrades

The default barrier is given by

$$LD = \bar{L}De^{\lambda Z-\lambda^2/2}, \tag{18}$$

where L is the random recovery rate given default, $\bar{L} = E(L)$, Z is a standard normal random variable and $\lambda^2 = Var(\ln L)$. Finger (2002) provides an approximate solution to the survival probability using a time-shifted Brownian motion, which yields the following result[20]

$$q(t) = \Phi\left(-\frac{A_t}{2} + \frac{\ln d}{A_t}\right) - d \cdot \Phi\left(-\frac{A_t}{2} - \frac{\ln d}{A_t}\right), \tag{19}$$

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

$$\begin{aligned} d &= \frac{V_0}{\bar{L}D}e^{\lambda^2}, & (20)\\ A_t^2 &= \sigma_V^2 t + \lambda^2. & (21) \end{aligned}$$

A.1.1 The CDS Spread and Hedge Ratio

Assuming constant interest rates, the CDS spread for maturity T is found by inserting the survival probability (19) in equation (6), yielding

$$c(0,T) = r(1-R)\frac{1-q(0)+H(T)}{q(0)-q(T)e^{-rT}-H(T)}, \tag{22}$$

[20] In essence, the uncertainty in the default barrier is shifted to the starting value of the Brownian motion. In particular, the approximation assumes that W_t starts at an earlier time than $t=0$. As a result, the default probability is non-zero for even very small t, including $t=0$. In other models such as Leland & Toft (1996), the survival probability $q(0)=1$.

where

$$
\begin{aligned}
H(T) &= e^{r\xi}\left(G(T+\xi)-G(\xi)\right), && (23)\\
G(T) &= d^{z+1/2}\Phi\left(-\frac{\ln d}{\sigma_V\sqrt{T}}-z\sigma_V\sqrt{T}\right)+d^{-z+1/2}\Phi\left(\frac{\ln d}{\sigma_V\sqrt{T}}+z\sigma_V\sqrt{T}\right) && (24)\\
\xi &= \frac{\lambda^2}{\sigma_V^2}, && (25)\\
z &= \sqrt{\frac{1}{4}+\frac{2r}{\sigma_V^2}}, && (26)
\end{aligned}
$$

and $G(T)$ is given in Reiner & Rubinstein (1991).

When determining the hedge ratio corresponding to the model spread, we assume that t is small compared to the maturity of the CDS contract T. Following Yu (2006), the contract value (7) is then approximated by

$$
\begin{aligned}
\pi(0,T) &= \left(c(0,T)-c\right)\int_0^T e^{-rs}q(s)\,ds && (27)\\
&= \frac{c(0,T)-c}{r}\left(q(0)-q(T)e^{-rT}-H(T)\right),
\end{aligned}
$$

where $c(0,T)$ is a function of the value of equity in equation (22), and c is the market spread at initiation.[21]

Using equation (8) and the product rule, the hedge ratio is found as

$$
\delta(0,T) = N*\frac{d\pi(0,T)}{dS} = \frac{N}{r}\frac{\partial c(0,T)}{\partial S}\left(q(0)-q(T)e^{-rT}-H(T)\right), \qquad (28)
$$

where N denotes the number of shares outstanding. The second term in the product rule is zero, since by definition c is numerically equal to $c(0,T)$, evaluated at the equity value S. Finally, $\frac{\partial c(0,T)}{\partial S}$ is found numerically.

A.2 Leland & Toft (1996)

Equation (14) may be written as

$$
v(V_t) = V_t + \tau\frac{C}{r}\left(1-\left(\frac{V_t}{V_B}\right)^{-x}\right) - \alpha V_B\left(\frac{V_t}{V_B}\right)^{-x}, \qquad (29)
$$

[21] Yu (2006) interprets this equation in his appendix. Equation (27) represents the value of a contract entered into one instant ago at spread c, that now has a quoted spread of $c(0,T)$ due to a change in the value of equity.

with the value of debt $D(V_t)$

$$D(V_t) = \frac{C}{r} + \left(P - \frac{C}{r}\right)\left(\frac{1-e^{r\Upsilon}}{r\Upsilon} - I\left(\Upsilon\right)\right) + \left(\left(1-\alpha\right)V_B - \frac{C}{r}\right) J\left(\Upsilon\right), \quad (30)$$

and equity $S(V_t)$

$$\begin{aligned} S(V_t) = V_t + \tau\frac{C}{r}\left(1 - \left(\frac{V_t}{V_B}\right)^{-x}\right) - \alpha V_B\left(\frac{V_t}{V_B}\right)^{-x} \\ - \frac{C}{r} - \left(P - \frac{C}{r}\right)\left(\frac{1-e^{r\Upsilon}}{r\Upsilon} - I\left(\Upsilon\right)\right) \\ - \left(\left(1-\alpha\right)V_B - \frac{C}{r}\right) J\left(\Upsilon\right), \end{aligned} \quad (31)$$

and default barrier V_B

$$V_B = \frac{\frac{C}{r}\left(\frac{A}{r\Upsilon} - B\right) - \frac{AP}{r\Upsilon} - \frac{\tau C x}{r}}{1 + \alpha x - \left(1-\alpha\right)B}. \quad (32)$$

The components of the above formulae are

$$\begin{aligned} A &= 2ae^{-r\Upsilon}\Phi\left(a\sigma_V\sqrt{\Upsilon}\right) - 2z\Phi\left(z\sigma_V\sqrt{\Upsilon}\right) && (33) \\ &\quad -\frac{2}{\sigma_V\sqrt{\Upsilon}}\phi\left(z\sigma_V\sqrt{\Upsilon}\right) + \frac{2e^{-r\Upsilon}}{\sigma_V\sqrt{\Upsilon}}\phi\left(a\sigma_V\sqrt{\Upsilon}\right) + \left(z-a\right), \\ B &= -\left(2z + \frac{2}{z\sigma_V^2\Upsilon}\right)\Phi\left(z\sigma_V\sqrt{\Upsilon}\right) && (34) \\ &\quad -\frac{2}{\sigma_V\sqrt{\Upsilon}}\phi\left(z\sigma_V\sqrt{\Upsilon}\right) + \left(z-a\right) + \frac{1}{z\sigma_V^2\Upsilon}, && (35) \\ I\left(\Upsilon\right) &= \frac{1}{r\Upsilon}\left(K\left(\Upsilon\right) - e^{-r\Upsilon}F\left(\Upsilon\right)\right), && (36) \end{aligned}$$

$$K\left(\Upsilon\right) = \left(\frac{V}{V_B}\right)^{-a+z}\Phi\left(j_1\left(\Upsilon\right)\right) + \left(\frac{V}{V_B}\right)^{-a-z}\Phi\left(j_2\left(\Upsilon\right)\right), \quad (37)$$

$$F\left(\Upsilon\right) = \Phi\left(h_1\left(\Upsilon\right)\right) + \left(\frac{V}{V_B}\right)^{-2a}\Phi\left(h_2\left(\Upsilon\right)\right), \quad (38)$$

$$
\begin{aligned}
J(\Upsilon) &= \frac{1}{z\sigma_V\sqrt{\Upsilon}}\left(-\left(\frac{V}{V_B}\right)^{-a+z}\Phi\left(j_1(\Upsilon)\right)j_1(\Upsilon)\right. && (39)\\
&\quad \left.+\left(\frac{V}{V_B}\right)^{-a-z}\Phi\left(j_2(\Upsilon)\right)j_2(\Upsilon)\right), && (40)\\
j_1(\Upsilon) &= \frac{\left(-b-z\sigma_V^2\Upsilon\right)}{\sigma_V\sqrt{\Upsilon}};\ j_2(\Upsilon)=\frac{\left(-b+z\sigma_V^2\Upsilon\right)}{\sigma_V\sqrt{\Upsilon}}, && (41)\\
h_1(\Upsilon) &= \frac{\left(-b-a\sigma_V^2\Upsilon\right)}{\sigma_V\sqrt{\Upsilon}};\ h_2(\Upsilon)=\frac{\left(-b+a\sigma_V^2\Upsilon\right)}{\sigma_V\sqrt{\Upsilon}}, && (42)\\
a &= \frac{\left(r-\rho-(\sigma_V^2/2)\right)}{\sigma_V^2}, && (43)\\
b &= \ln\left(\frac{V_t}{V_B}\right), && (44)\\
z &= \frac{\sqrt{\left(\left(a\sigma_V^2\right)^2+2r\sigma_V^2\right)}}{\sigma_V^2}, && (45)\\
x &= a+z. && (46)
\end{aligned}
$$

$\phi(\cdot)$ and $\Phi(\cdot)$ denote the density of the normal distribution and the cumulative distribution function, respectively.

A.2.1 The CDS Spread and Hedge Ratio

Using equation (38), the risk-neutral survival probability at horizon t is

$$
\begin{aligned}
q(t) &= 1-F(t) && (47)\\
&= 1-\left(\Phi\left(h_1(t)\right)+\left(\frac{V}{V_B}\right)^{-2a}\Phi\left(h_2(t)\right)\right).
\end{aligned}
$$

Assuming constant interest rates, the CDS spread for maturity T is found by inserting the survival probability (47) in equation (6), yielding

$$
0 = c(0,T)\int_0^T e^{-rs}q(s)ds+(1-R)\int_0^T e^{-rs}q'(s)ds. \tag{48}
$$

Integrating the first term by parts, yields

$$
0 = \frac{c(0,T)}{r}\left(1-e^{-rT}q(T)+\int_0^T e^{-rs}q'(s)ds\right)+(1-R)\int_0^T e^{-rs}q'(s)ds, \tag{49}
$$

where the integral $\int_0^T e^{-rs} q'(s) ds$ is given by $K(T)$ in equation (37), following Reiner & Rubinstein (1991). Then,

$$0 = \frac{c(0,T)}{r} \left(1 - e^{-rT} q(T)\right) - \left(\frac{c(0,T)}{r} + (1-R)\right) K(T), \tag{50}$$

which allows us to obtain a closed-form solution for the CDS spread

$$c(0,T) = r\,(1-R) \frac{K(T)}{(1 - e^{-rT} q(T) - K\,(T))}. \tag{51}$$

Again, following Yu (2006) when determining the hedge ratio that correspond to the model spread, we assume that t is small compared to the maturity of the CDS contract T. Then, the contract value (7) is approximated by

$$\begin{aligned} \pi(0,T) &= (c\,(0,T) - c) \int_0^T e^{-rs} q\,(s)\,ds. \\ &= \frac{c\,(0,T) - c}{r} \left(1 - e^{-rT} q(T) - K\,(T)\right), \end{aligned} \tag{52}$$

where $c\,(0,T)$ is a function of the value of equity in equation (51), and c is the market spread at initiation.

Similar to CreditGrades, the hedge ratio is found using equation (8)

$$\delta\,(0,T) = \frac{N}{r} \frac{\partial c\,(0,T)}{\partial S} \left(1 - e^{-rT} q(T) - K\,(T)\right). \tag{53}$$

However, in Leland & Toft (1996) the CDS spread is not an explicit function of the equity value. Therefore, $\frac{\partial c(0,T)}{\partial S}$ is found numerically using

$$\frac{\partial c\,(0,T)}{\partial S} = \frac{\partial c\,(0,T)}{\partial V} \frac{\partial V}{\partial S} = \frac{\partial c\,(0,T)}{\partial V} \frac{1}{\frac{\partial S}{\partial V}}. \tag{54}$$

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Table 1: Sample Characteristics

This table reports sample characteristics for the 221 obligors. First, the average characteristics are calculated for each obligor over time, then averaged across ratings. N is the number of obligors and spread is the composite CDS quote. While the historical equity volatility HV is calculated from a 250-day rolling window of equity returns, the implied equity volatility IV is inferred from 30-day at-the-money put options. The leverage ratio lev is total liabilities divided by the sum of total liabilities and equity market capitalization, and size is the sum of total liabilities and equity market capitalization in millions of dollars. Finally, $corr$ is the correlation between changes in the CDS spread and the equity value, averaged across ratings.

Rating	N	Spread	HV	IV	Lev.	Size	Corr.
AAA	4	16	0.284	0.227	0.197	142,619	-0.107
AA	11	23	0.267	0.257	0.216	95,237	-0.050
A	80	40	0.305	0.293	0.354	40,274	-0.089
BBB	109	103	0.346	0.337	0.502	25,431	-0.124
BB	15	270	0.386	0.377	0.524	13,667	-0.056
B	1	355	0.554	0.555	0.564	34,173	-0.261
NR	1	172	0.229	0.219	0.450	11,766	-0.129

Table 2: Descriptive Statistics of Implied Parameters

This table reports the central implied parameters from CreditGrades and Leland & Toft (1996), calibrated with a historical volatility HV and option-implied volatility IV. While the first measure is calculated from a 250-day rolling window of equity returns, the latter is implied from 30-day at-the-money put options. The descriptive statistics for the payout rate, global recovery and bond recovery are calculated across obligors. The remaining variables are first averaged over time, before the statistics are calculated across obligors. The equity value, asset value and default barrier are measured in millions of dollars. The upper three rows report the summary statistics of calibration targets from the equity and equity options market. The global recovery rate is the mean global recovery on all liabilities of the firm, while the bond recovery is the recovery rate on the specific debt issue underlying the CDS. Finally, the payout rate is calculated from historical dividend yields and relative interest expenses.

Variable	Mean	Median	Std. dev.	Min	Max
Equity value	20,592	9,479	33,425	919	238,995
HV	0.329	0.313	0.106	0.175	0.989
IV	0.318	0.302	0.090	0.135	0.717
		Panel A. CreditGrades HV			
Asset value	29,895	14,839	46,655	1,360	337,381
Asset vol.	0.228	0.213	0.085	0.084	0.583
Default barrier	8,556	3,846	15,892	59	154,585
Global rec.	0.799	0.573	0.772	0.009	6.025
		Panel B. CreditGrades IV			
Asset value	26,189	12,914	40,418	1111	294,685
Asset vol.	0.232	0.227	0.079	0.0843	0.552
Default barrier	4,901	2,199	9,071	14	93,838
Global rec.	0.549	0.285	0.719	0.0097	5.715
		Panel C. Leland & Toft HV			
Asset value	34,837	18,100	53,727	2,008	417,807
Asset vol.	0.179	0.167	0.073	0.0382	0.446
Default barrier	12,445	5,939	32,871	591	374,849
Bond rec.	-17.410	-0.443	129.611	-1,858	0.919
Payout rate	0.020	0.020	0.011	0	0.059
		Panel D. Leland & Toft IV			
Asset value	34,502	17,897	52,035	1972	373,672
Asset vol.	0.167	0.156	0.069	0.0077	0.413
Default barrier	12,762	6,105	33,360	593	364,376
Bond rec.	-3.554	0.233	18.256	-222.69	0.835
Payout rate	0.020	0.020	0.011	0	0.059

Table 3: Holding Period Returns Based on CreditGrades

This table shows the holding period returns resulting from CreditGrades CG with a historical volatility HV and option-implied volatility IV. The maximum holding period HP is either 30 or 180 days. Trigger denotes the minimum threshold between the market and model spread before positions are initiated. Rating denotes whether the strategy is implemented on investment grade or speculative grade obligors. N is the number of trades, N_{conv} the number of trades ending in convergence, and Neg is the percentage of trades ending in negative return. The mean and median returns are in percentages.

Model	HP	Trigger	Rating	N	N_{conv}	Neg.	Mean	Median	Std.dev.	Min	Max
Panel A. CreditGrades Holding Period Returns (30 Days)											
CG HV	30	0.5	Inv	45,190	789	0.45	0.01	0.04	1.16	-24.39	25.42
		0.5	Spec	1,860	0	0.47	0.28	0.08	3.38	-11.07	16.66
CG IV	30	0.5	Inv	53,559	2,787	0.32	0.33	0.13	1.75	-23.22	66.22
		0.5	Spec	1,598	231	0.27	2.46	0.74	10.20	-28.57	90.18
CG HV	30	2	Inv	27,212	46	0.41	0.05	0.06	0.84	-9.09	25.42
		2	Spec	824	0	0.38	0.84	0.47	2.76	-6.63	12.41
CG IV	30	2	Inv	46,179	727	0.32	0.28	0.13	1.38	-17.80	38.64
		2	Spec	380	19	0.11	2.06	1.36	4.96	-3.31	89.76
Panel B. CreditGrades Holding Period Returns (180 Days)											
CG HV	180	0.5	Inv	45,190	7,088	0.40	-0.08	0.15	3.10	-36.25	35.88
		0.5	Spec	1,860	3	0.43	0.17	0.38	5.50	-24.02	15.18
CG IV	180	0.5	Inv	53,559	6,231	0.27	1.13	0.39	3.58	-25.18	89.74
		0.5	Spec	1,598	665	0.18	6.58	2.08	16.83	-28.46	124.99
CG HV	180	2	Inv	27,212	1,488	0.30	0.26	0.26	2.00	-26.99	14.84
		2	Spec	824	0	0.16	2.64	1.48	3.76	-6.42	15.18
CG IV	180	2	Inv	46,179	2,504	0.27	0.95	0.38	3.14	-12.87	58.71
		2	Spec	380	103	0.08	4.61	2.61	8.12	-0.63	100.52

Table 4: Holding Period Returns Based on Leland & Toft

This table shows the holding period returns resulting from Leland & Toft (1996) LT with a historical volatility HV and option-implied volatility IV. The maximum holding period HP is either 30 or 180 days. Trigger denotes the minimum threshold between the market and model spread before positions are initiated. Rating denotes whether the strategy is implemented on investment grade or speculative grade obligors. N is the number of trades, N_{conv} the number of trades ending in convergence, and Neg is the percentage of trades ending in negative return. The mean and median returns are in percentages.

Model	HP	Trigger	Rating	N	N_{conv}	Neg.	Mean	Median	Std.dev.	Min	Max
Panel A. Leland & Toft Holding Period Returns (30 Days)											
LT HV	30	0.5	Inv	50,196	1,857	0.41	0.15	0.07	1.39	-19.05	38.39
		0.5	Spec	2,496	81	0.33	0.99	0.61	4.35	-40.44	94.04
LT IV	30	0.5	Inv	54,708	3,305	0.32	0.31	0.13	1.64	-31.46	65.21
		0.5	Spec	2,438	337	0.27	2.48	0.88	10.04	-37.16	106.59
LT HV	30	2	Inv	36,673	260	0.38	0.13	0.08	0.99	-16.06	17.05
		2	Spec	1,598	4	0.31	0.86	0.59	2.37	-14.00	13.59
LT IV	30	2	Inv	45,139	1,239	0.32	0.24	0.12	1.22	-21.61	21.55
		2	Spec	1,370	101	0.21	2.76	0.88	11.17	-16.73	106.59
Panel B. Leland & Toft Holding Period Returns (180 Days)											
LT HV	180	0.5	Inv	50,196	7,964	0.35	0.49	0.22	3.01	-86.92	55.60
		0.5	Spec	2,496	226	0.21	2.90	1.67	5.96	-20.39	94.04
LT IV	180	0.5	Inv	54,708	7,966	0.28	1.07	0.37	3.62	-47.01	89.32
		0.5	Spec	2,438	673	0.13	7.02	2.41	17.20	-39.32	147.05
LT HV	180	2	Inv	36,673	2,428	0.31	0.42	0.25	2.02	-86.92	42.43
		2	Spec	1,598	11	0.16	3.14	1.67	4.16	-14.00	16.22
LT IV	180	2	Inv	45,139	3,921	0.28	0.82	0.34	2.94	-39.70	49.71
		2	Spec	1,370	194	0.09	5.47	2.26	12.66	-2.94	117.00

Table 5: Monthly Excess Returns

This table shows the summary statistics of monthly capital structure arbitrage excess returns resulting from CreditGrades CG and Leland & Toft (1996) LT, calibrated with a historical HV and option-implied volatility IV. The maximum holding period HP is 180 days. Trigger denotes the minimum threshold between the market and model spread before positions are initiated. Rating denotes whether the strategy is implemented on investment grade or speculative grade obligors. In case of a month with no trades, a zero excess return is assumed, and N denotes the number of months with non-zero returns. Neg is the fraction of months with negative excess return. The mean and median returns are in percentages, and the t-statistics for the means are corrected for a first-order serial correlation. Sharpe denotes the annualized Sharpe ratio. The coverage is 24 months from October 2002 to September 2004.

Model	HP	Trigger	Rating	N	Neg.	Mean	t-Stat.	Median	Min	Max	Skew.	Kurt.	Corr.	Sharpe
Panel A. CreditGrades Monthly Excess Returns														
CG HV	180	0.5	Inv	24	0.83	-0.25	-2.13	-0.19	-1.33	0.51	-0.61	1.36	0.36	-2.15
		0.5	Spec	22	0.58	-0.34	-0.76	-0.14	-4.06	2.59	-0.29	0.45	0.37	-0.78
CG IV	180	0.5	Inv	24	0.29	0.41	3.72	0.50	-0.37	1.75	0.68	0.52	0.29	2.63
		0.5	Spec	24	0.25	2.82	2.13	1.22	-6.47	22.06	1.86	3.40	0.02	1.51
CG HV	180	2	Inv	24	0.75	-0.18	-1.52	-0.11	-1.33	0.49	-1.24	2.87	0.43	-1.65
		2	Spec	22	0.21	0.93	2.31	1.04	-3.98	5.75	0.03	1.55	-0.04	1.63
CG IV	180	2	Inv	24	0.25	0.44	2.26	0.42	-0.37	3.22	2.48	8.65	0.27	2.07
		2	Spec	18	0.13	1.33	2.23	0.52	-1.74	13.43	3.38	13.60	-0.05	1.57
Panel B. Leland & Toft Monthly Excess Returns														
LT HV	180	0.5	Inv	24	0.58	0.01	0.06	-0.05	-1.02	1.20	0.41	2.26	0.26	0.04
		0.5	Spec	23	0.21	1.99	2.86	1.32	-2.64	12.50	1.78	3.57	0.06	2.02
LT IV	180	0.5	Inv	24	0.25	0.45	3.41	0.40	-0.37	2.16	1.08	1.00	0.32	2.41
		0.5	Spec	23	0.16	3.04	2.62	1.43	-3.51	18.39	1.97	3.24	-0.02	1.85
LT HV	180	2	Inv	24	0.63	-0.06	-0.82	-0.11	-0.82	0.61	0.05	0.71	0.06	-0.58
		2	Spec	18	0.13	-0.09	-0.10	0.51	-18.07	2.56	-4.20	19.24	0.06	-0.07
LT IV	180	2	Inv	24	0.25	0.27	3.64	0.25	-0.31	1.09	0.27	-0.04	0.28	2.56
		2	Spec	23	0.08	2.39	3.65	1.32	-1.17	12.50	1.85	3.43	0.13	2.57

Table 6: Regression Results

This table reports the results from regressing capital structure arbitrage monthly percentage excess returns on the excess returns of equity and bond market portfolios. The models underlying the strategy are CreditGrades CG and Leland & Toft (1996) LT, calibrated with a historical HV and option-implied volatility IV. The strategy is implemented separately on investment grade and speculative grade obligors. $S\&PINDS$ is the excess return on the S&P Industrial Index. $LHIBAAI$ and $LHHYBBI$ are the excess returns on the Lehman Brothers Baa and Ba Intermediate Index, respectively. The coverage is 24 months beginning October 2002 and ending September 2004. Standard errors are shown in parantheses, and ***, ** and * denote significance at 1, 5 and 10 percent, respectively.

Strategy	Intercept	S&PINDS	LHIBAAI	LHHYBBI	R^2
CG HV Inv	-0.57*	0.09	7.29	-14.40*	0.21
	(0.28)	(2.27)	(7.06)	(7.80)	
CG HV Spec	1.96	-2.61	-53.73	77.25*	0.17
	(1.48)	(12.02)	(37.30)	(41.19)	
CG IV Inv	-0.15	6.13	-26.18**	12.77	0.35
	(0.49)	(3.96)	(12.29)	(13.58)	
CG IV Spec	3.76	9.11	-45.06	81.11	0.16
	(2.21)	(18.00)	(55.87)	(61.70)	
LT HV Inv	-0.59**	1.51	-1.86	-8.44	0.32
	(0.21)	(1.74)	(5.41)	(5.98)	
LT HV Spec	1.76	33.36	39.03	-40.44	0.08
	(3.18)	(25.91)	(80.41)	(88.80)	
LT IV Inv	0.27	2.34	-13.22*	12.13*	0.32
	(0.24)	(1.98)	(6.78)	(6.14)	
LT IV Spec	7.04***	-22.35	-21.91	121.69*	0.30
	(2.22)	(18.04)	(55.98)	(61.82)	

Figure 1: Sears, Roebuck and Company

This figure illustrates the fundamentals behind capial structure arbitrage. In panel A, we depict market CDS spreads together with model spreads in Leland & Toft (1996) LT inferred from historical HV and option-implied volatilities IV. In panel B, the corresponding spreads are depicted based on CreditGrades CG. Panel C depicts the historical and option-implied volatility, where the first is calculated from a rolling 250-day window of equity returns, and the latter is inferred from 30-day at-the-money puts. Finally, panel D illustrates the total market value of equity in millions of dollars.

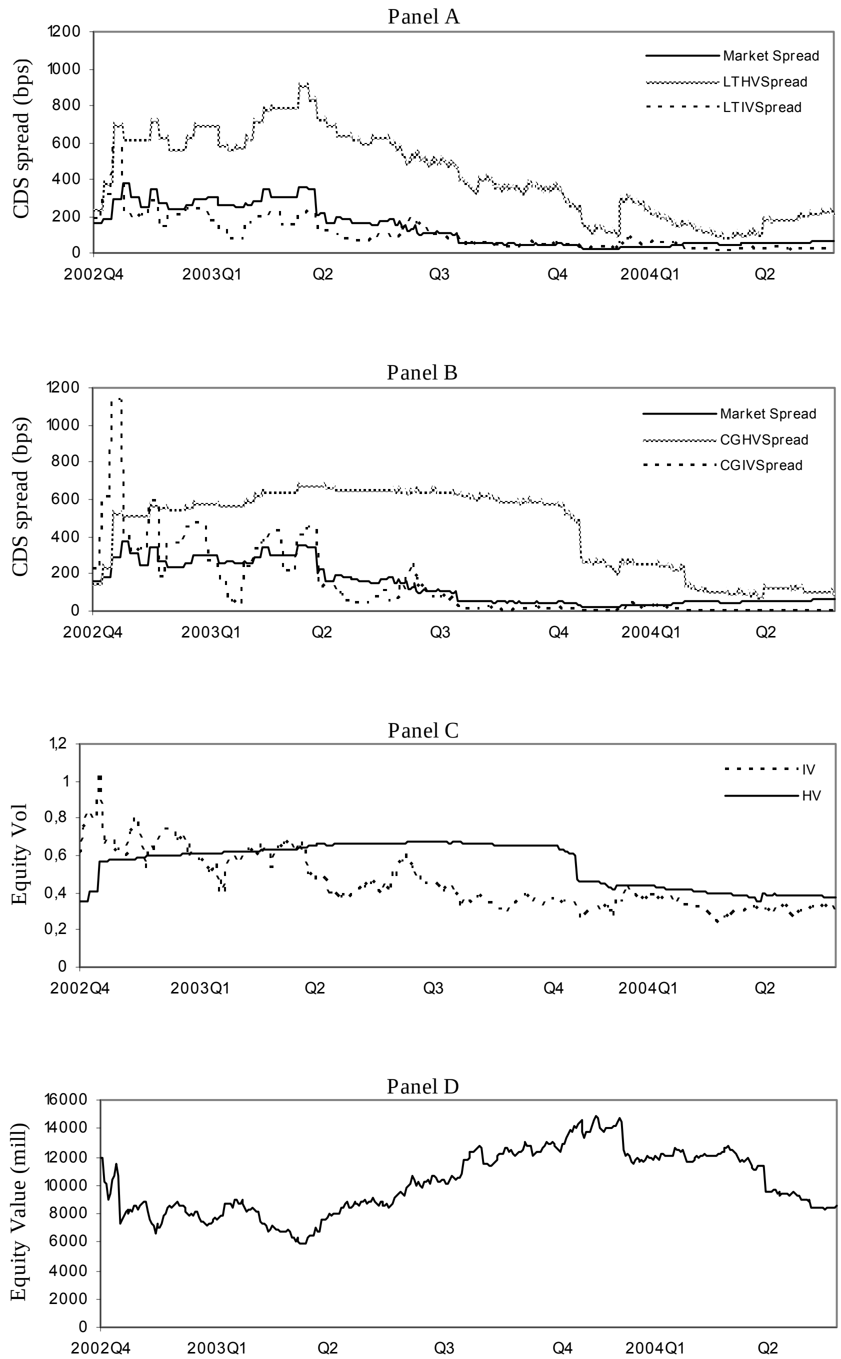

Figure 2: Time Warner

This figure illustrates the fundamentals behind capial structure arbitrage. In panel A, we depict market CDS spreads together with model spreads in Leland & Toft (1996) LT inferred from historical HV and option-implied volatilities IV. In panel B, the corresponding spreads are depicted based on CreditGrades CG. Panel C depicts the historical and option-implied volatility, where the first is calculated from a rolling 250-day window of equity returns, and the latter is inferred from 30-day at-the-money puts. Finally, panel D illustrates the total market value of equity in millions of dollars.

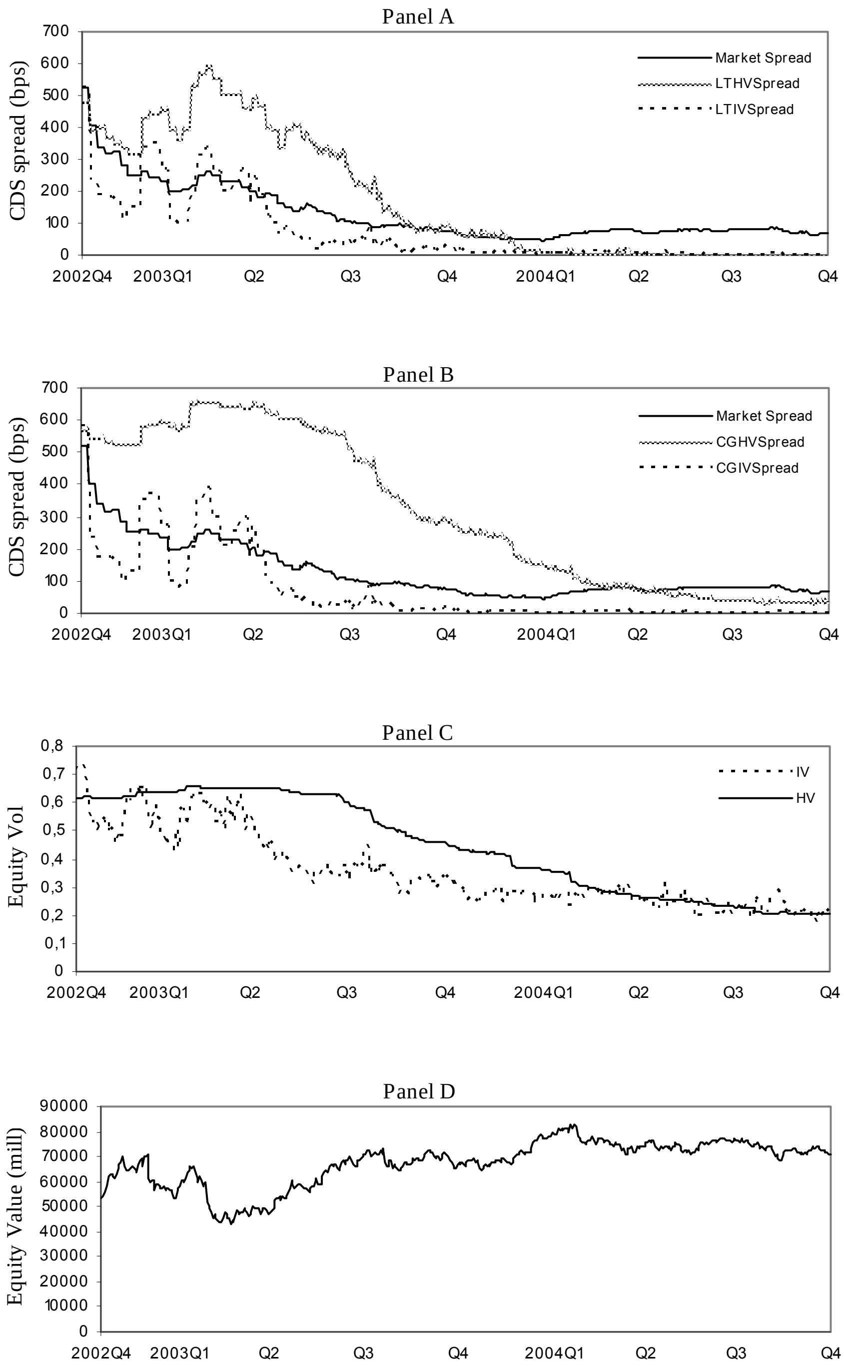

Figure 3: Motorola

This figure illustrates the fundamentals behind capial structure arbitrage. In panel A, we depict market CDS spreads together with model spreads in Leland & Toft (1996) LT inferred from historical HV and option-implied volatilities IV. In panel B, the corresponding spreads are depicted based on CreditGrades CG. Panel C depicts the historical and option-implied volatility, where the first is calculated from a rolling 250-day window of equity returns, and the latter is inferred from 30-day at-the-money puts. Finally, panel D illustrates the total market value of equity in millions of dollars.

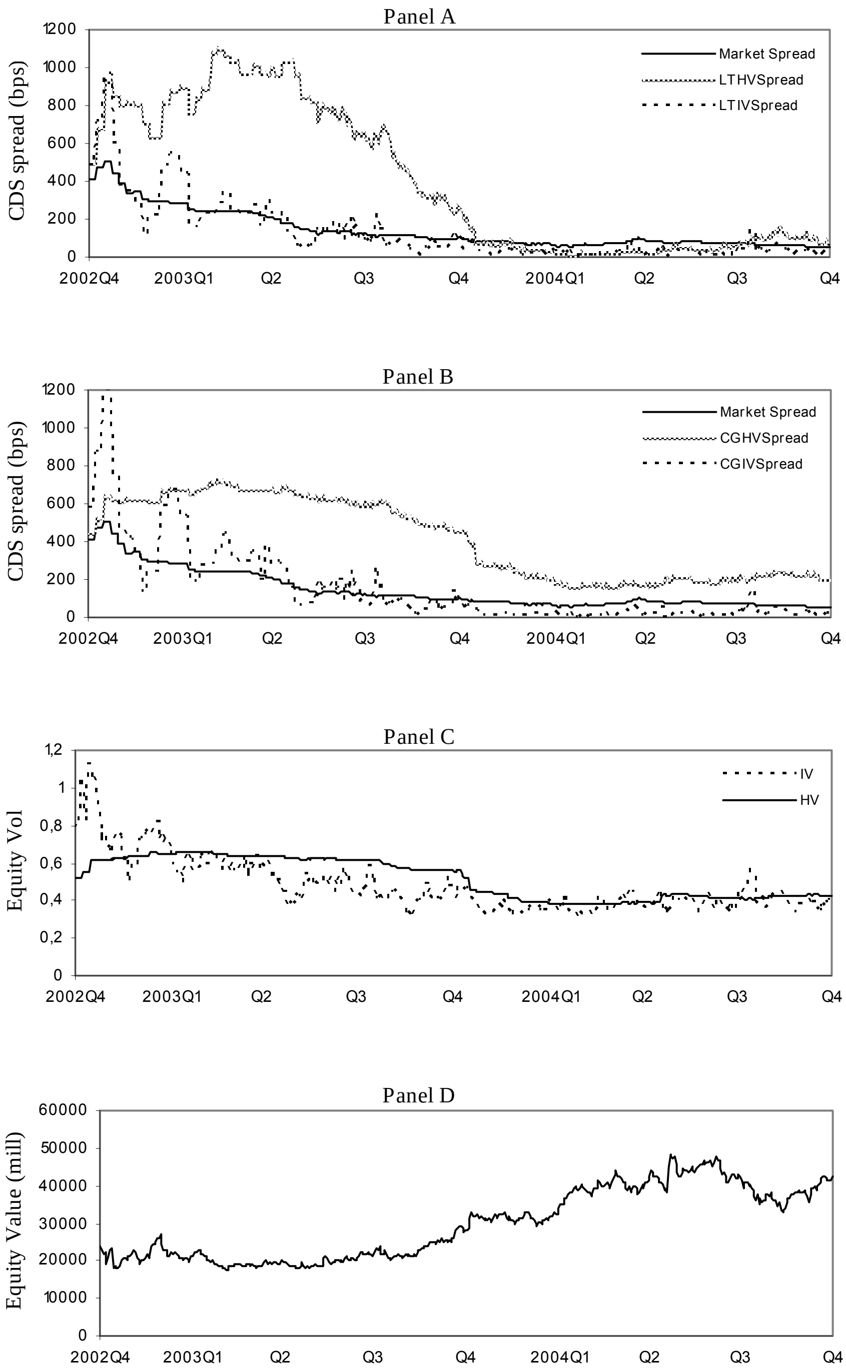

Figure 4: Mandalay Resort Group

This figure illustrates the fundamentals behind capial structure arbitrage. In panel A, we depict market CDS spreads together with model spreads in Leland & Toft (1996) LT inferred from historical HV and option-implied volatilities IV. In panel B, the corresponding spreads are depicted based on CreditGrades CG. Panel C depicts the historical and option-implied volatility, where the first is calculated from a rolling 250-day window of equity returns, and the latter is inferred from 30-day at-the-money puts. Finally, panel D illustrates the total market value of equity in millions of dollars.